GENERAL ASSEMBLY

NEURAL NETWORKS

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COURSE

PRE-WORK

PRE-WORK REVIEW

- Understand Logistic Regression and link functions
- Be familiar with training and testing classifiers and regressors

OPENING

ARTIFICIAL NEURAL NETWORKS

OPENING

- Neural networks were first studied in the 1940s (!) as a model of biological neural networks

- Many advances since then have improved the ability to train and apply neural networks

- Good for both classification and regression but difficult to interpret model behaviors

- Deep learning in the past few years has been highly successful for otherwise difficult problems

OPENING

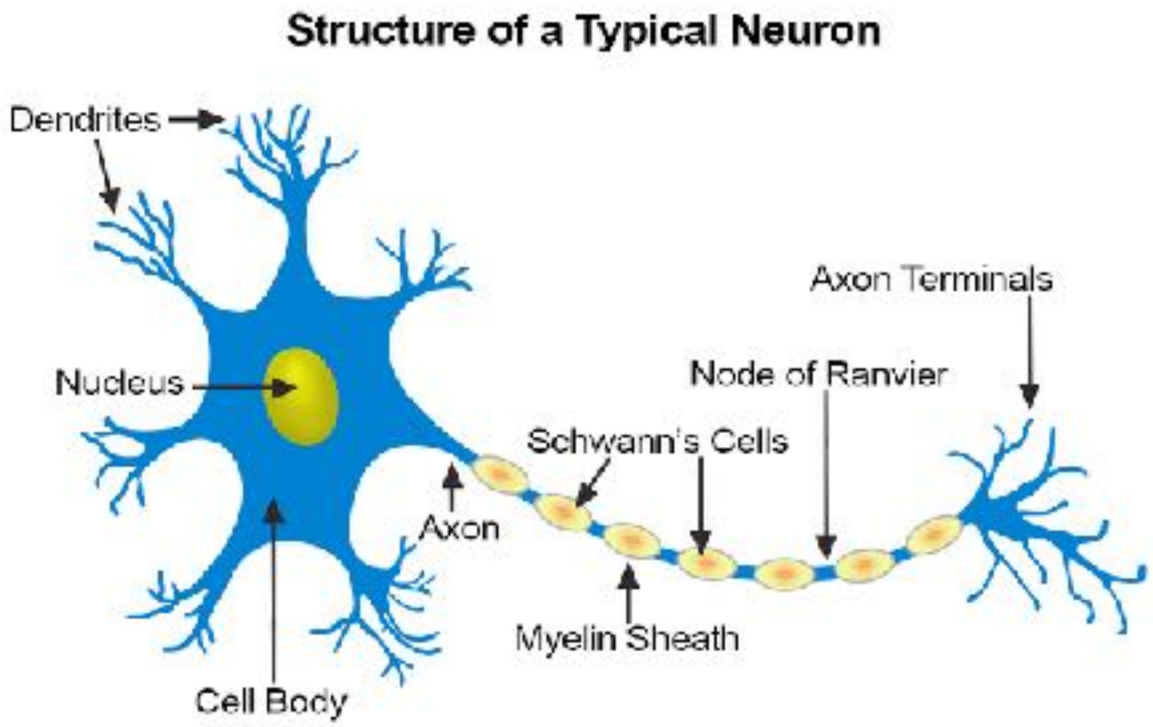
- Today we will focus on types of neural networks and their applications, and skip some of the more technical details
- Specifically we'll skip training neural networks -- there are many methods in various situations and the details can be tedious (but not particularly difficult)
- Methods include backpropagation, gradient descent, and Hessian-free learning

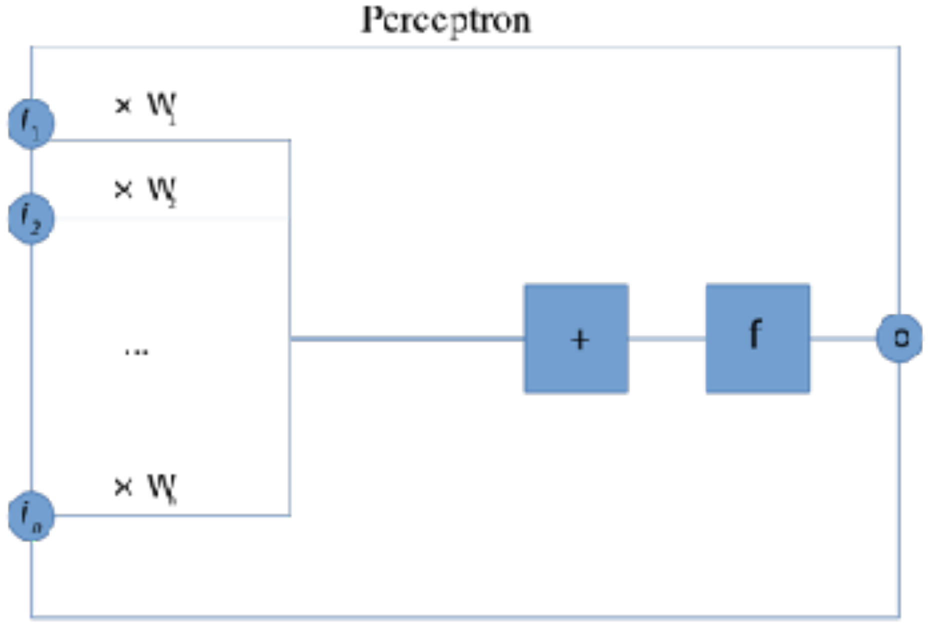
INTRODUCTION

PERCEPTRON

PERCEPTRON

- Perceptrons are the simplest example of a neural network
- The idea is to emulate a single neuron

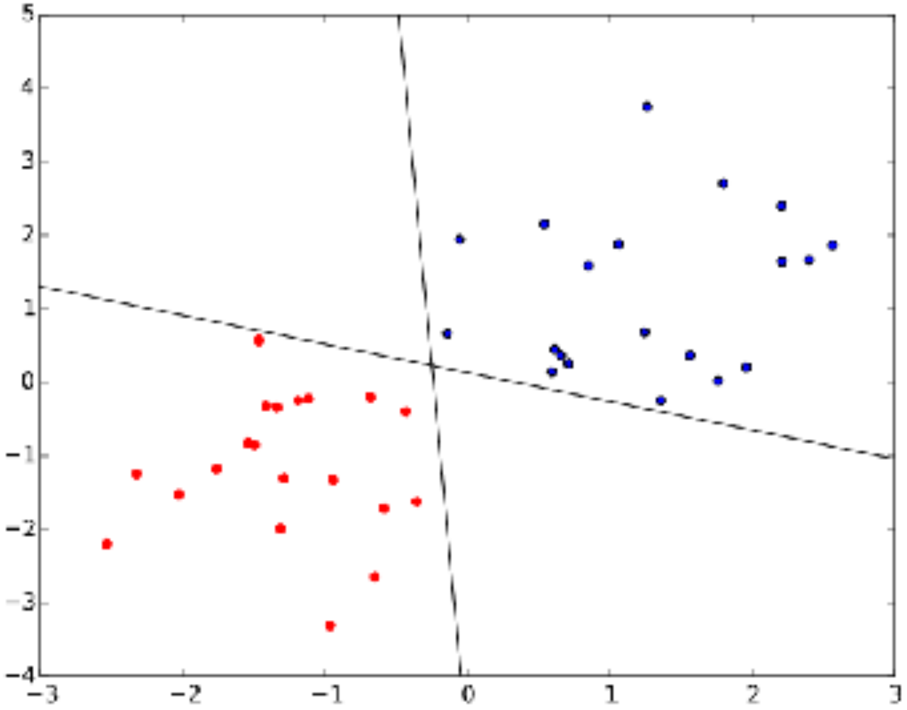


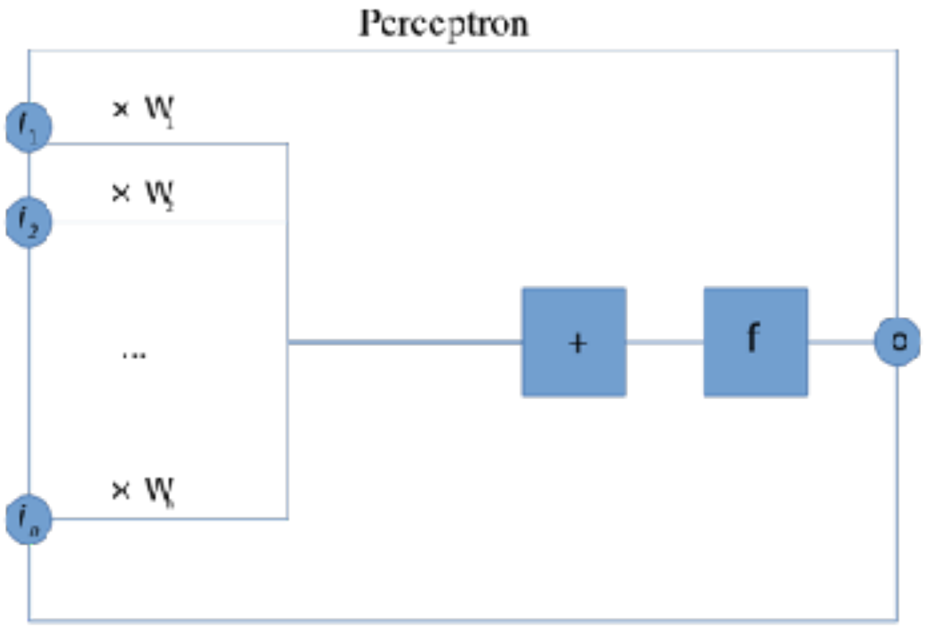


$$o = f\left(\sum_{k=1}^{n} i_k \cdot W_k\right)$$

PERCEPTRON

- Perceptrons are the simplest example of a neural network
- Given n inputs and an activation or link function f
- The perceptron computes a linear separating curve

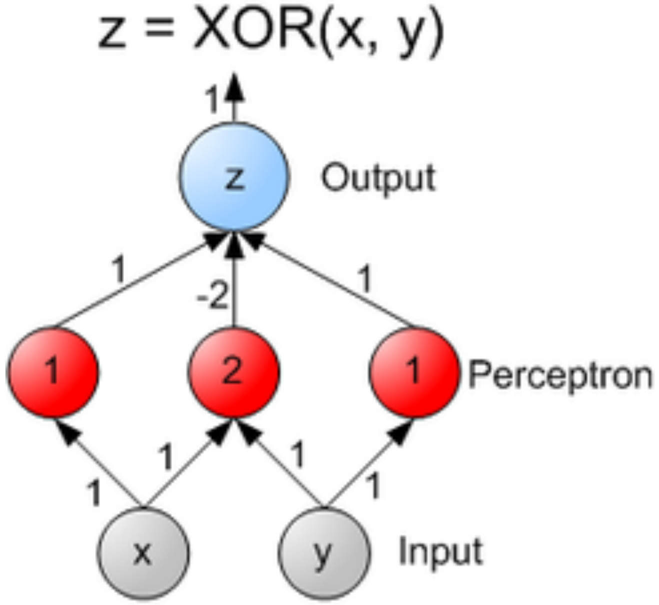




$$o = f\left(\sum_{k=1}^{n} i_k \cdot W_k\right)$$

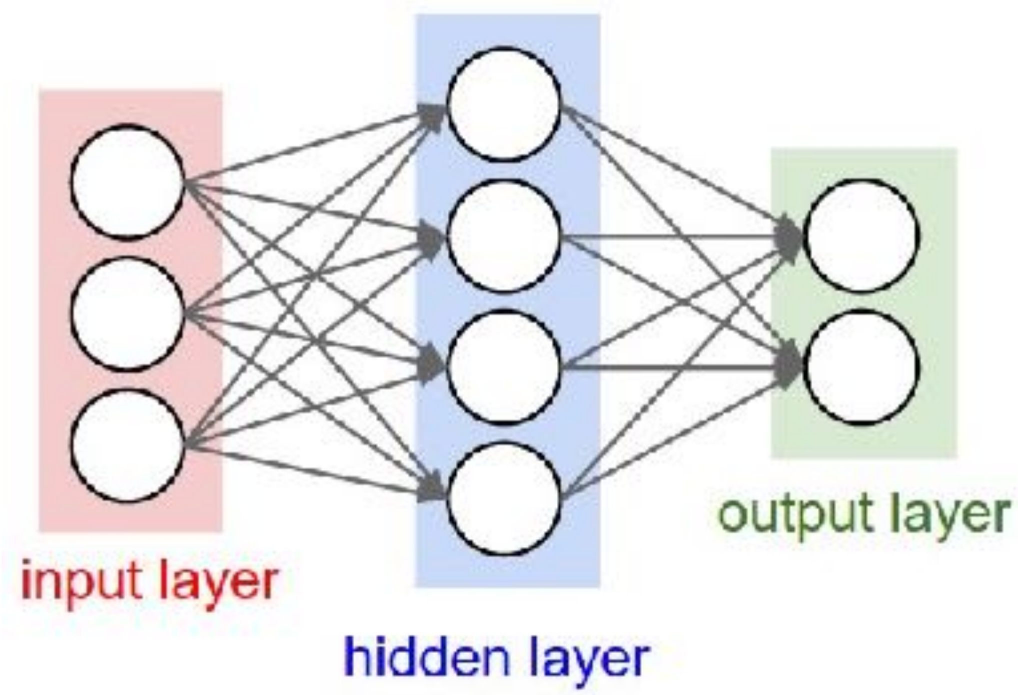
PERCEPTRON

- Common activation functions are linear, logistic, tanh, and softmax
- We'll see shortly that some are better for classification, some for regression
- Perceptrons can be combined into multilayer perceptrons or feed-forward network



FEED FORWARD NN

- Source



FEED FORWARD NN

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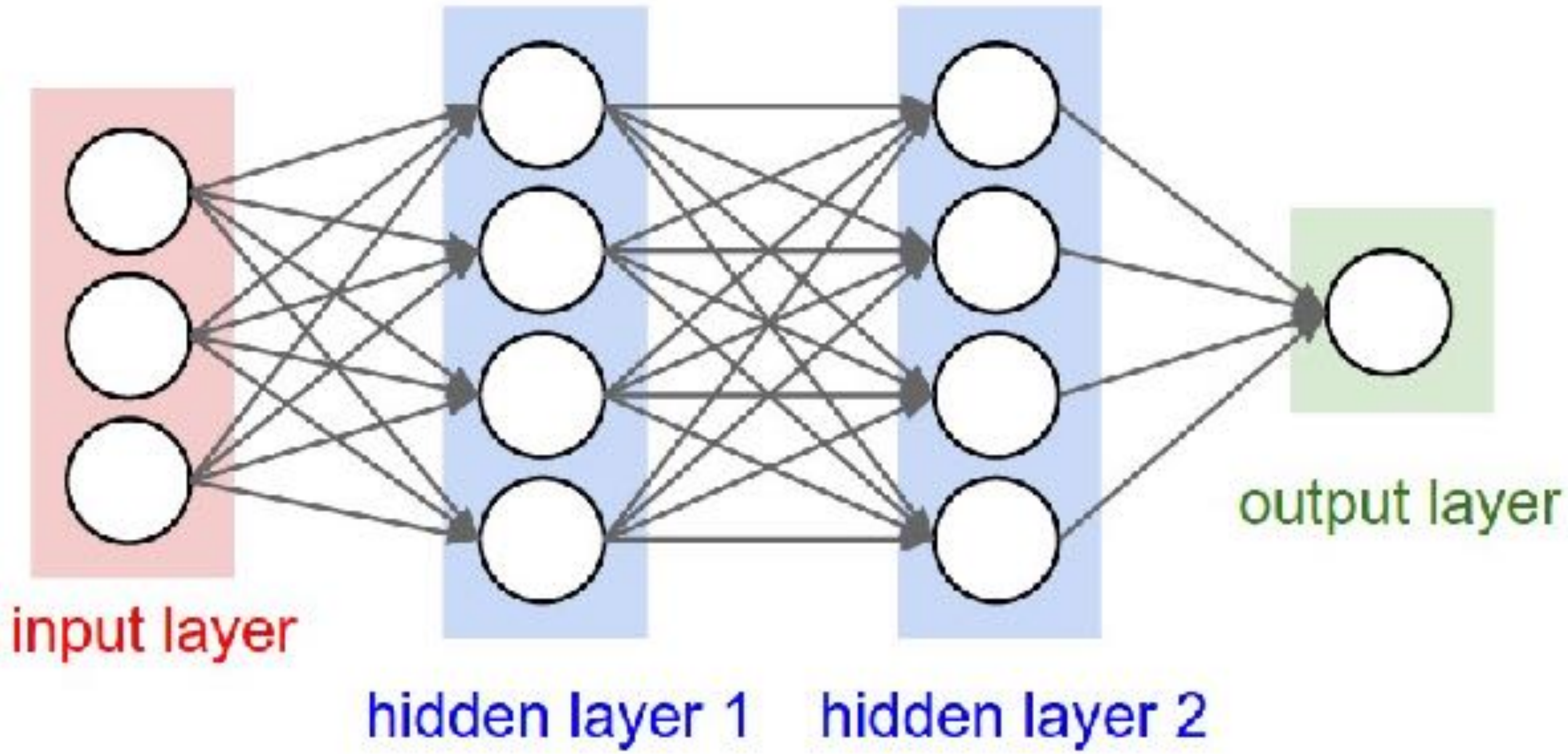

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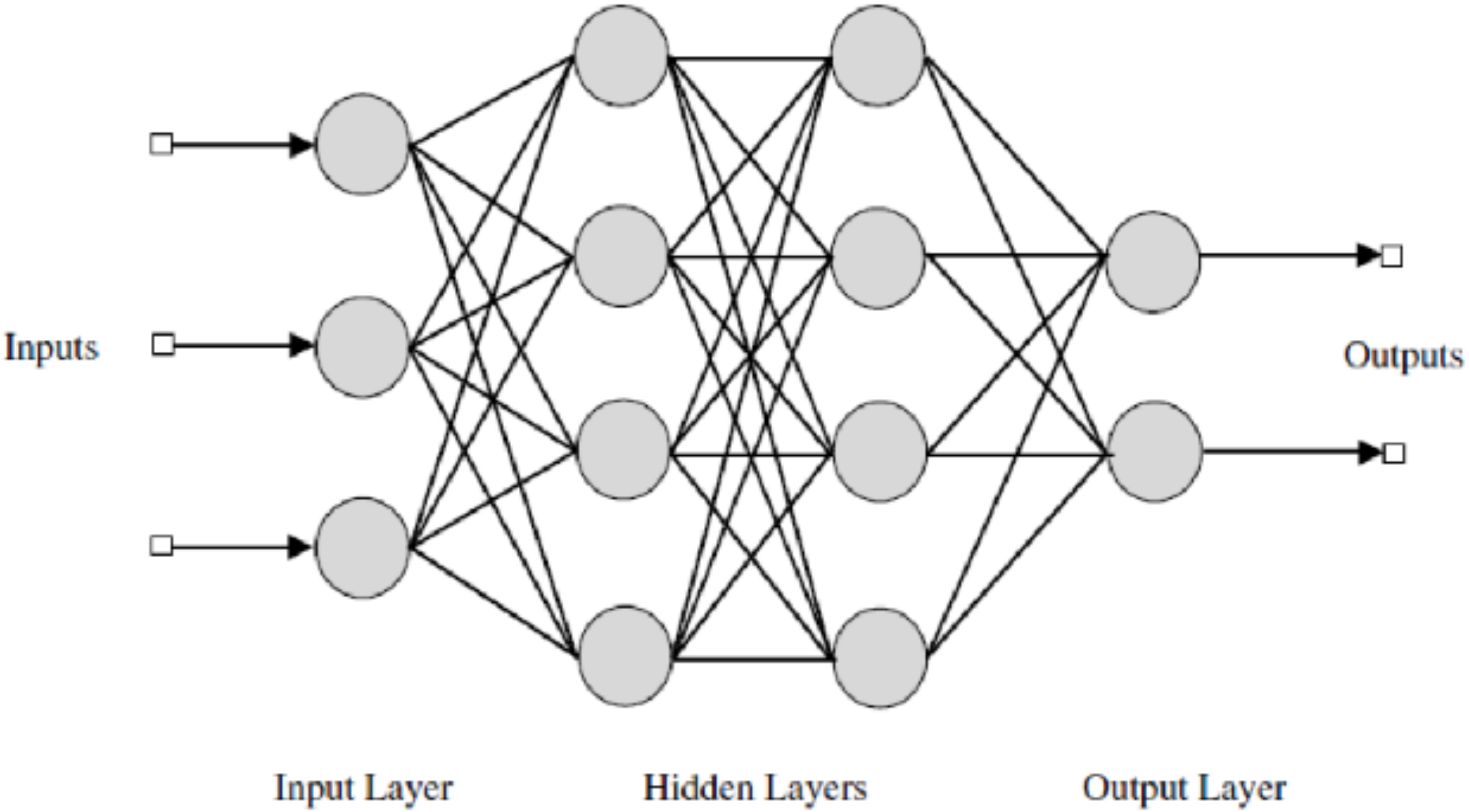

FEED FORWARD NN

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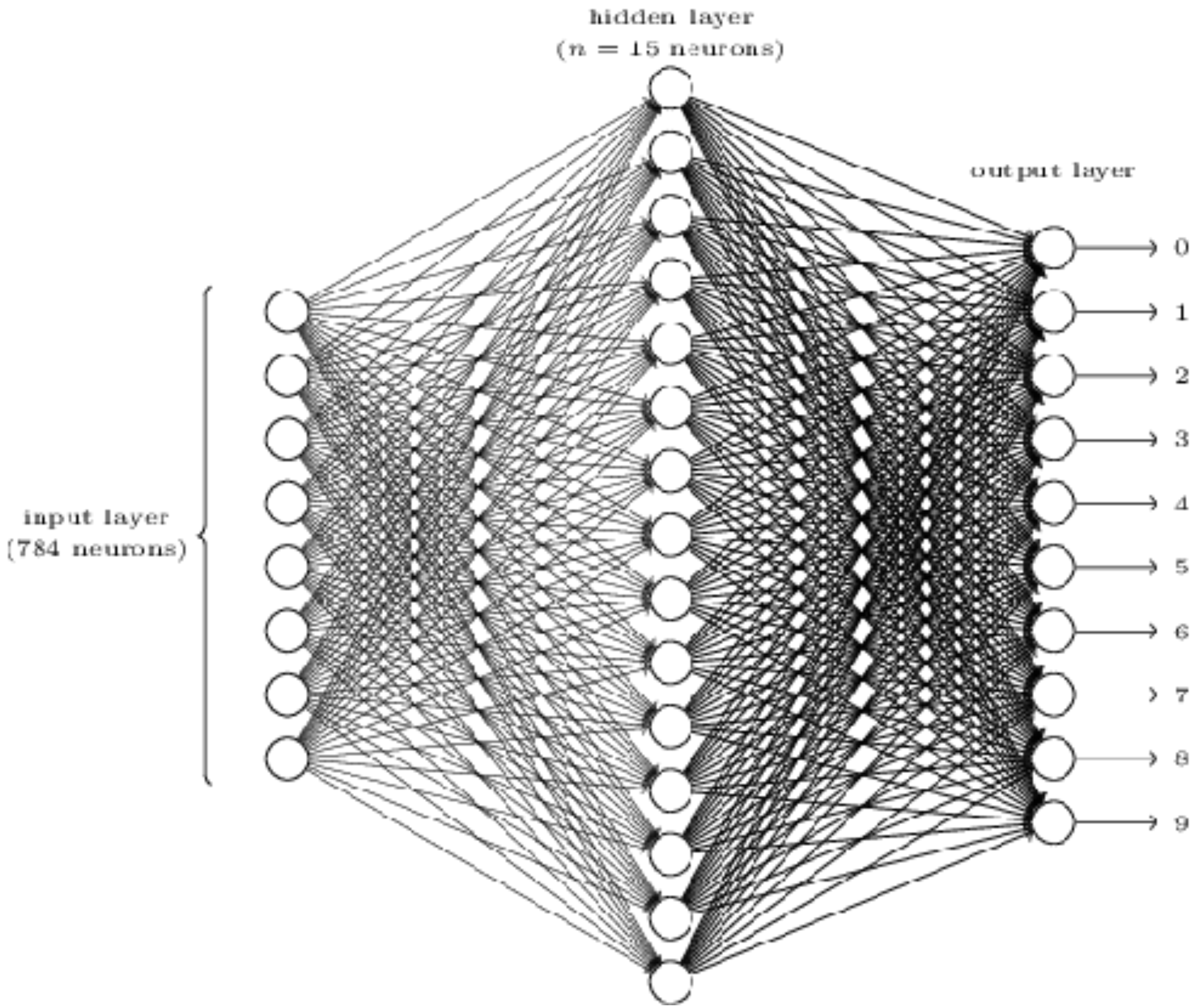


FEED FORWARD NN

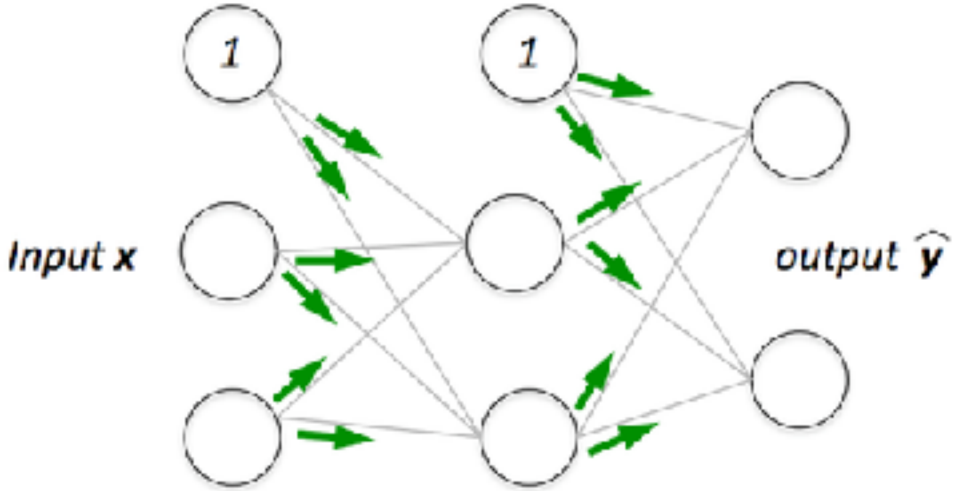
- Typically we use
    - Tanh or logistic layers for input
    - Linear layers for regression output
    - Logistic or Tanh for binary output
    - Softmax for n-class output (yields probabilities)

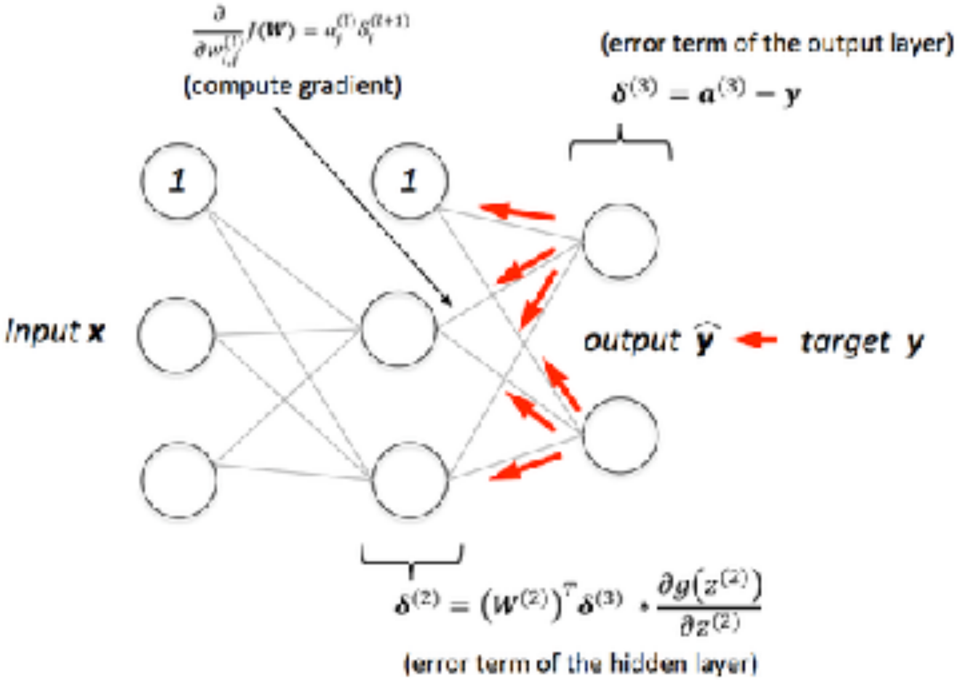
GUIDED PRACTICE

TRAINING

TRAINING

- Feed forward neural networks can be trained with backpropagation
- Source




$\frac{\partial}{\partial w_{ij}^{(l)}} J(W) = a_j^{(l)} \delta_i^{(l+1)}$
(compute gradient)
(error term of the output layer)
$\delta^{(3)} = a^{(3)} - y$
1
1
Input x
output $\hat{y}$
target y
$\delta^{(2)} = (W^{(2)})^T \delta^{(3)} \cdot \frac{\partial g(z^{(2)})}{\partial z^{(2)}}$
(error term of the hidden layer)

TRAINING

- Key Parameters
  - Learning Rate (gradient descent for training)
  - Epochs: number of backpropagation passes (over entire dataset)
  - Batch size: how many training points used at a time to update weights

- Model others behaves as usual with
  - model.predict
  - model.predict_classes

TRAINING

- Tips
    - If the error jumps around per epoch, decrease the learning rate
    - Taking too long to train: use higher learning rate or batch_size
    - High error after convergence?
        - More hidden layers / neurons
        - Normalize data or use PCA

INTRODUCTION

UNIVERSAL APPROXIMATION THEORY

UNIVERSAL APPROXIMATION

- One major reason that neural networks are useful is the Universal Approximation Theorem

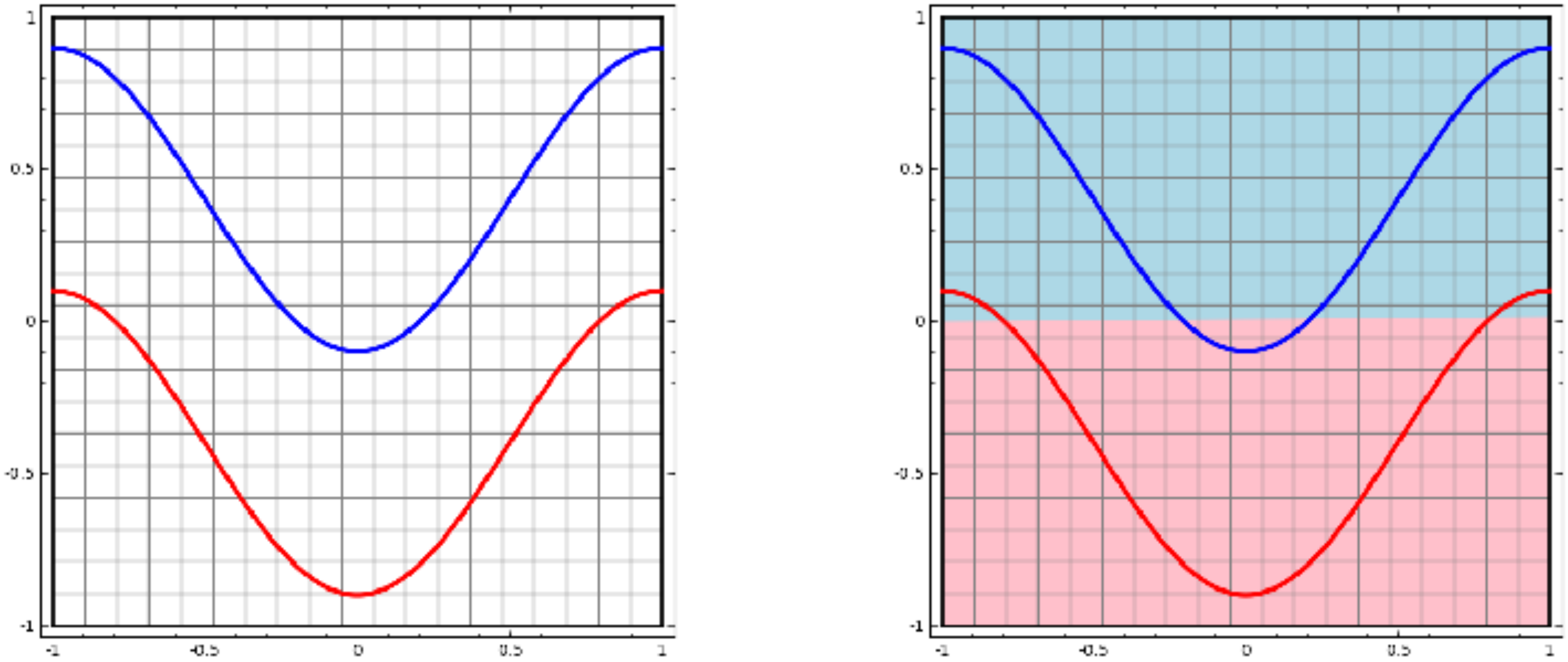
- The result basically says that many real vector-valued functions can be approximated arbitrarily well with *some* feed-forward neural network

- This is why neural networks are useful for regression -- given enough data and the right network structure they can fit many common data sets

CLASSIFICATION WITH NEURAL NETWORKS

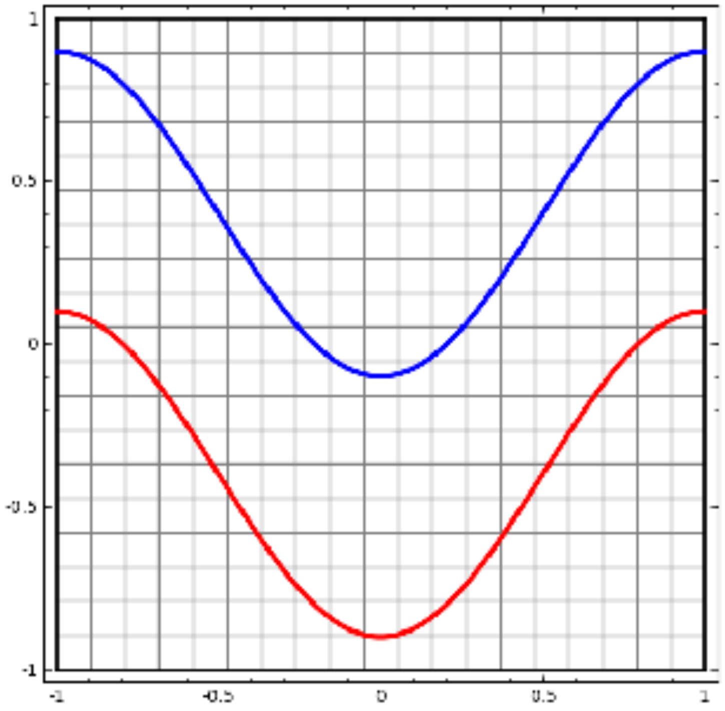
CLASSIFICATION

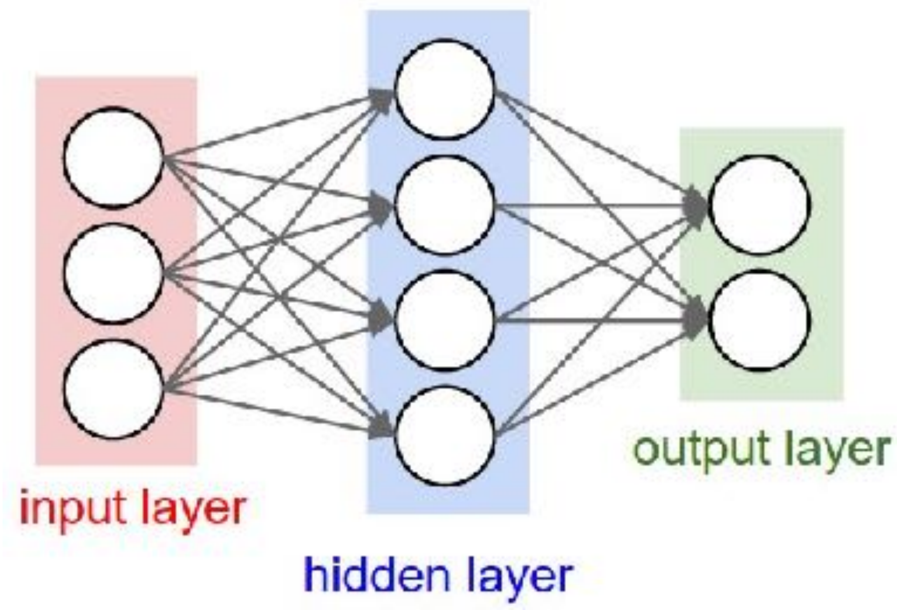
- Neural Networks are also extremely useful for classification (source)
- No hidden layers:

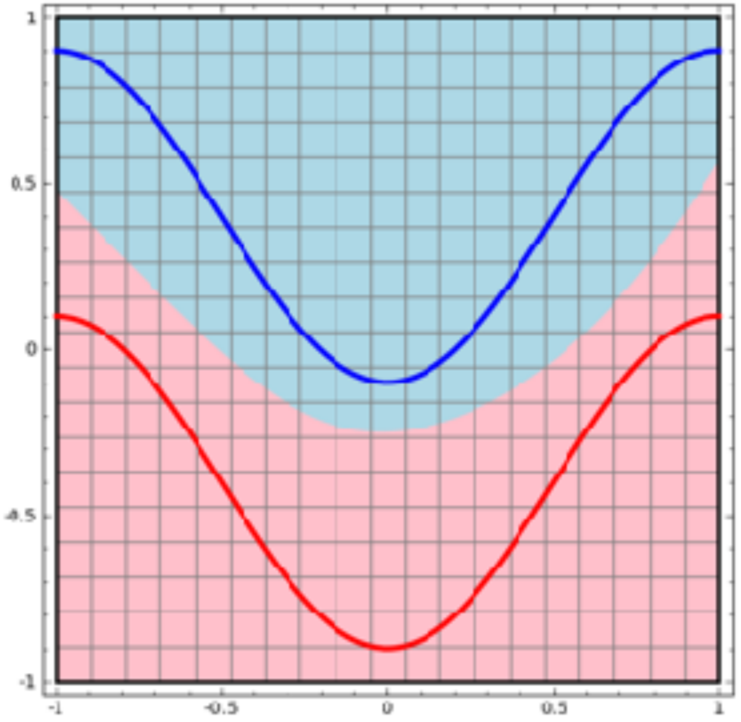


CLASSIFICATION

- Neural Networks are also extremely useful for classification (source)
- One hidden layer:







CLASSIFICATION

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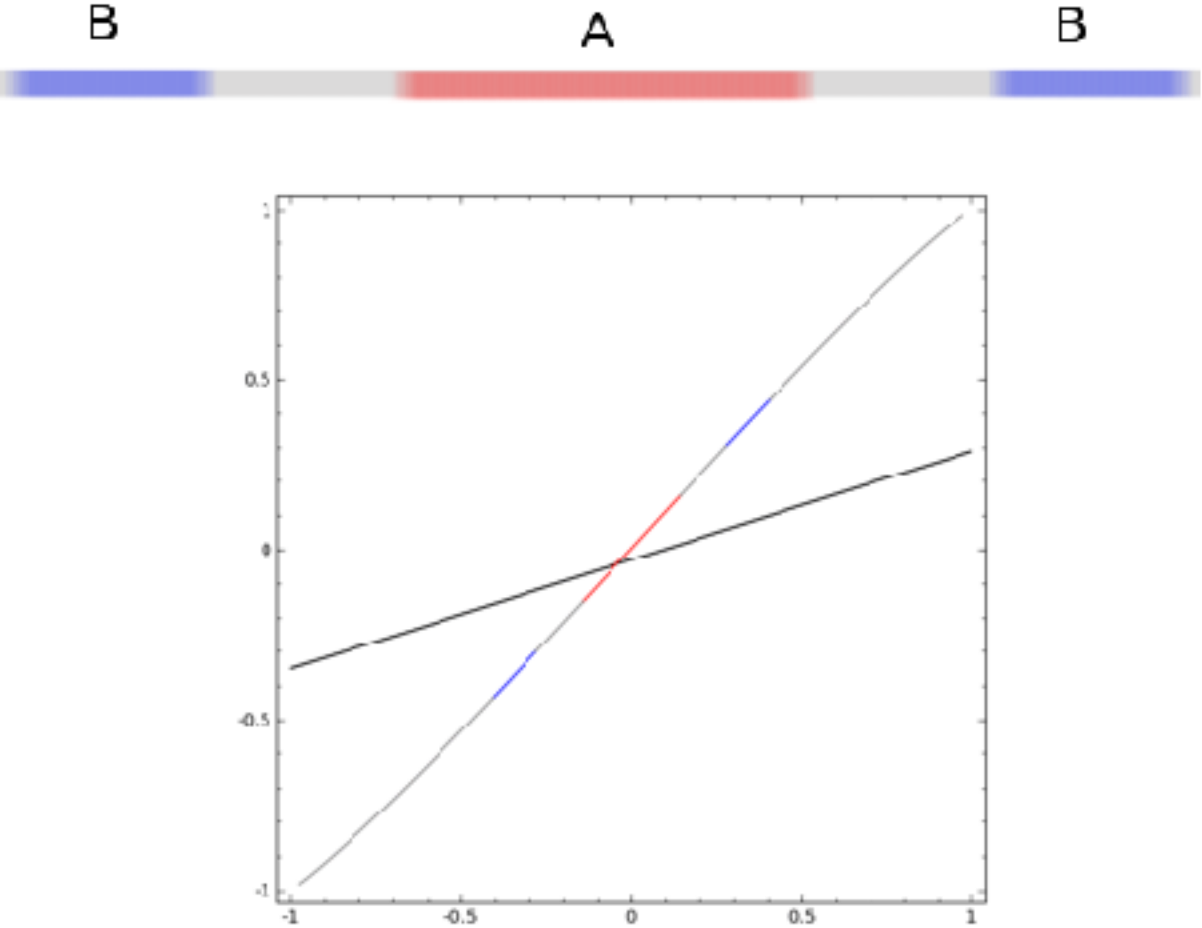
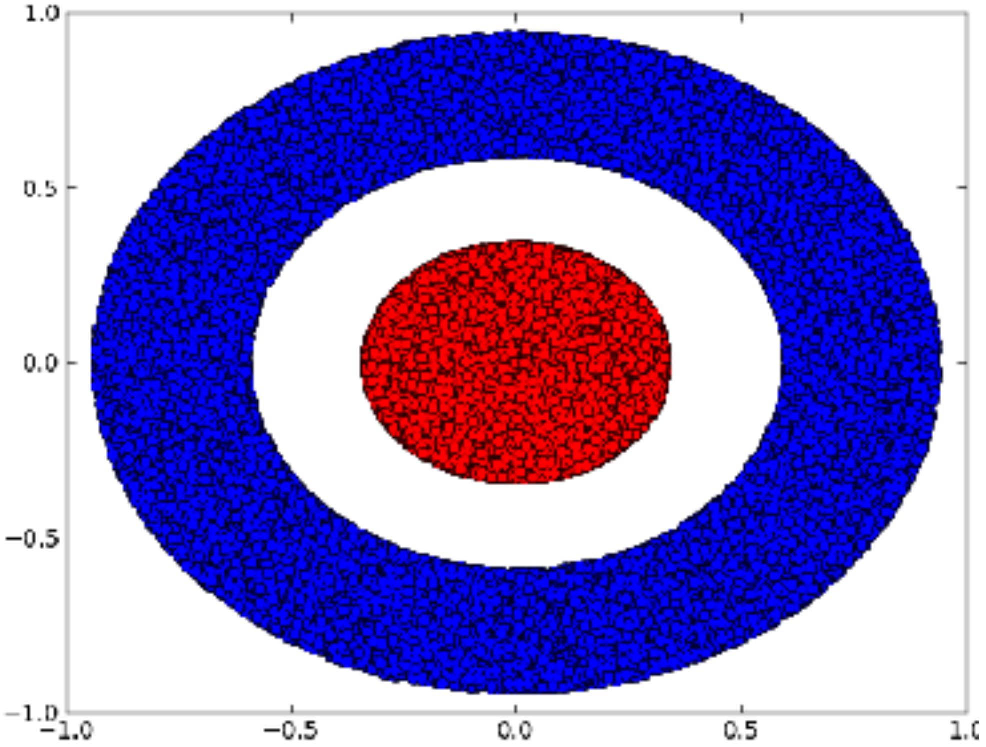
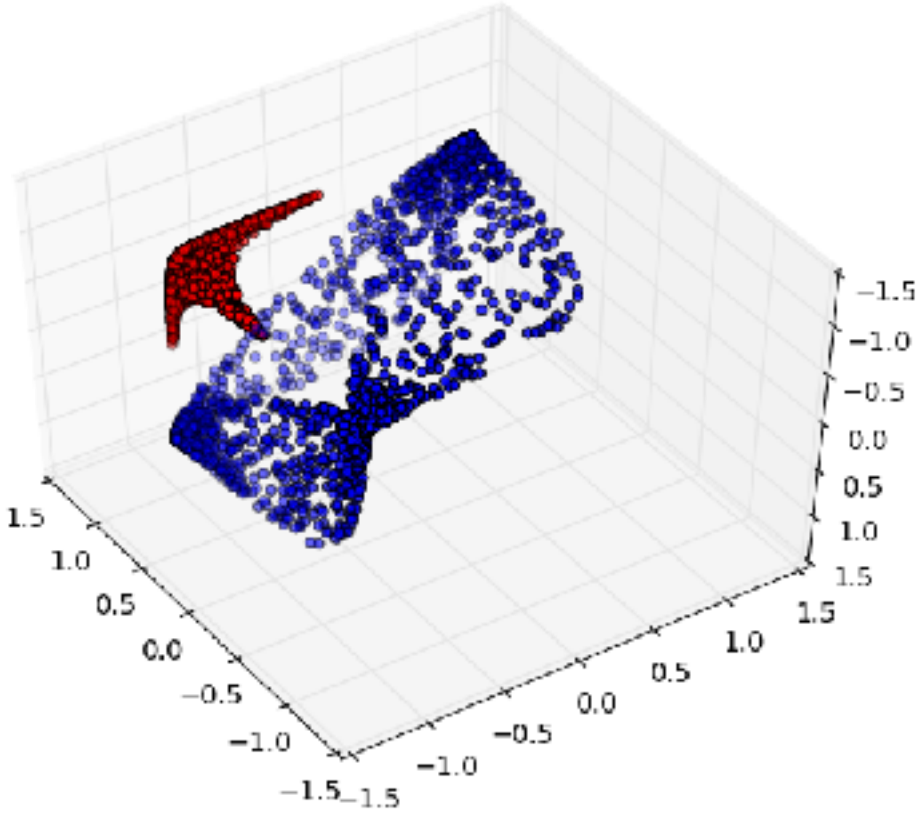


CLASSIFICATION

- Neural Networks are also extremely useful for classification (source)





CLASSIFICATION

- The neural network transforms the data topologically (no tears or breaks) and then separates the data with a hyperplane

- NNs are capable of handling difficult data sets, including:
    - Image processing: recognizing hand-written characters
    - Image compression
    - Financial forecasting
    - Many others

ACTIVITY: KNOWLEDGE CHECK

EXERCISE

ANSWER THE FOLLOWING QUESTIONS

1. Let’s practice using neural networks for classification. For each of the four datasets, experiment with the number of layers and neurons to find the best model
2. Also take a look at this visualization

DELIVERABLE

Answers to the above questions

GUIDED PRACTICE

NEURAL NETWORKS IN PYTHON

NN IN PYTHON

- There are many NN libraries for python and other languages
- Python
  - Theano
  - Keras
  - Lasagne
  - TensorFlow
  - Scikit Learn support for NN coming in 0.18
- Lua
  - Torch

- Some of these libraries utilize GPUs for (much) faster training

NN IN PYTHON

- Let’s look at some examples in Keras
    - Regression
    - Classification

GUIDED PRACTICE

DESIGNING NEURAL NETWORKS

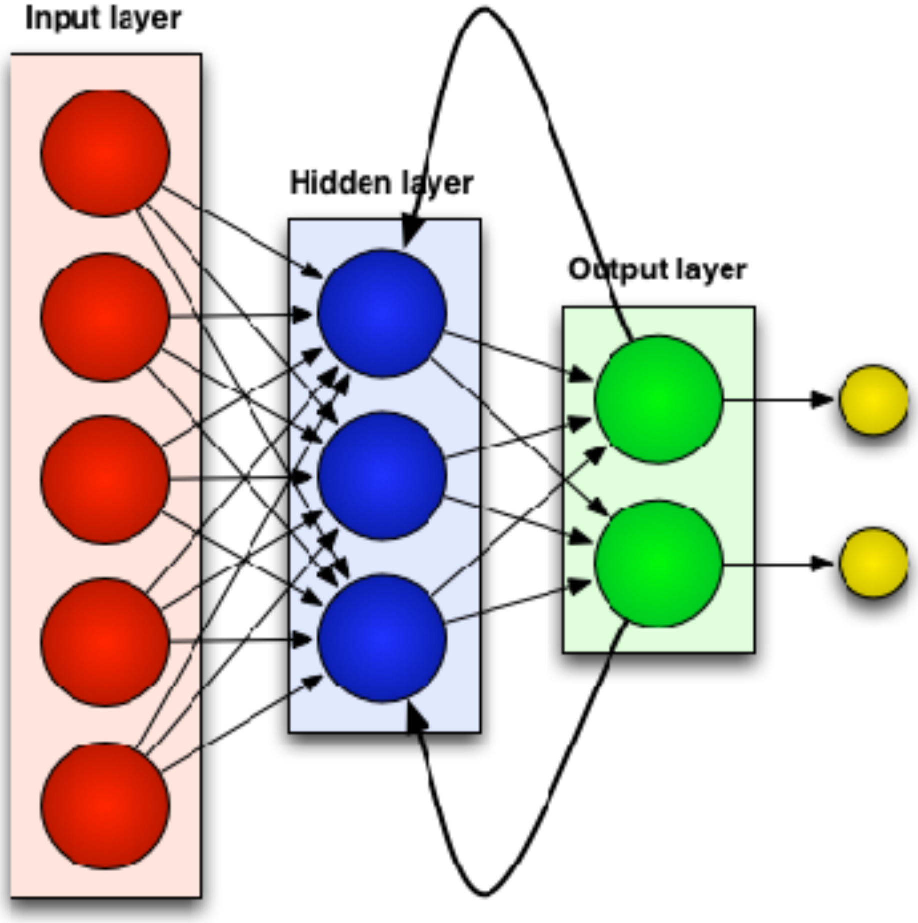
NN IN PYTHON

- Network design is a hard problem
    - Experience helps
    - Evolutionary algorithms are useful for design
    - Nice (free) book available

RECURRENT NEURAL NETWORKS

RECURRENT NEURAL NETWORKS

- Recurrent Neural Networks contain loops (source)

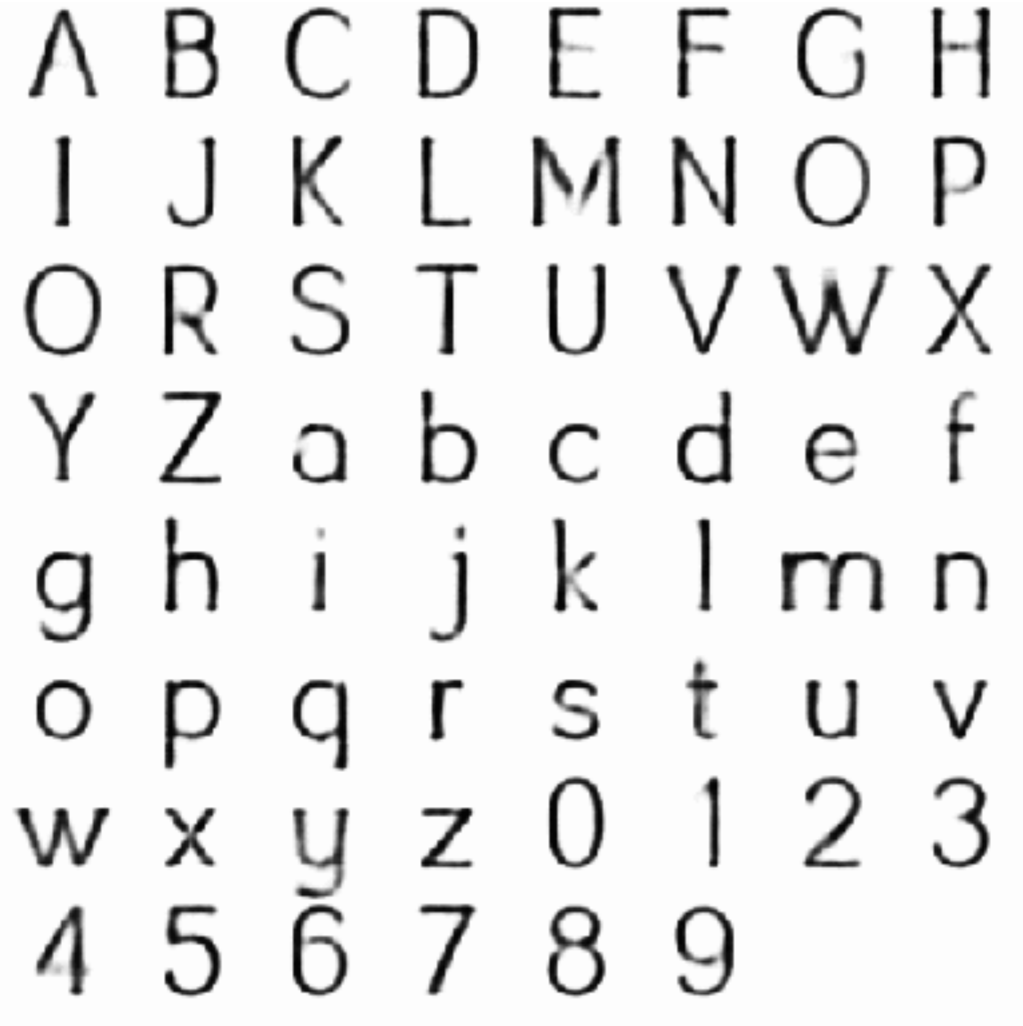


RECURRENT NEURAL NETWORKS

- Recurrent Neural Networks contain loops
- This implements feedback and gives neural networks “memory” or context
- Particularly good for predicting sequences, translating text, recognizing objects in images, speech translation
- Commonly referred to as **deep learning**, involving both feature extraction and modeling
- Nice intro here

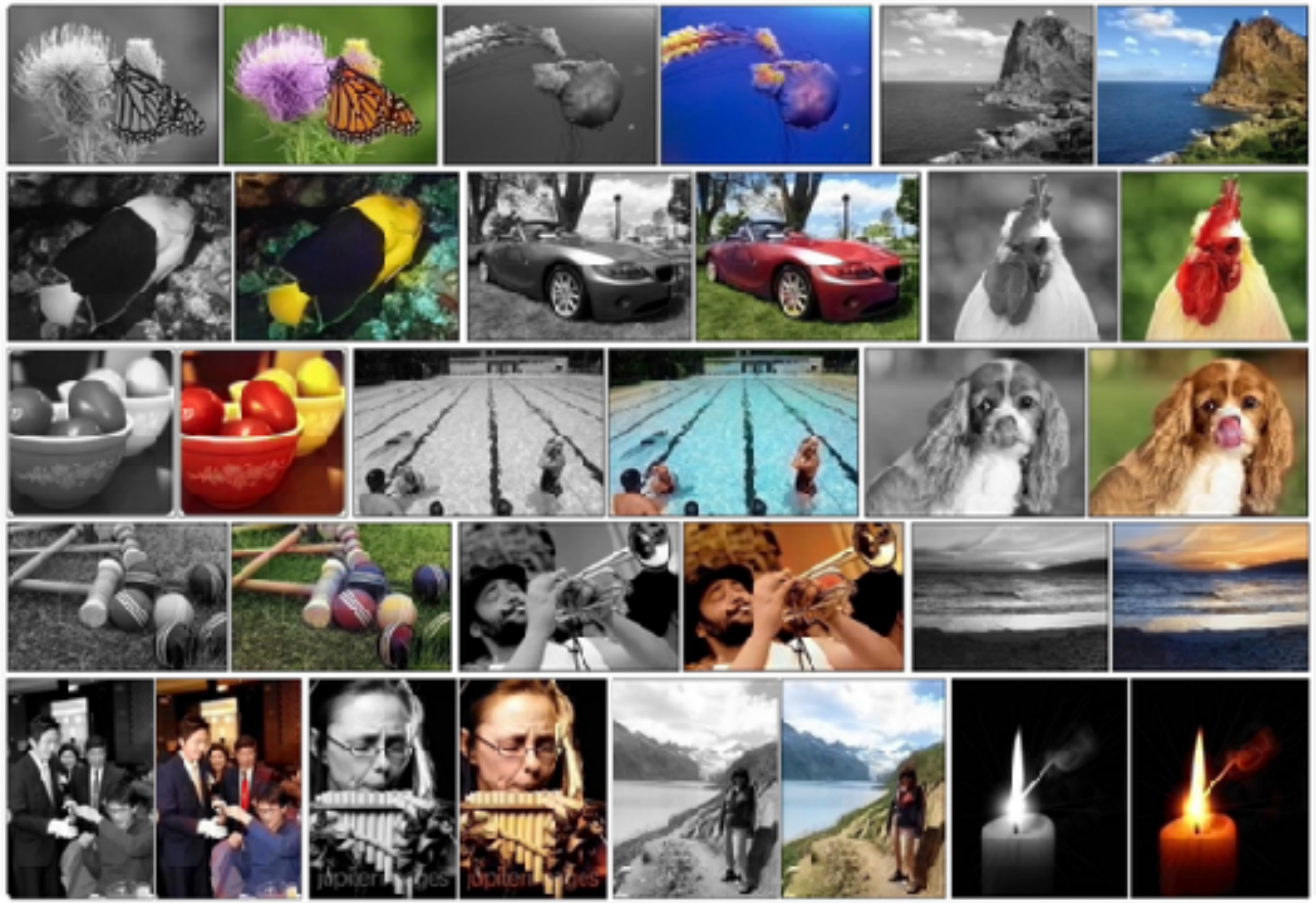
RECURRENT NEURAL NETWORKS

- RNN font analysis



RECURRENT NEURAL NETWORKS

- Automatic Colorization with CNN



RECURRENT NEURAL NETWORKS

- RNN font analysis
- Automatic Colorization with CNN
- Automatic translation
- Deep Learning Applications

BOOSTING AND XGBOOST

BOOSTING

- Boosting: combining multiple ‘weak learners’ to get a ‘strong learner’
- Weak learners: Model only slightly correlated with true model, but better than random
- Strong learners: Model can get arbitrarily close to true model
- Why weak learners? They are simple. E.g. a one-level decision tree

BOOSTING

- First such algorithm: AdaBoost
- AdaBoost is a generalized methodology
- It can be applied to many different learning models
- Another such algorithm: XGBoost
- XGBoost applies boosting to decision trees **(how is it different from Random Forests?)**

ACTIVITY: KNOWLEDGE CHECK

EXERCISE

ANSWER THE FOLLOWING QUESTIONS

1. Let's practice using boosting with XGBoost. Install XGBoost with the following command:

   ```
   conda install -c aterrel xgboost=0.4.0
   ```

2. Work through http://machinelearningmastery.com/develop-first-xgboost-model-python-scikit-learn/

DELIVERABLE

Answers to the above questions

CONCLUSION

TOPIC REVIEW

CONCLUSION: Neural Networks

Pros:

- Flexible
- Good for a variety of tasks
- Good for many types of data

Cons:

- Can require a lot of data
- Training may be slow
- Many parameters to tune
- Many layer types and activations
- Black Box model

CONCLUSION

- Many more examples for Keras available
- Recommended articles: Convolutional NN,
- Advanced machine learning methods you should explore include Bayesian methods and deep learning

COURSE

BEFORE NEXT CLASS

BEFORE NEXT CLASS

DUE DATE

- Project: Final Project, Part 5!!

LESSON

EXIT TICKET

DON’T FORGET TO FILL OUT YOUR EXIT TICKET