Machine Learning applied to Planetary Sciences

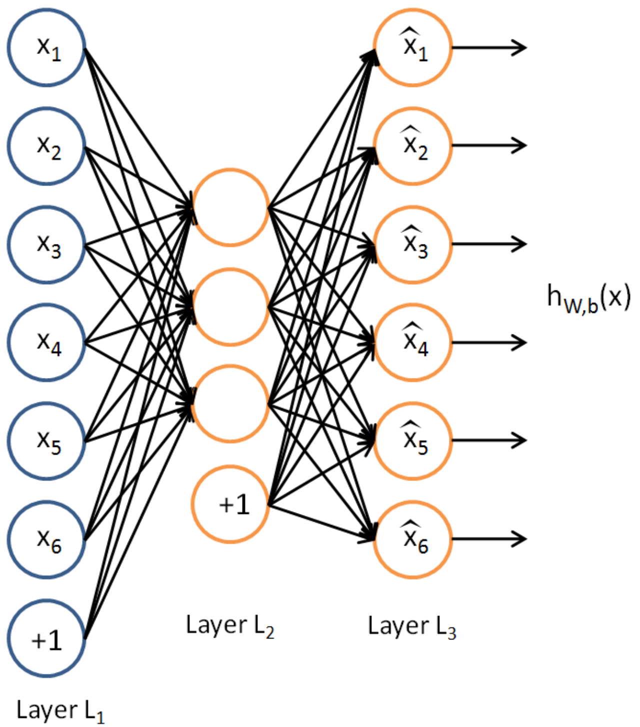
PTYS 595B/495B

Leon Palafox

https://leonpalafox.github.io/MLClass/

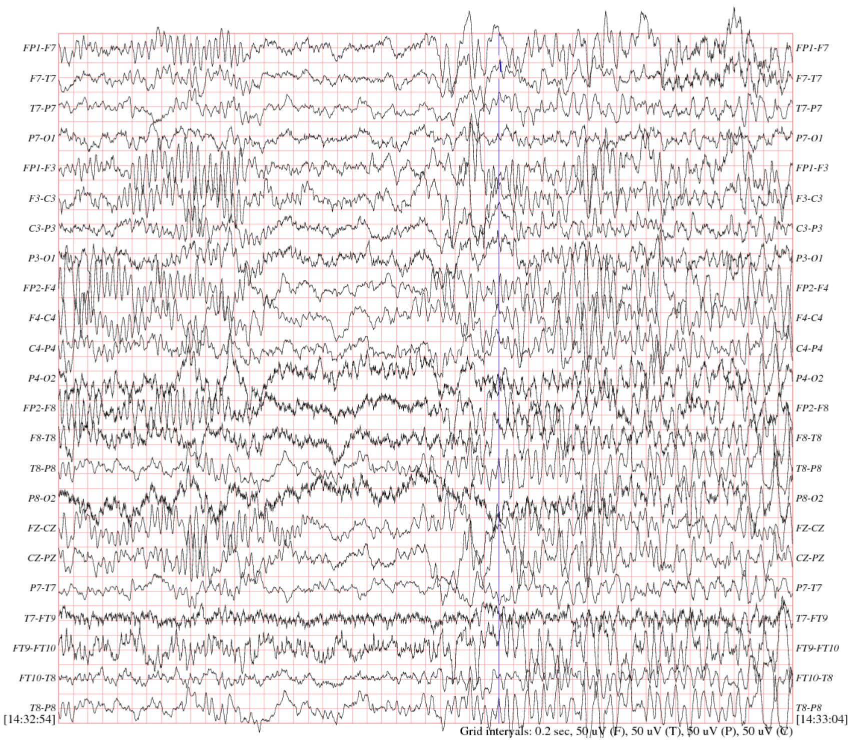
Autoencoders

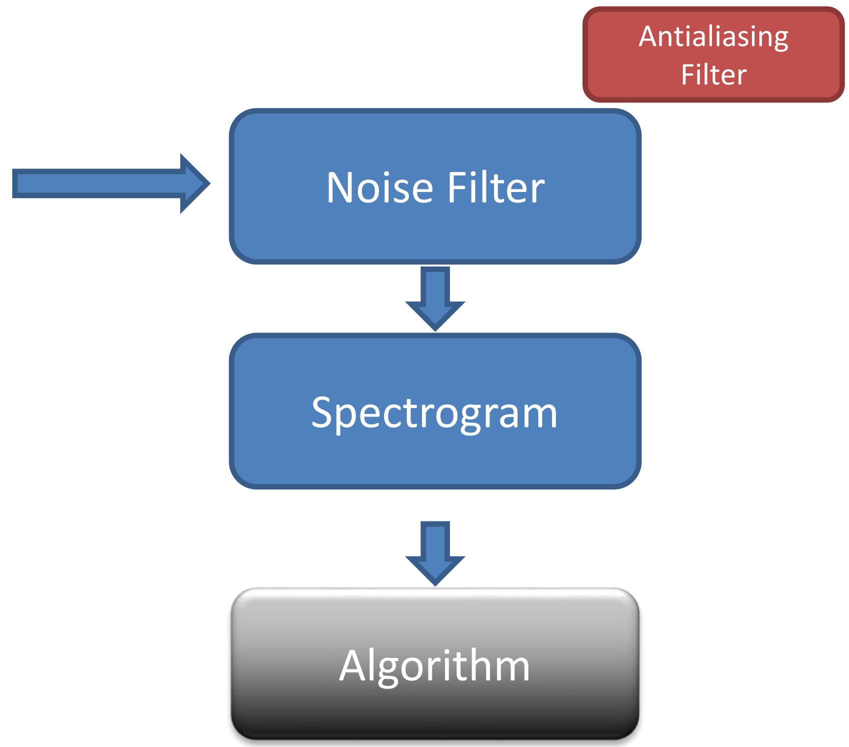
- An autoencoder is a NN where the output and the input are the same.



Preprocessing Data

- It’s a pain, but is needed





Representation Learning

- Deep Nets are undergoing through a rebranding (again).
- One of the main problems in many fields, is that you have to go through many steps before you can use any algorithm.
- This is called preprocessing, and there are many sophisticated techniques to go about it.
- Deep Nets, via the autoencoder learn all of this transformations.
- This new area is being called representation learning.

Convolutional Neural Nets

Convolutional Neural Nets

- CNNs were one particular architecture of NNs that was not hurt by the AI winter.
  - They had very good overall results
  - They do not need to be deep, since that is not their main strength
- They are incredibly useful and joint with the developments in Deep Nets, a state of the art technique.
- Among many characteristics that they have, is that they are transformation invariant. (translation, scale, rotation).
- They also let us learn local features, instead of general features of the image.

Image Transformations

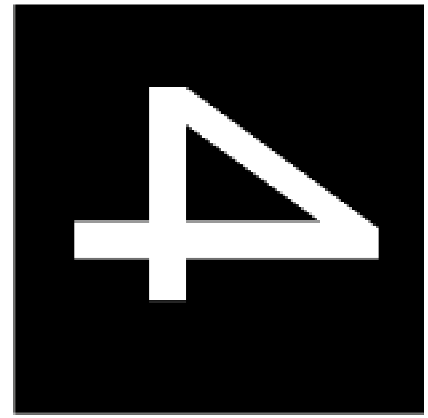


Image Transformations

- How do we deal with these transformations without CNNs
  - Transform the examples ahead and get an artificially large dataset.
  - MNIST: 60,000 x 4 (rotation) x 4 (Translation) x 2 (scaling)
    - 1,920,000
    - This is an approach that many algorithms do end up using.
  - I only assumed 4 degrees of freedom, they could be more. (stretching, shearing)
  - What if we had voxels (3D pixels)
- **Use an architecture that “learns” the transformations.**

Local Features and Stationarity

- If we describe not the image as a whole, but the statistics of the image.
  - You could account for transformations within the algorithm.
- Furthermore, patches of the image have the same statistics.
  - As long as you preserve the order, you can wiggle all the images around as well as the pixels, and the classifier should work.

Classifiers and local features

- Most classifiers do not account for local features in images.
- Naïve Bayes (popular NLP classifier) actually has as a requirement that pixels are uncorrelated.
- Traditional Neural Nets can learn relationships between images, but not between pixels.
- Of course, there are other options, but out-of-the-box classifiers don’t work well.

Stationarity

- Stationary datasets
  - Images, traditional classification datasets.
  - You can scramble them around and the classification should not be affected.
  - *The probability does not change with a shift on time*
- Non-stationary sets
  - Time series, terrain profiles

Stock Market

You are hired to create a classifier that will sell or buy.

Images

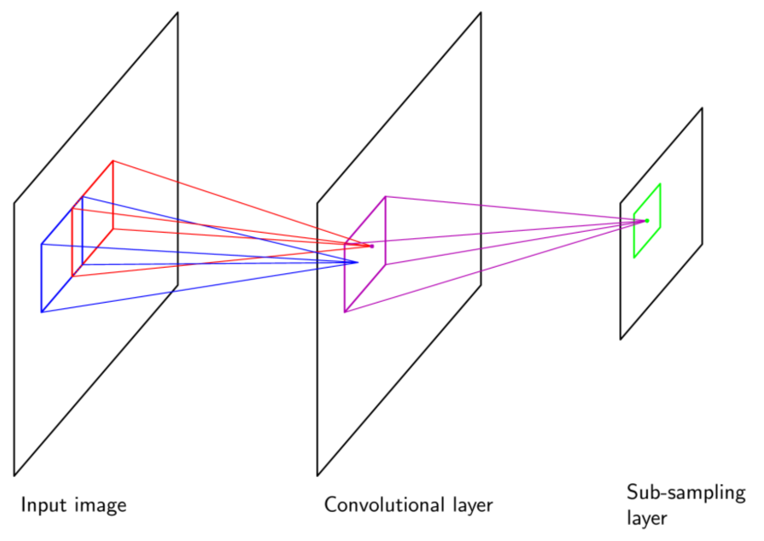
Images and Stationarity

- Since images are stationary, is safe to assume that we can train an autoencoder with patches of large images.
- Small parts of the image have the same statistics as large parts of the image.
- Furthermore, if all the image dataset has the same nature (RGB images, natural scenes), we can pre-train in small patches and then classify whole images.

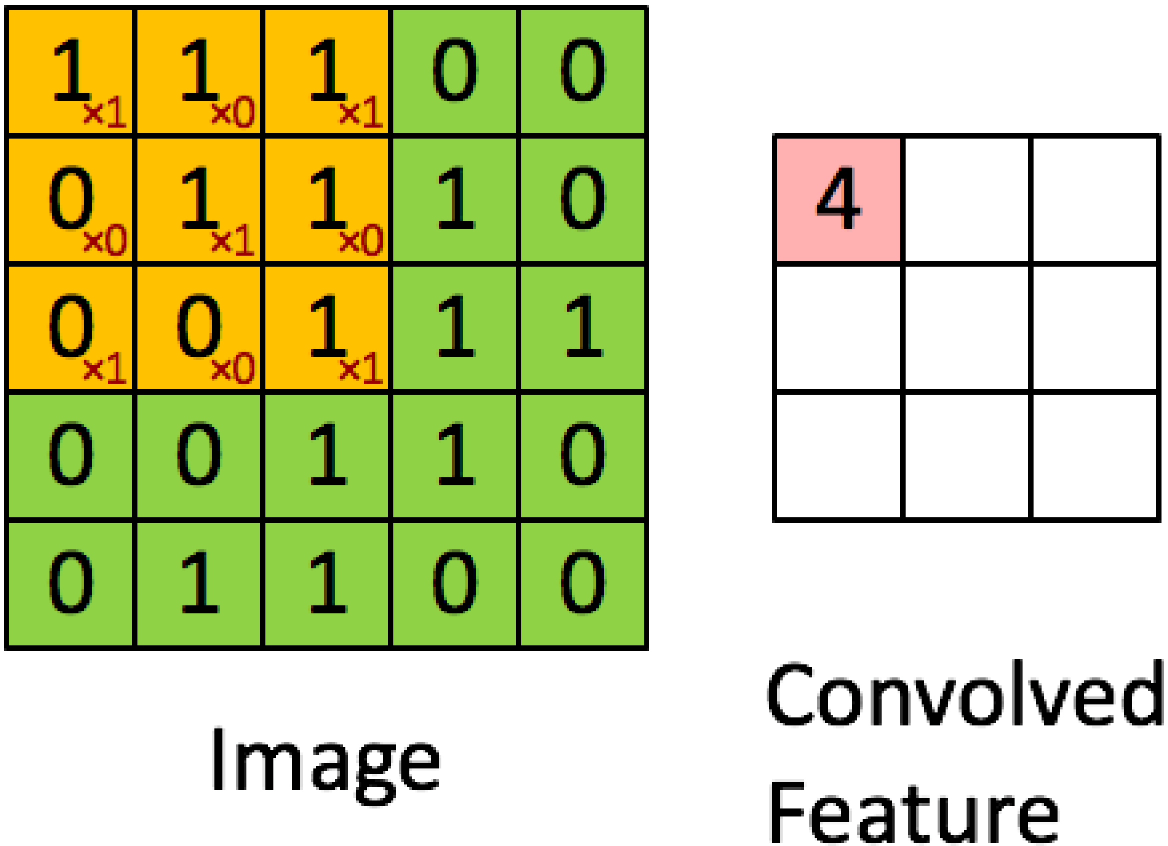
Convolution

Convolutional Neural Nets

- The logic is that the training will take advantage of the invariances in the network.
- The network will learn invariant features, instead of general ones.



Convolution



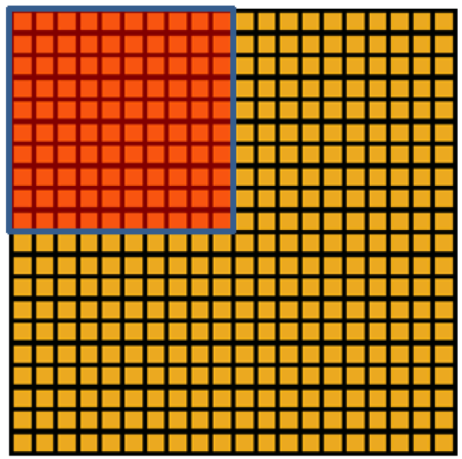
Connection to NN

- Given a large r x c image
  - Train an autoencoder on small a x b patches from the image.
  - This will learn k features.
  - Now, using that autoencoder, we run a feedfoward evaluation to obtain all the features of the image.
  - k x (r-a+1) x (c-b+1) features
  - If k is 400, in 96 x 96 images, we would have around 3 million features.

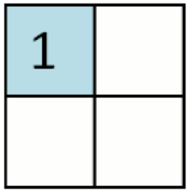
Pooling

- Once we have learned the convolved features, we need to take advantage of the locality.
- We choose adjacent features, and can either take the max or the mean .
- The size of the pooling is defined by the user.
- This way we reduce the number of features and at the same time we take advantage of locality.

Pooling



Convolved feature



Pooled feature

Analysis

- By the end of the training a CNN training scheme is similar to training with an artificially large dataset.
  - Similar results
- Pooling actually decreases the number of weights in the actual network (The autoencoder did most of the heavy lifting)
- Sharing weights is the reason the CNN takes into account local features instead of global ones.

Applications

- We can train the CNN with random patches of many images.
- Then we can make prediction over images datasets.
- Applications?
  - Occluded Images were there is suddenly an obstacle.
  - Video is a set of time dependent pictures, the fact that there is an extra dimension does not eliminate the fact that the image is stationary.

https://www.youtube.com/watch?v=qrzQ_AB1DZk