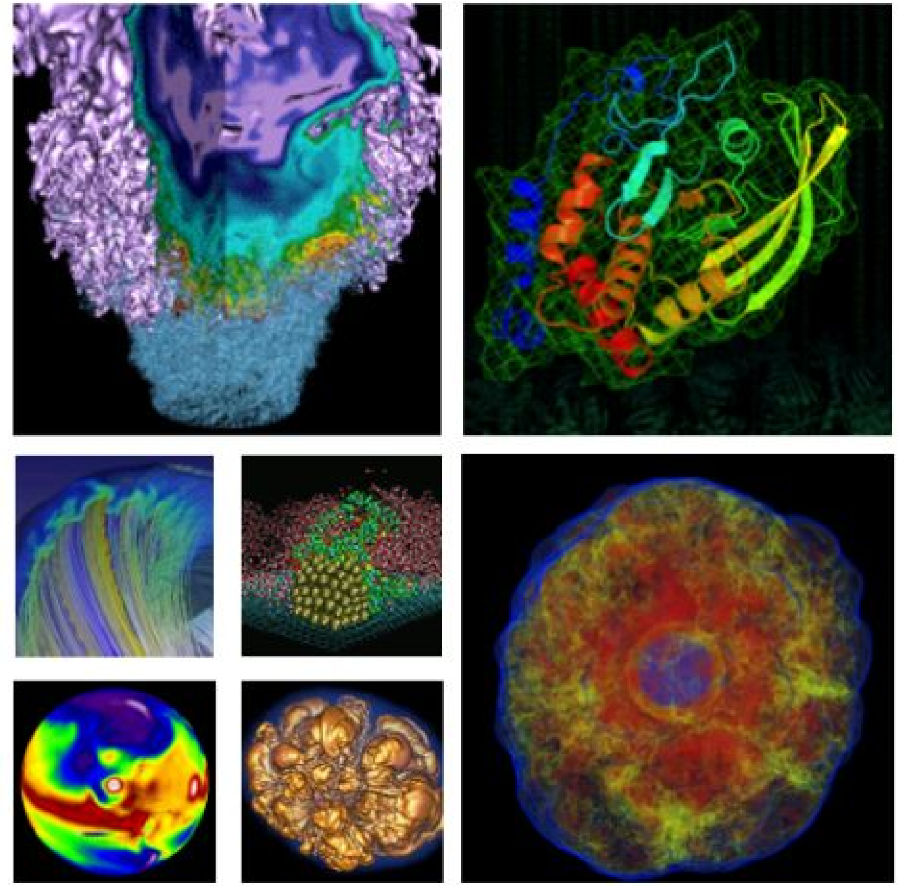
ML Tools @ NERSC (Plus A Science Example!)



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Available Tools

Deep Learning Frameworks

- **Theano** - flexibility, not for beginners (good for research)
- **Keras / Lasagne** - Theano-based but higher-level for ease of use
- **TensorFlow** - ease of use and flexibility, large, growing community, some *multi-node support*
- **Caffe** - high performance (IntelCaffe with performance highly optimised for KNL), *multinode (no programming necessary)*

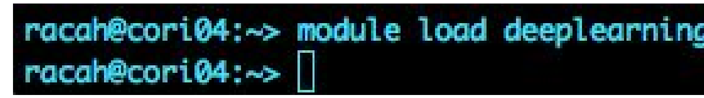
General Machine Learning:

- **Scikit-Learn -** great for non-image based machine learning, easy to use, support for wide range of algorithms
- **Spark -** *multinode*, great for data parallel, relatively easy to use, support for only a subset of ML algorithms

How Do I Use These Tools at NERSC?

Deep Learning Module

- Python deep learning tools available under the deep learning module
- Just one module load call and then they are ready to be imported in your python script!



Scikit-Learn

- available in standard python module and deep learning

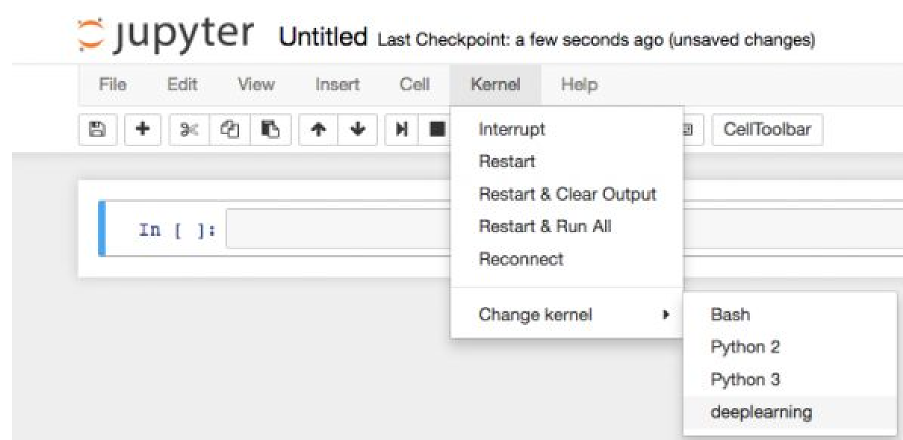
Caffe and Spark

- available as separate modules

<u>**Interactive computing:**</u>

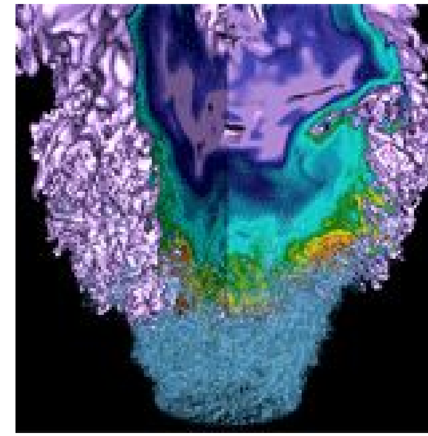
Q: You a big Jupyter notebook fan?!

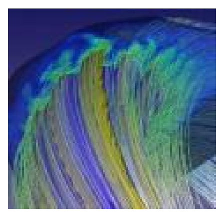
A: No problem. The iPython deeplearning kernel allows for interactively using the deep learning module python tools

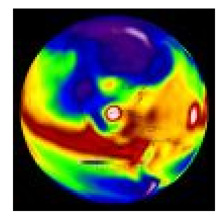


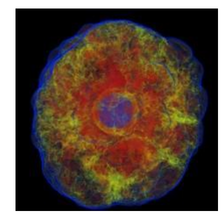
For more information visit http://www.nersc.gov/users/data-analytics/data-analytics/deep-learning/

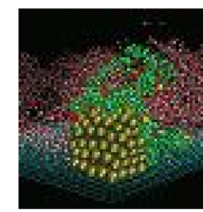
Science Problem!
Daya Bay Antineutrino Detector Analysis











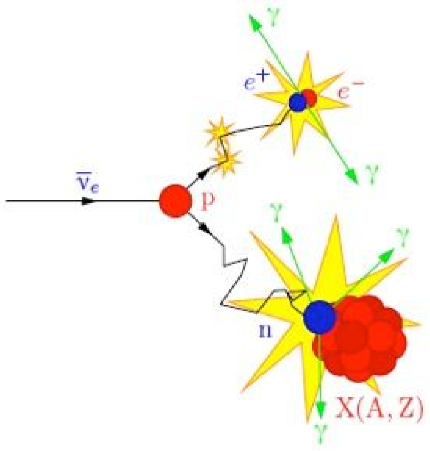
Daya Bay Reactor Neutrino Experiment

Goal:

- Determine neutrino parameter, θ_{13},
- Will provide clues to extend Standard Model

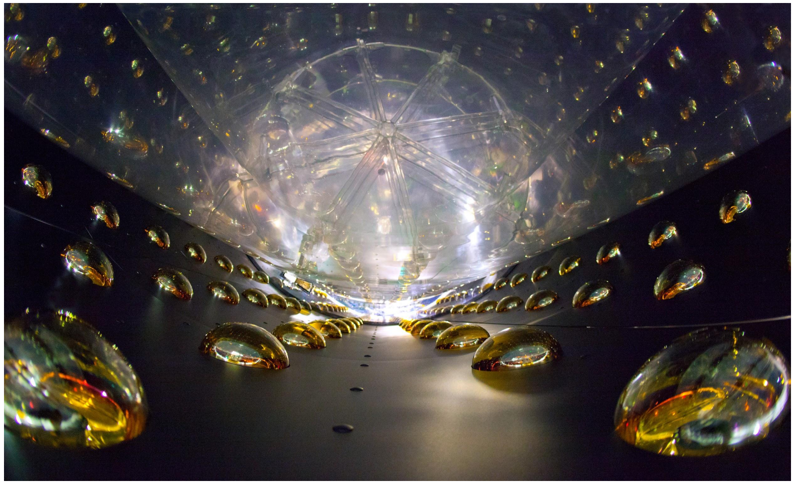
Experiment

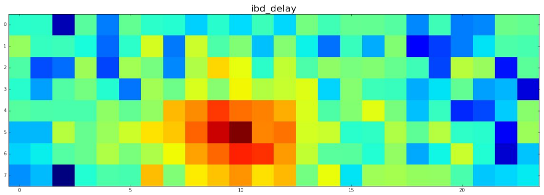
- Inverse Beta Decay (IBD)
    - o antrineutrino reacts with a proton, decays to a positron and neutron
    - o Reaction measured by antineutrino detector



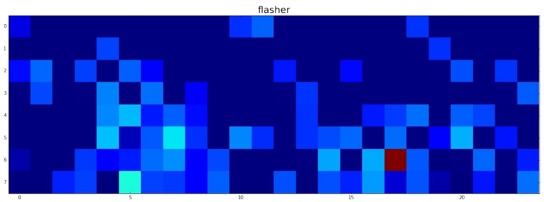
Experiment

- Detectors
  - (192 PMT sensors in cylinder) measuring charge.
  - Events above a certain energy “trigger” a snapshot
- Snapshots (8x24 arrays of floats) analyzed in order to infer θ_{13}
- Signal events
  - IBD prompt (positron)
  - IBD delay (neutron)
    - Occurs several microseconds after
- Non-neutrino events = backgrounds:
  - Flasher (detector malfunction)
  - Muon
  - Other
    - Everything else
    - (contains false negatives?)

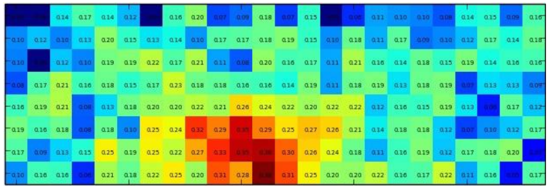




IBD delay candidate



flasher

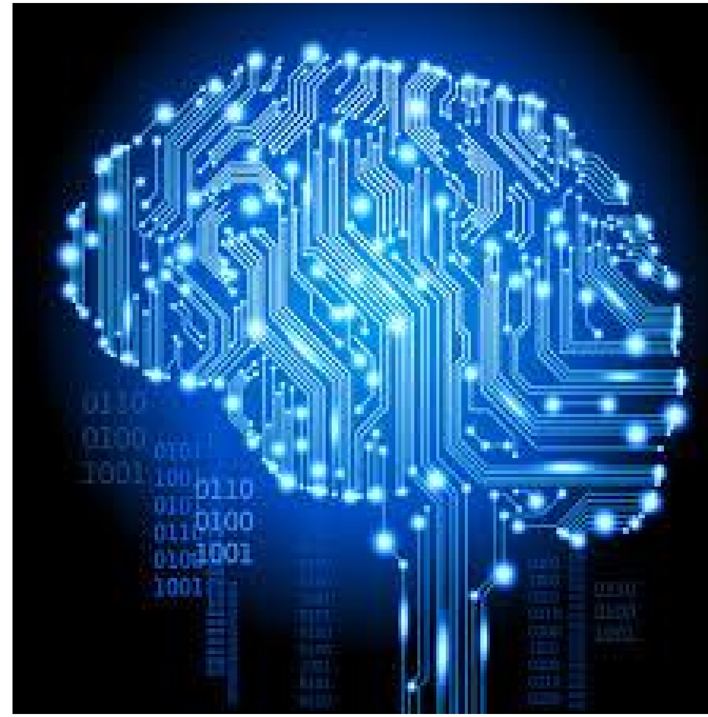


Other (potential false negative)

Why Deep Learning?

Deep learning could help:

- More powerfully discriminate between signal and noise
- Identify new unexpected sources of noise
- Determine structure in the signal as well as in the different types of noise
- Would be interesting to see if deep learning could group together different physical phenomena



Our Approach

- Learn an *unsupervised* feature vector using a **convolutional autoencoder**
- This can help cluster related events, revealing patterns

Convolutional Autoencoder

What is a Convolutional AE?

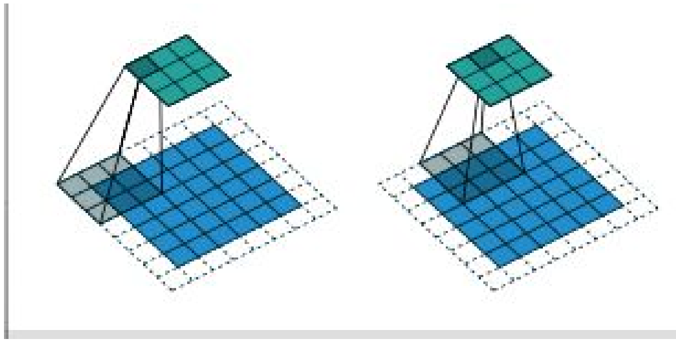
- neural network trained to reconstruct its input
- **Encoder**
  - Transforms input image into **“feature” vector**
- **Decoder**
  - Attempts to reconstruct input image from **this vector**
- When certain restrictions applied to network
  - forced to learn only the most important features of data

Why an autoencoder?

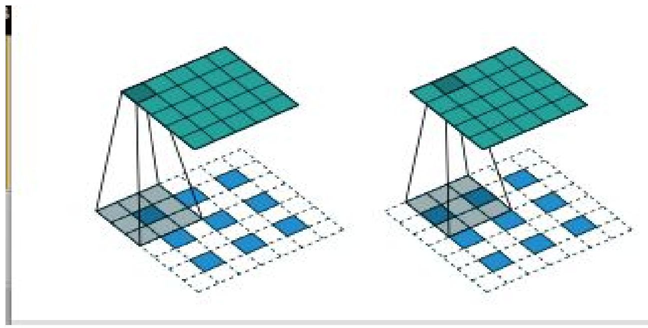
- Manifold Assumption
  - We assume most of the data sample images come from small number of physical events

Why convolutional networks?

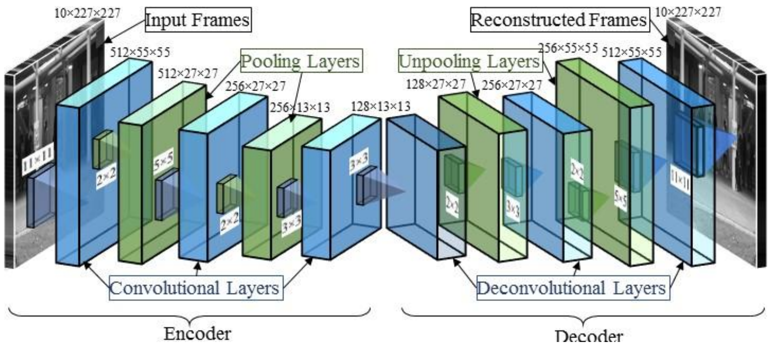
- We treat our data as images
  - Parameter sharing/Translation equivariance
    - Fewer parameters to learn
    - Translating a feature results in an identical but translated representation
  - Translation Invariance
    - **whether** feature is present important, not so much **where** it is
  - Both important



Convolution Operation



Deconvolution Operation



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