

Machine Learning applied to Planetary Sciences

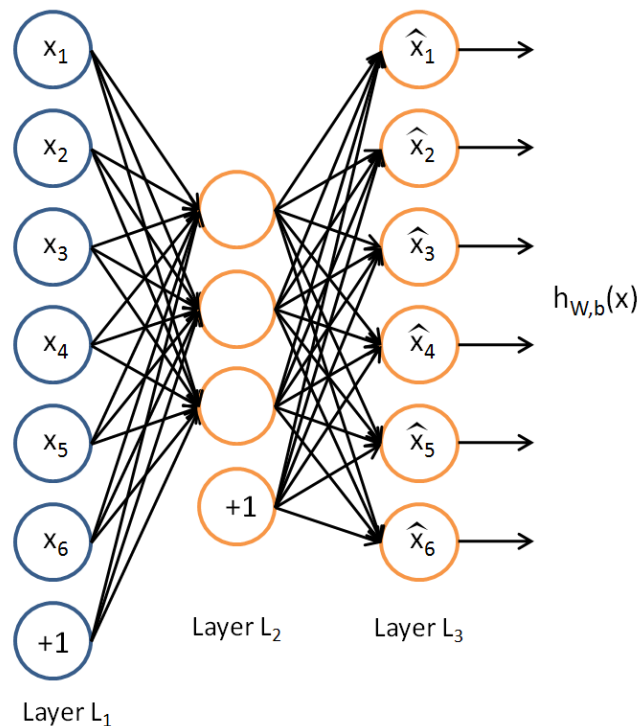
PTYS 595B/495B

Leon Palafox

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

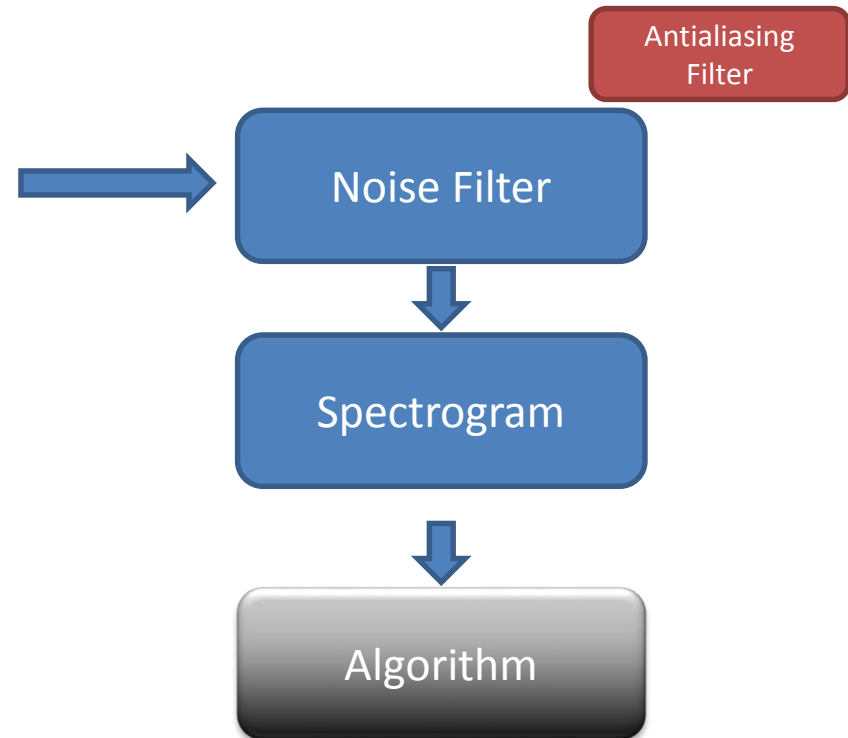
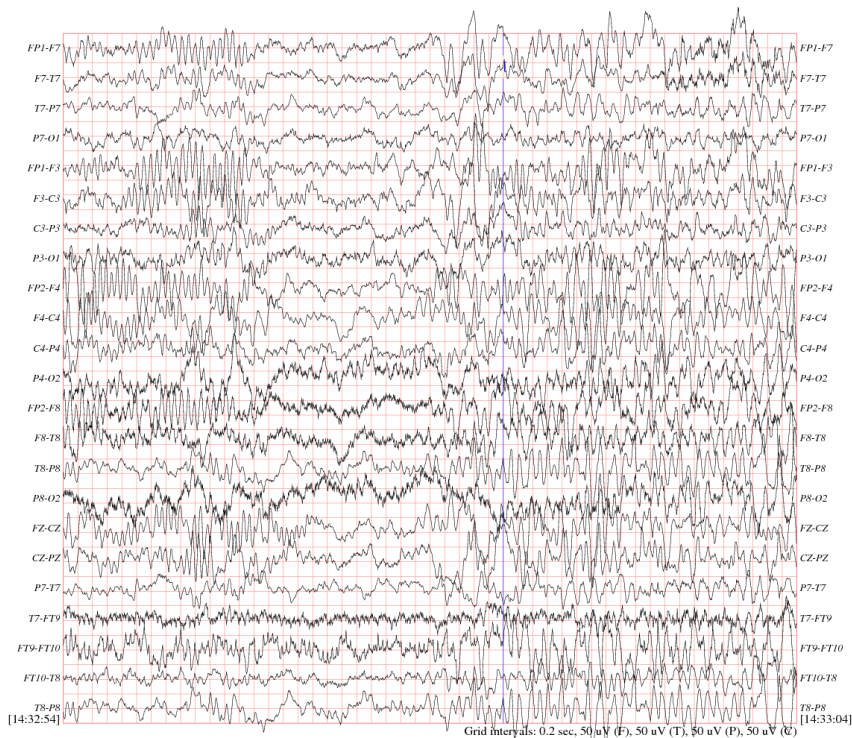
Autoencoders

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



Preprocessing Data

- It's a pain, but is needed



Convolutional Neural Nets

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.**

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



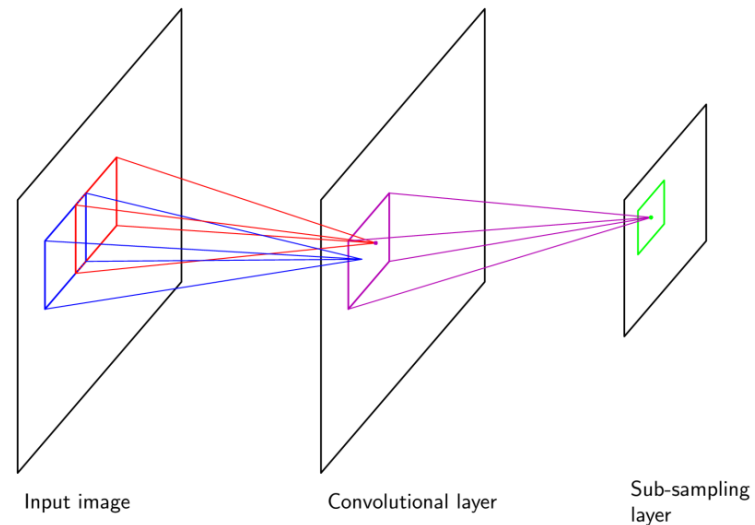
You are hired to create a classifier that will sell or buy.

Images



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

1 _{x1}	1 _{x0}	1 _{x1}	0	0
0 _{x0}	1 _{x1}	1 _{x0}	1	0
0 _{x1}	0 _{x0}	1 _{x1}	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

Convolved
Feature

Convolution

1 _{x1}	1 _{x0}	1 _{x1}	0	0
0 _{x0}	1 _{x1}	1 _{x0}	1	0
0 _{x1}	0 _{x0}	1 _{x1}	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

Convolved
Feature

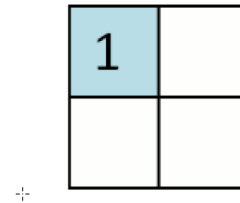
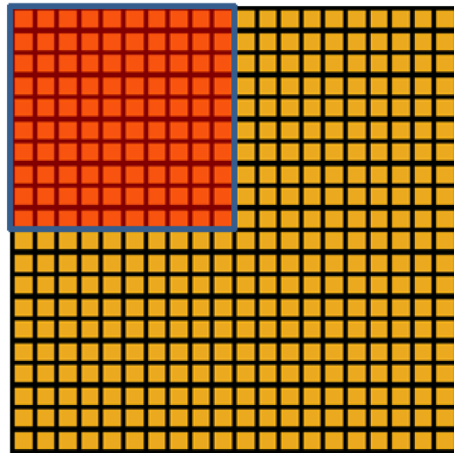
Connection to NN

- Given a large $r \times c$ image
 - Train an autoencoder on small $a \times b$ patches from the image.
 - This will learn k features (convolutions).
 - Now, using that autoencoder, we run a feedforward evaluation to obtain all the features of the image.
 - $k \times (r-a+1) \times (c-b+1)$ features
 - If k is 400, in 96×96 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.

Disadvantages

- This approach is ad-hoc for images (or look alike).
- Trying to use it in time-series or other 1D data is not necessarily a good idea.
 - Long training times
- Unless you use Theano/TensorFlow/MatConvNet/Torch is hard to do real work.

Frameworks

- [Theano](#):
 - Facebook's platform
 - Python
 - Windows, Linux, Mac OSX
- [TensorFlow](#):
 - Google's platform
 - Python/C++
 - Linux, Mac OSX
- [Lua/Torch](#)
 - More academic oriented (a bot of Google though)
 - Lua (different language)
 - Linux

Applications

- We can train the CNN with random patches of many images.
- Then we can make prediction over images datasets.
- Applications?
 - Occluded Images where 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

TensorFlow

- [Installing TensorFlow](#)
- [CNN Tutorial](#)