**Class** is 170.

# Announcements

**Matlab Grader homework,**
1 and 2 (of less than 9) homeworks Due 22 April **tonight,** Binary graded.
167, 165,164 has done the homework. (**If you have not done HW talk to me/TA!**)
Homework 3 due **5 May**
**Homework 4 (SVM +DL) due ~24 May**

**Jupiter "GPU" home work released Wednesday. Due 10 May**

**Projects: 39 Groups formed. Look at Piazza for help.**
**Guidelines is on Piazza**
**May 5** proposal due. TAs and Peter can approve.

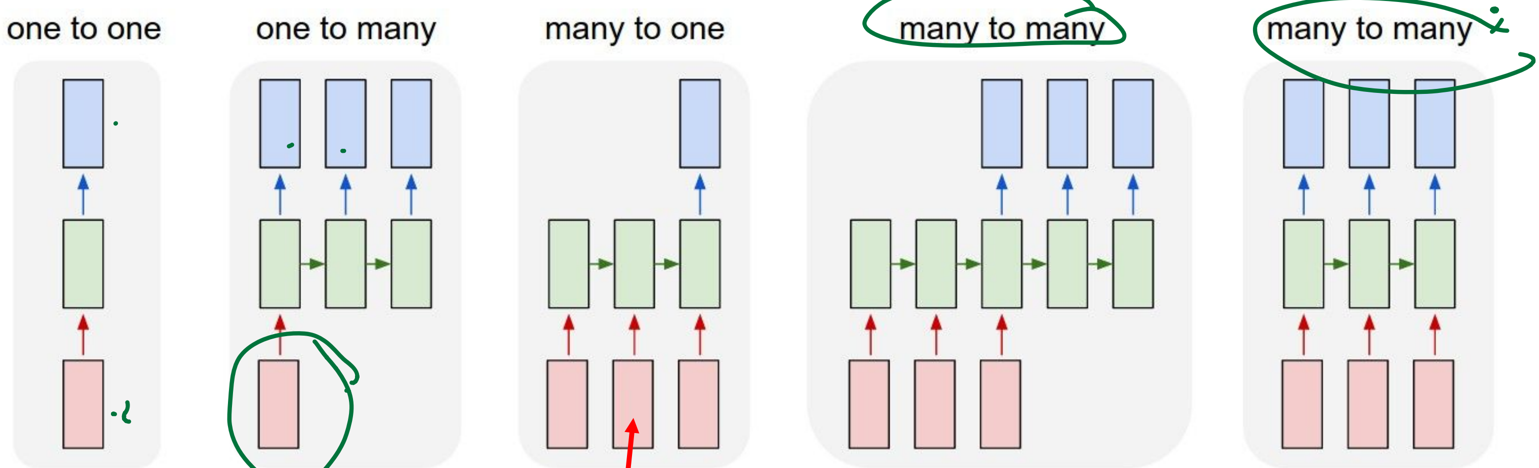
**Today:**

- Stanford CNN 10, CNN and seismics

Wednesday

- Stanford CNN 11, SVM, (Bishop 7),
- Play with Tensorflow playground before class http://playground.tensorflow.org
  Solve the spiral problem

# Recurrent Neural Networks: Process Sequences




e.g. **Image Captioning**
image -> sequence of words

e.g. **Sentiment Classification**
sequence of words -> sentiment

e.g. **Machine Translation**
seq of words -> seq of words

**Vanilla Neural Networks**

**Video classification on frame level**

# Recurrent Neural Network

We can process a sequence of vectors **x** by applying a **recurrence formula** at every time step:

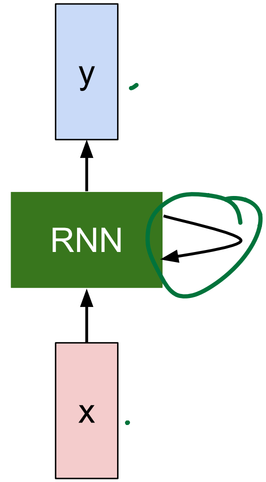
$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state

some function with parameters W

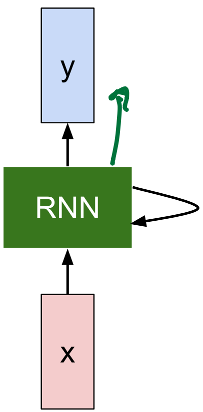
old state

input vector at some time step




# (Vanilla) Recurrent Neural Network

The state consists of a single *"hidden"* vector **h**:

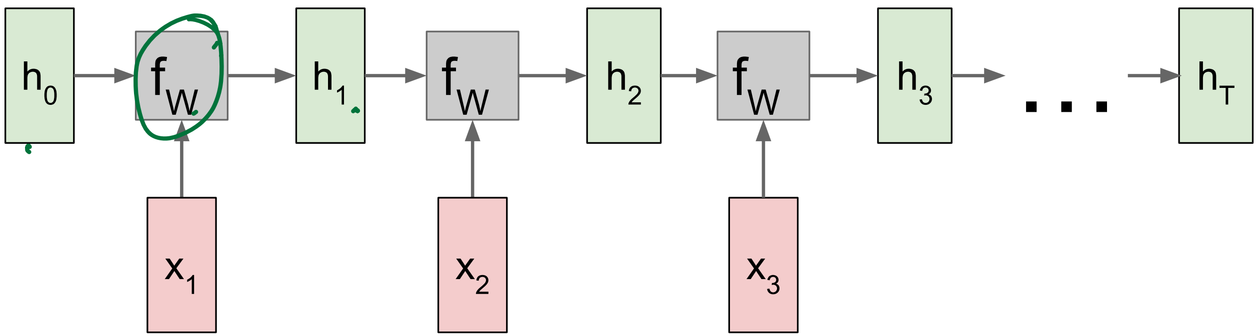



$$h_t = f_W(h_{t-1}, x_t)$$ s

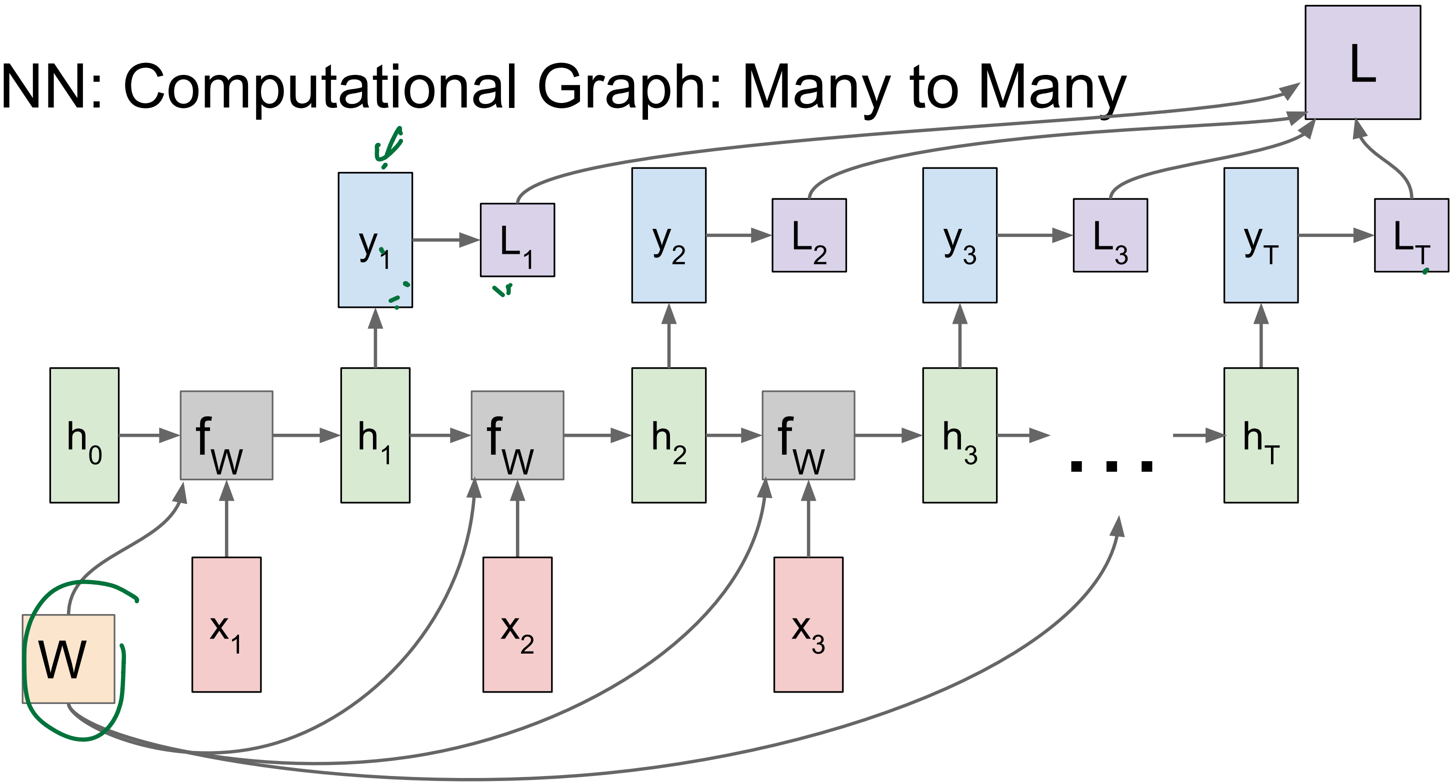
$$h_t = \tanh(W_{hh} h_{t-1} + W_{xh} x_t)$$

$$y_t = W_{hy} h_t$$

# RNN: Computational Graph



# RNN: Computational Graph: Many to Many



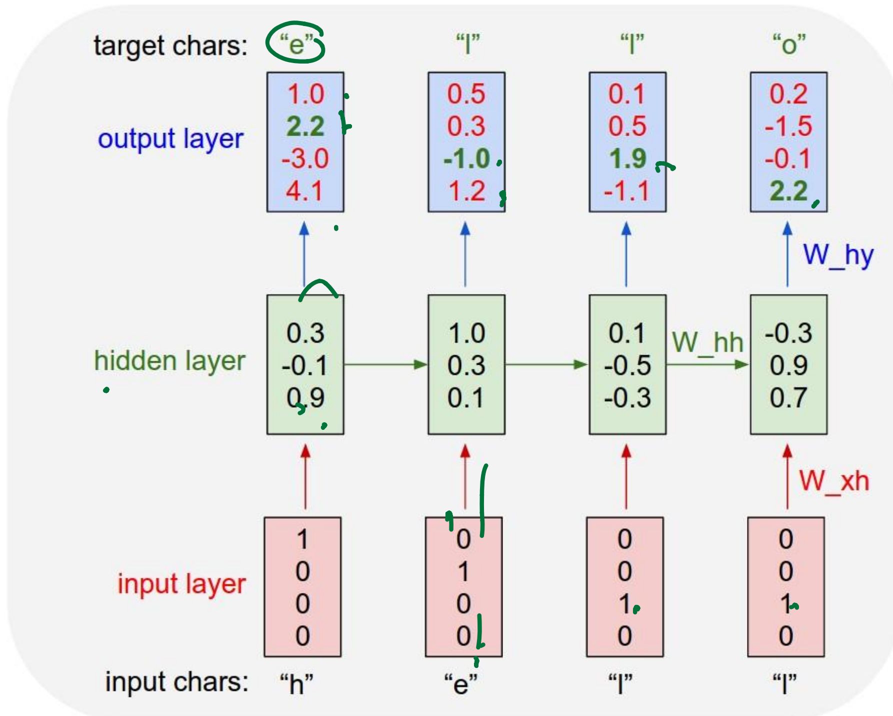
## Example: Character-level Language Model

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

$$y_t = W_{hy}h_t$$

Vocabulary: [h,e,l,o]

Example training sequence: **"hello"**



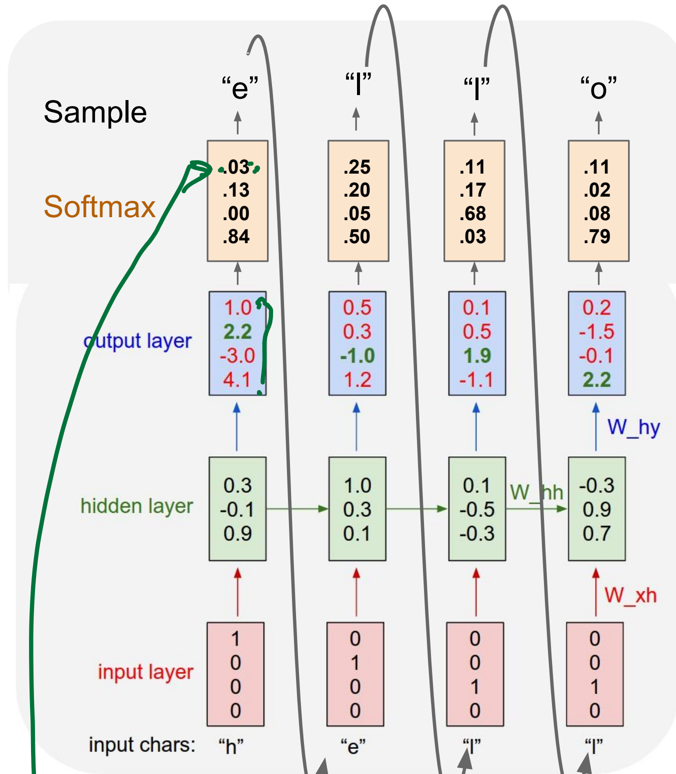

$$h = \begin{bmatrix}1\\0\\0\\0\end{bmatrix} \quad e = \begin{bmatrix}0\\1\\0\\0\end{bmatrix} \quad l = \begin{bmatrix}0\\0\\1\\0\end{bmatrix}$$

$$o = \begin{bmatrix}0\\0\\0\\1\end{bmatrix}$$

**Example: Character-level Language Model Sampling**

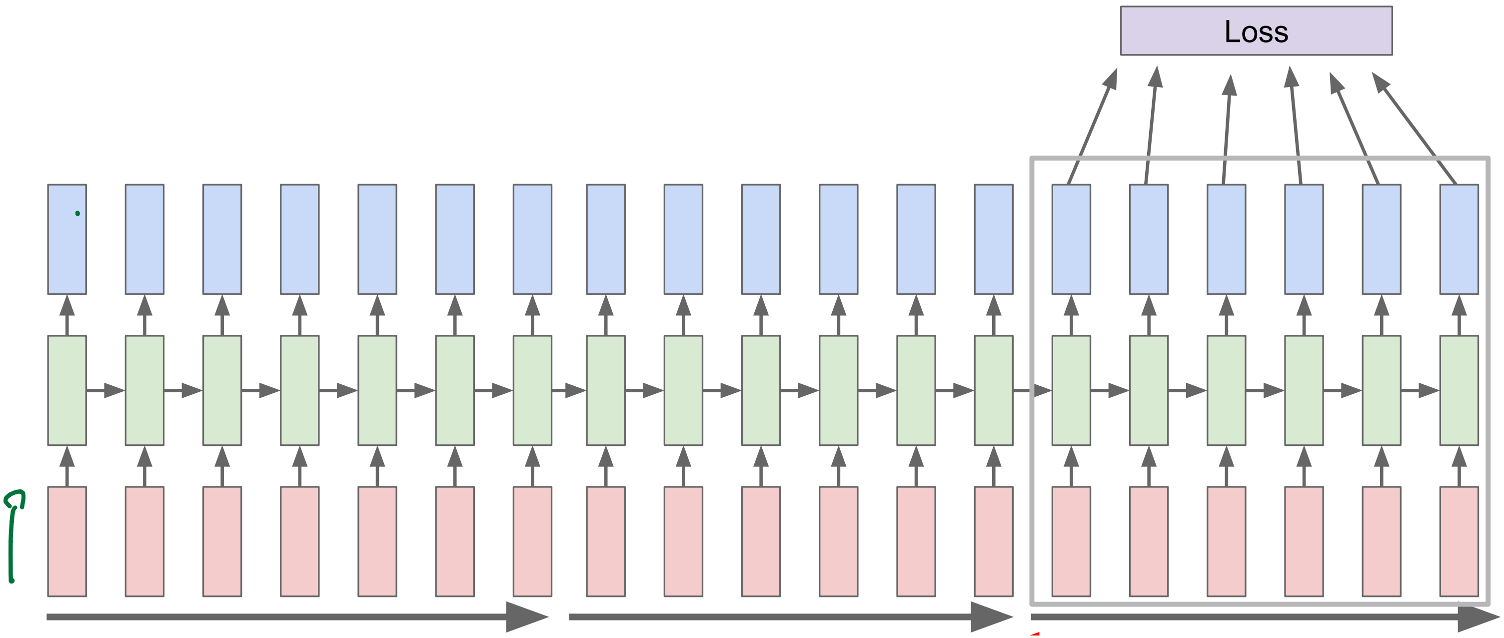
Vocabulary: [h,e,l,o]

At test-time sample characters one at a time, feed back to model




$$\frac{e^{1}}{e^{1}+e^{2.2}+e^{-3}+e^{4.1}}$$

# **Truncated** Backpropagation through time



# Long Short Term Memory (LSTM)

**Vanilla RNN**

$$h_t = \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$

**LSTM**

Cell state

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

$$c_t = f \odot c_{t-1} + i \odot g$$

$$h_t = o \odot \tanh(c_t)$$

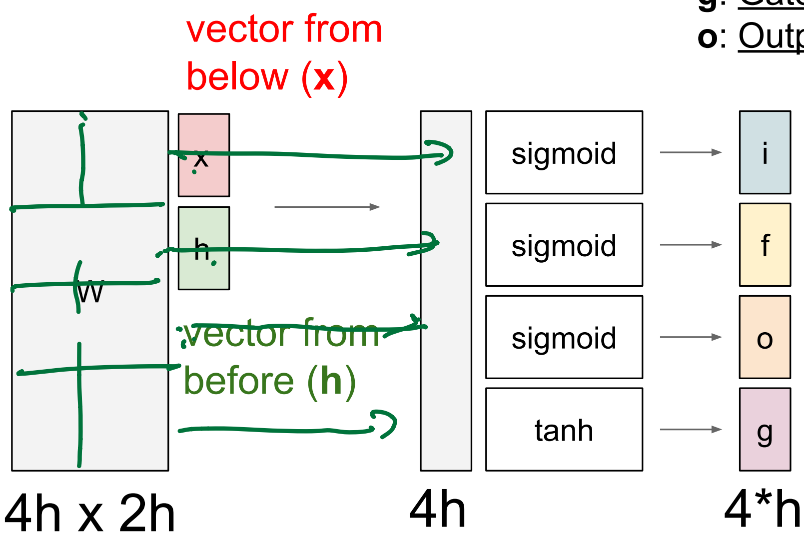
Hochreiter and Schmidhuber, "Long Short Term Memory", Neural Computation 1997

Hidden state h(t)
Cell state c(t)

# Long Short Term Memory (LSTM)

*[Hochreiter et al., 1997]*

**f**: Forget gate, Whether to erase cell
**i**: Input gate, whether to write to cell
**g**: Gate gate (?), How much to write to cell
**o**: Output gate, How much to reveal cell



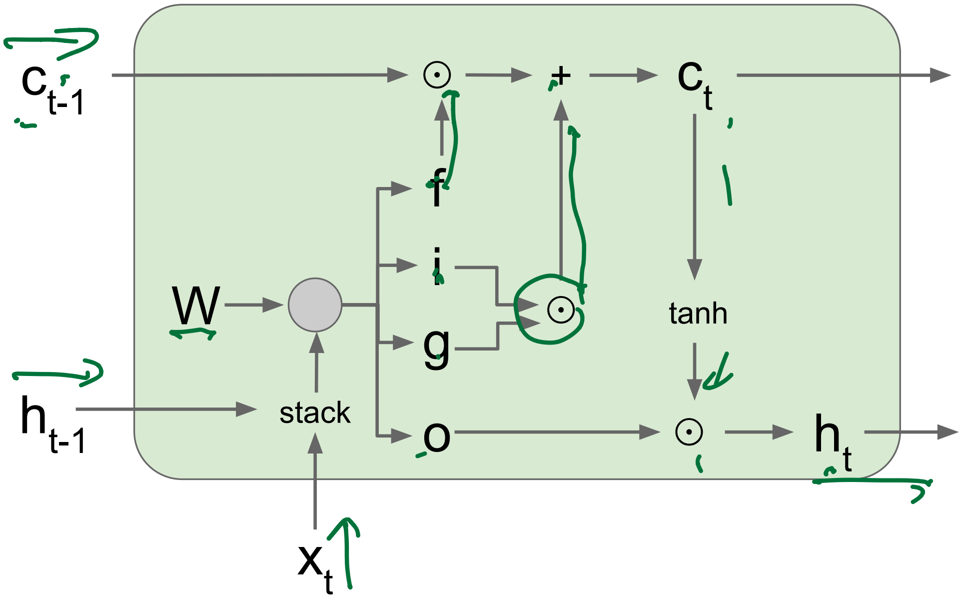

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

$$c_t = f \odot c_{t-1} + i \odot g$$

$$h_t = o \odot \tanh(c_t)$$

# Long Short Term Memory (LSTM)

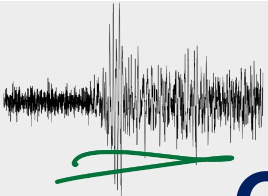
*[Hochreiter et al., 1997]*

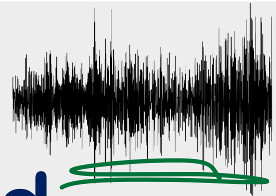



$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

$$c_t = f \odot c_{t-1} + i \odot g$$

$$h_t = o \odot \tanh(c_t)$$





# Classifying emergent and impulsive seismic noise in continuous seismic waveforms

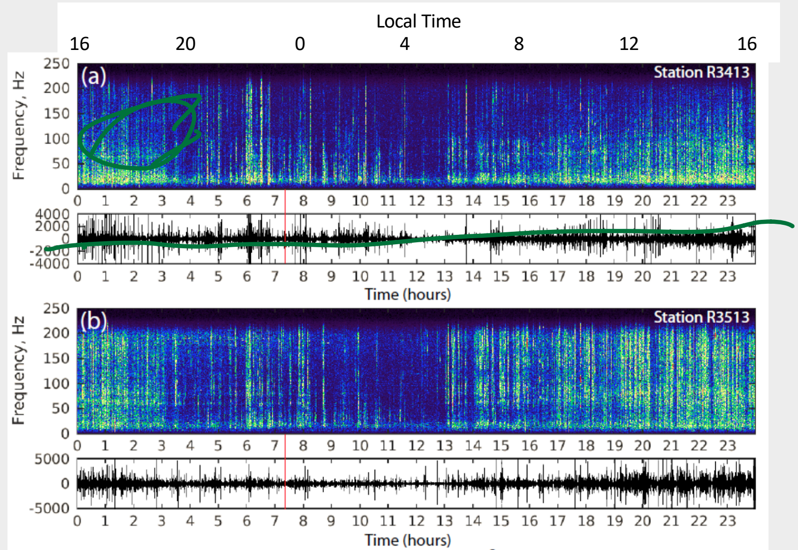
Christopher W Johnson

NSF Postdoctoral Fellow

UCSD / Scripps Institution of Oceanography

# The problem

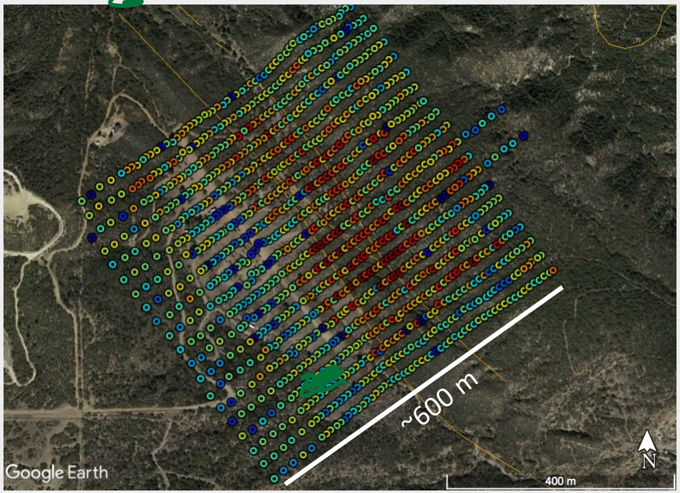
- **Identify material failures in the upper 1 km of the crust**
- **Separate microseismicity (M<1)**
- **59-74% of daily record is not random noise**
  - **Earthquake <1%**
  - **Air-traffic ~7%**
  - **Wind ~6%**
- **Develop new waveform classes**
  - **air-traffic, vehicle-traffic, wind, human, instrument, etc.**




*Ben-Zion et al., GJI 2015*

# The data

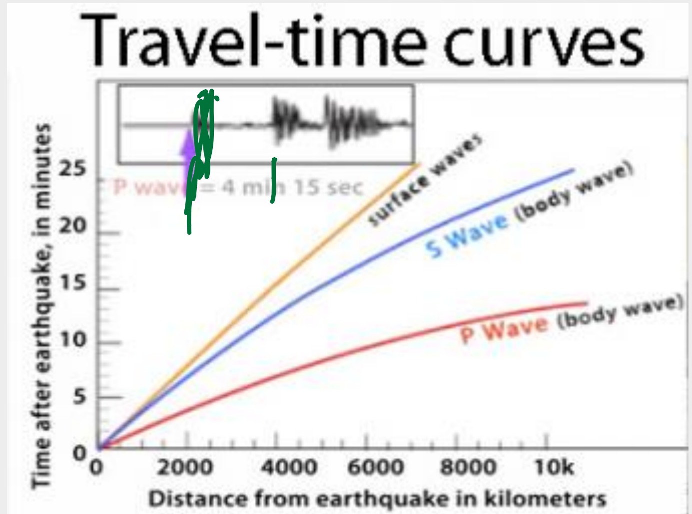
- **2014 deployment for ~30 days**
  - **1100 vertical 10Hz geophones**
  - **10-30 m spacing**
  - **500 samples per second**
  - **1.6 Tb of waveform data**
- **Experiment design optimized to explore properties and deformation in the shallow crust; upper 1km**
  - **High res. velocity structure**
  - **Imaging the damage zone**
  - **Microseismic detection**




*Ben-Zion et al., GJI 2015*

# Earthquake detection

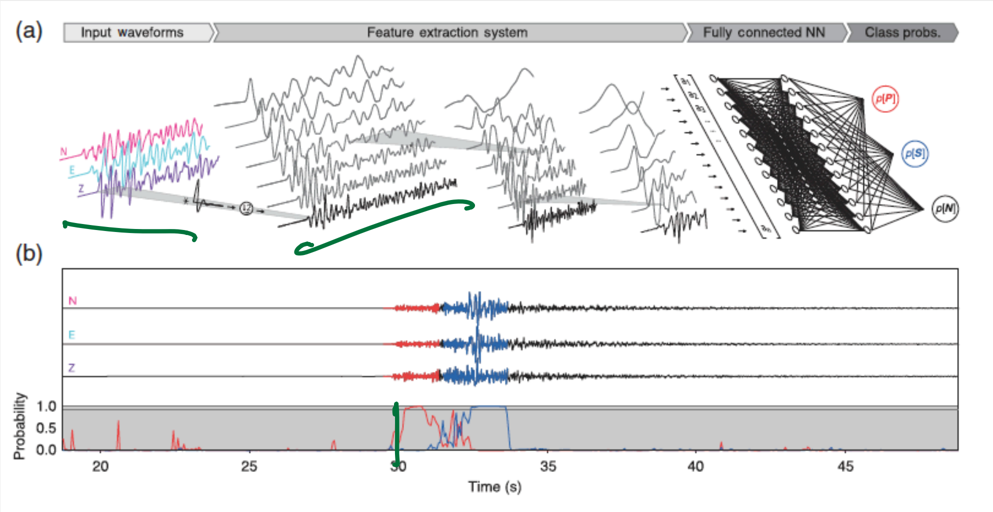
- **Distributed region sensor network**
- **Source location random, but expected along major fault lines**
- **P-wave (compression) & S-wave (shear) travel times**
- **Grid search / regression to obtain location**
- **Requires robust detections for small events**




from IRIS website

# Recent advances in seismic detection

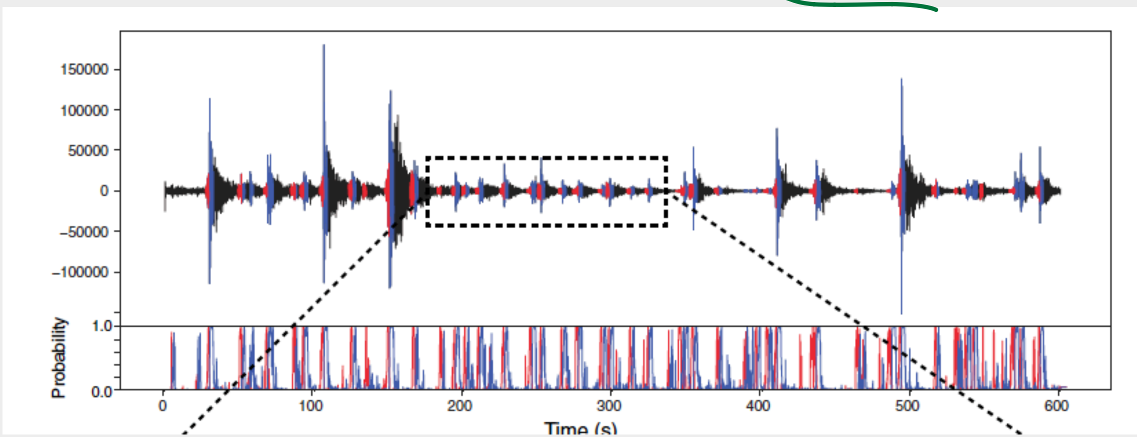
- **3-component seismic data (east, north, vert)**
- **CNN**
  - **Each component is channel**
  - **Softmax probability**




Ross et al., BSSA 2018

# Recent advances in seismic detection

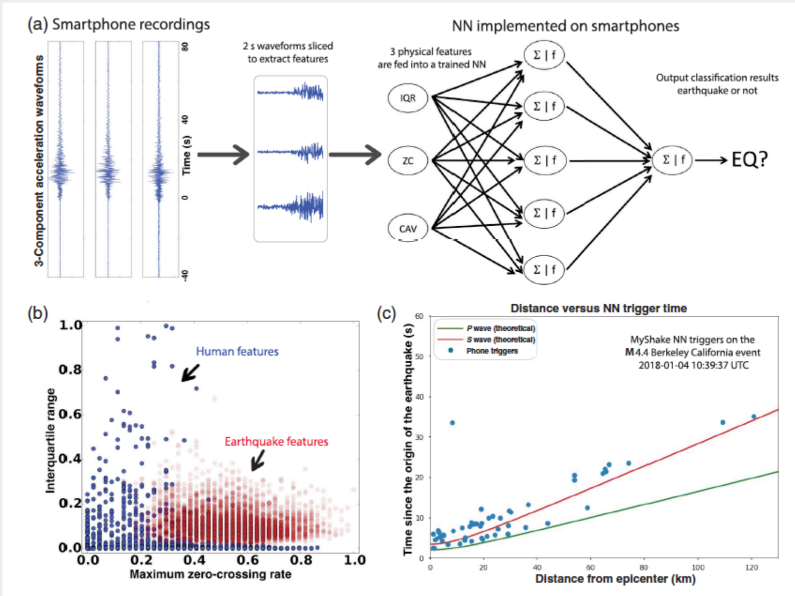
- **Example of continuous waveform**
- **Every sample is classified as noise, P-wave, or S-wave**
  - **Outperforms traditional methods utilizing STA/LTA**




Ross et al., BSSA 2018

# Future direction is seismology

- **Utilize accelerometer in everyone's smart phone**




Kong et al., SRL, 2018

# Research Approach and Objectives

- Need labeled data. This is >80% of the work!
  - Earthquakes
    - Arrival time obtained from borehole seismometer within array
  - Define noise
    - Develop new algorithm to produce 2 noise labels
  - Signal processing / spectral analysis
    - Calculate earthquake SNR
      - Discard events with SNR ~1
    - Waveforms to spectrogram
      - Matrix of complex values
      - Retain amplitude and phase
    - Each input has 2 channels
      - This is not a rule, just a choice

# Deep learning model – Noise Labeling

- Labeling is expensive
  - 1 day with 1100 geophones
    - ~1800 CPU hrs on 3.4GHz Xeon Gold (1.7hr/per daily record)
    - ~9000 CPU hrs on 2.6 GHz Xeon E5 on COMET (5x decrease)
- Noise training data
  - 1s labels
  - 1100 stations for 3 days
  - Use consecutive 4 s intervals
  - Calculate spectrogram

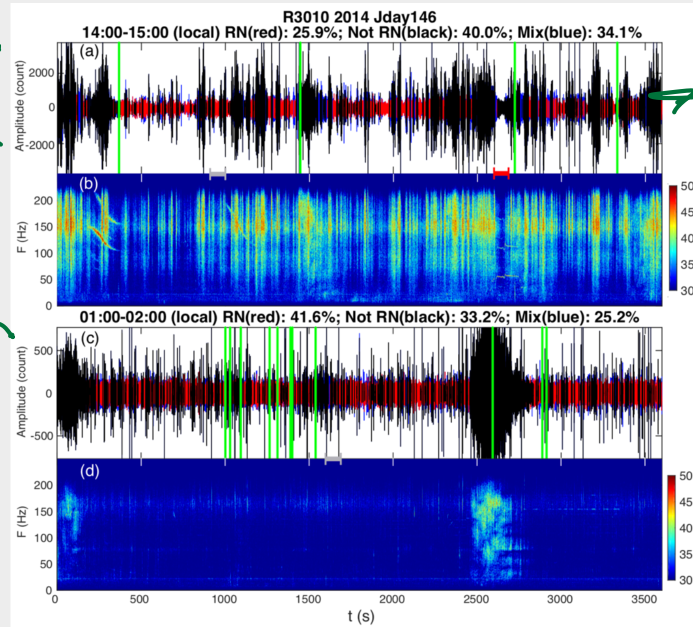
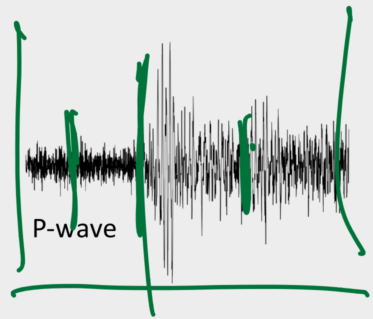
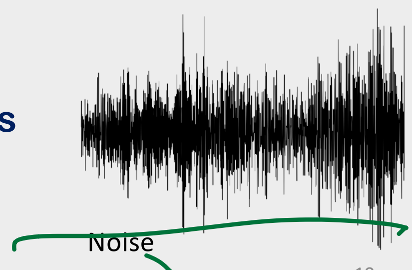



*Image from Meng, Ben-Zion, and Johnson, in GJI revisions*

# Deep learning model – Assemble data

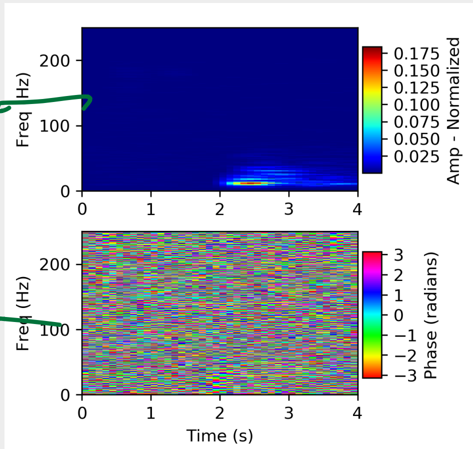
- Obtain earthquake arrival times
  - Extract 4s waveforms 1s before p-wave arrival
  - Vary start time within ±0.75s before p-wave
  - Use each event 5x to retain equal weight with noise
  - Filter 5-30 Hz, require SNR > 1.5
  - Obtain ~480,000 p-wave examples
  - Incorporates spatial variability across array
- Precalculate 2 noise labels
  - Use 4s of continuous labels
- Data set contains ~1.2 million labeled wavelets
  - Each API has input format
  - Shuffle data – Data must contain variability in subsets



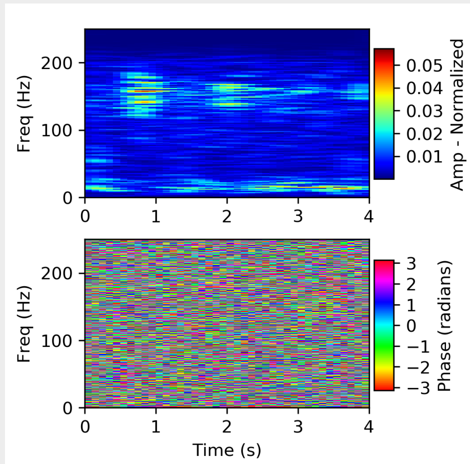



# Deep learning model - Labels

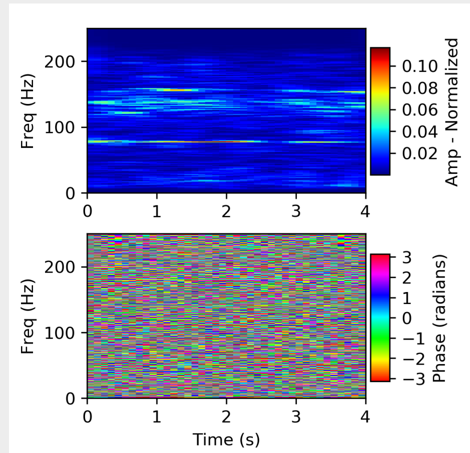
- Earthquake




- Random noise




- Not random noise




- Start with 3 labels
  - Equal number in each class
  - It is possible that non-random noise contains earthquakes
- STFT
  - Normalize waveform
  - Retain amp & phase
  - 2 layer input matrix

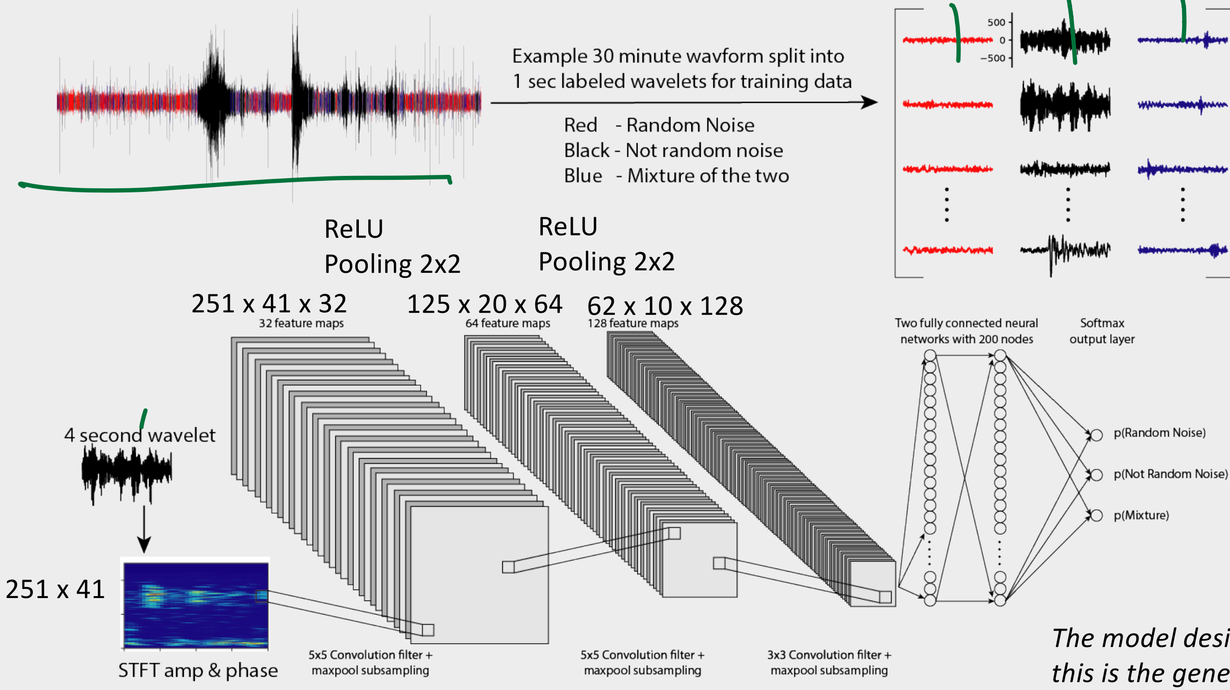
# Research Approach and Objectives

- Build Convolutional Neural Network
  - Filter size, # layers, activation func (ReLU),
  - Pooling, batch normalization
  - FCN, softmax
- Get the model working before fine tuning
  - Hyperparameters
    - Learning rate
      - Good start is 0.01; Adjust up/down by an order of magnitude
      - Test decay
        - Slow the learning rate with each epoch
  - Test model design
    - Improve model by systematically adjusting
      - If too many things change at once, which one helps / hurts
    - Batch size
      - 32-256 is a good start

# Software

- SKlearn
  - Data preprocessing
    - Train, Validate, Test
    - Shuffle
  - Model performance
    - Classification report
- Keras / Tensorflow
  - Keras uses Tensorflow backend
    - Great place to start learning
- Pytorch
  - Use if familiar with Python and CNN
  - Model is a class
    - Many examples exist

# Convolutional Neural Network



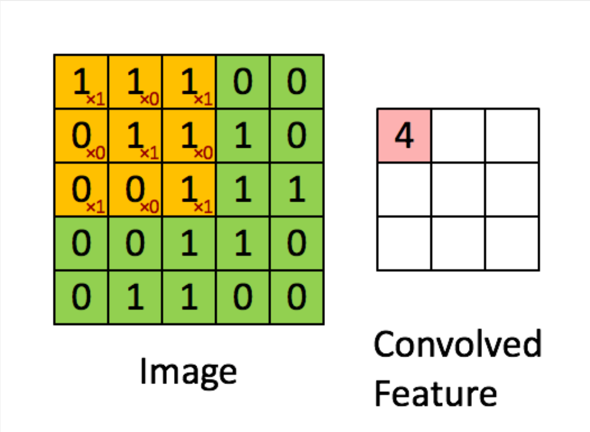

*The model design varies but this is the general setup*



4/

# Convolutional Neural Network

- Convolutional
  - Scan matrix by translating a mask or template and taking inner product
  - Each mask contains filter weights
  - Add bias to convolution output
  - Repeat for set number of output layers all using different weights
- Weights and biases are the only parameters
  - Number of parameters increases to the millions if using multiple hidden layers

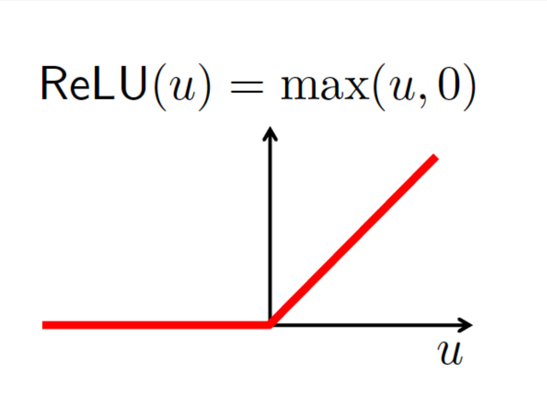



*from http://deeplearning.stanford.edu/*

# Convolutional Neural Network

- Rectifier
  - Rectified linear unit (ReLU)
  - Remove negative values
  - Otherwise the problem is linear

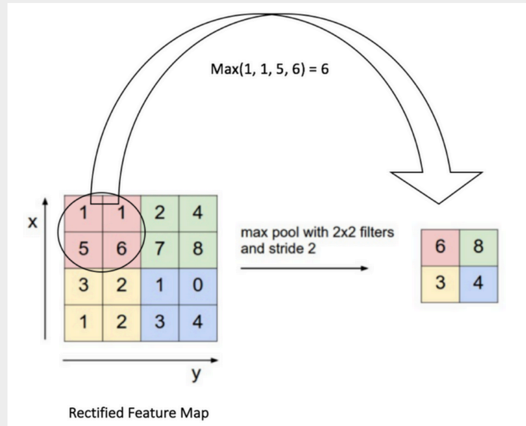
  - Can also try
    - tanh, Leaky ReLU, etc




*from algorithmia.com*

# Convolutional Neural Network

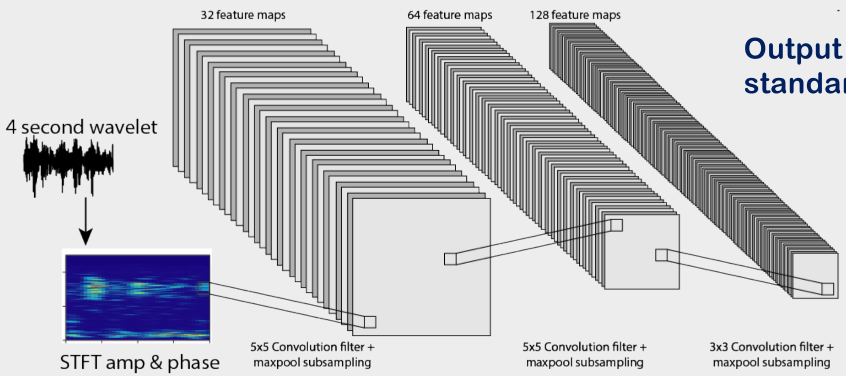
- Pooling
  - Down sample
  - Reduce dimensionality of subsequent layers
  - Common techniques
    - Max pooling (non-linear)
    - Avg. pooling (linear)
- After each pooling the filter kernel is 'zoomed out' from the input matrix




*from algorithmia.com*

# Convolutional Neural Network

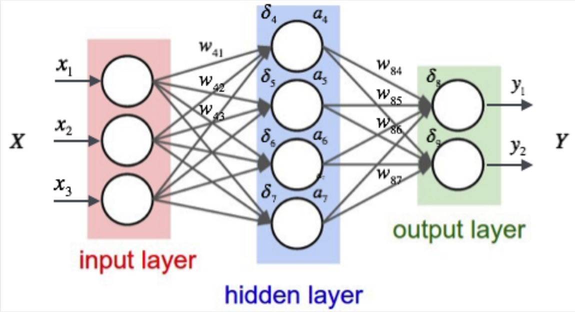
- **Advanced feature extraction technique**
- **Each layer has many filters detecting various features**



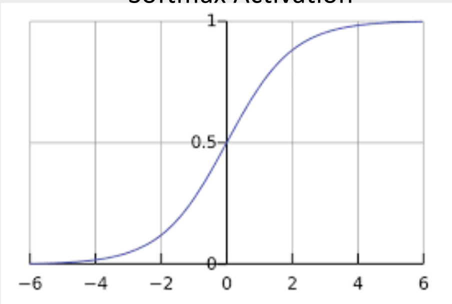

**Output ConvNet features to a standard neural network**

# Convolutional Neural Network

- Designed to learn complex neural decision path
  - Hidden layers with ReLU activation
    - Weights are trainable parameters
- Output final layer to softmax activation function
  - sum(output layer) = 1
  - Probability estimate for final layer
- Stochastic gradient descent
  - Adam optimization
    - Variable learning rate
- ConvNet models require >50k LABELED training examples; even more for very complex problems




Softmax Activation



# How is that actually done?

```
# Very simple Keras with Tensorflow backend example
model = Sequential()
# First filter
model.add(Conv2D(64, (5, 5), activation='relu', padding='same', input_shape=(n, o, p)))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
# Second filter
model.add(Conv2D(128, (3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
# Convolution operators are multi-dimension matrix. Flatten to array
model.add(Flatten())
# Send extracted features from convolutions to fully connected Neural Network
model.add(Dense(1024, activation='relu'))
model.add(BatchNormalization())
# Hidden layer
model.add(Dense(1024, activation='relu'))
model.add(BatchNormalization())
# Output layer with softmax activation
model.add(Dense(3, activation='softmax'))
```

# Model performance (on test data!!)

- Type I Error (precision)
  - Quantify false positive
  - Prediction correct
  - $\frac{True\ Positive}{True\ Positive + False\ Positive}$
- Type II Error (recall)
  - Quantify false negative
  - Prediction misclassifies
  - $\frac{True\ Positive}{True\ Positive + False\ Negative}$
- F1-score
  - Good = low FP and low FN
  - Bad = high FP and high FN
  - Perfect == 1
  - Failure == 0

**TP** = True Positives
**TN** = True Negatives
**FP** = False Positives
**FN** = False Negatives

| | p' (Predicted) | n' (Predicted) |
|---|---|---|
| p (Actual) | True Positive | False Negative |
| n (Actual) | False Positive | True Negative |

$$\textbf{Precision} = \frac{TP}{TP + FP} \qquad \textbf{Recall} = \frac{TP}{TP + FN}$$

$$\textbf{F1-score} = \frac{2 * precision * recall}{precision + recall}$$

# Deep learning model - Training

- Model training w/ ~930,000 2-layer spectral amp and phase
  - ~1 hour training time
- Validation and test
  - Good precision on earthquakes
  - Mislabeled noise data is expected
  - Random noise and non-random noise shows 80-88% precision
  - Non-random will contain some earthquakes producing

**Training metrics**

**Validation Set # 168587**

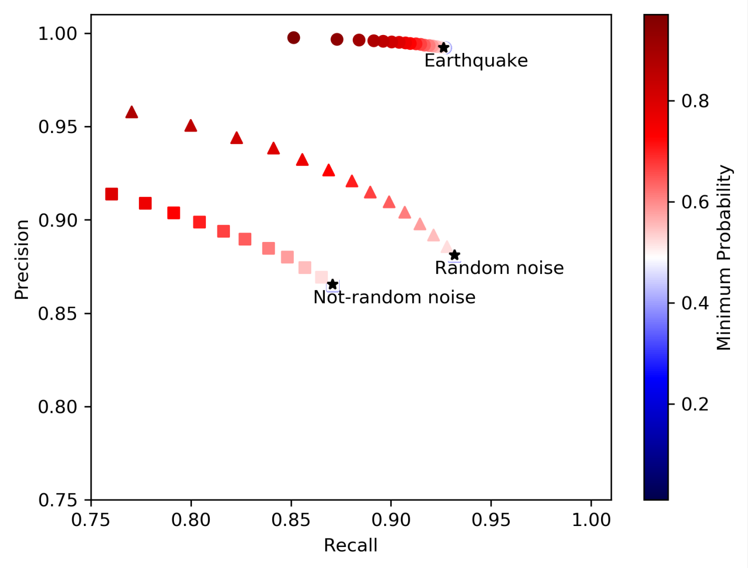
| | precision | recall | f1-score | support |
|---|---|---|---|---|
| EQ | 0.99 | 0.93 | 0.96 | 56107 |
| RN | 0.88 | 0.93 | 0.91 | 56298 |
| NRN | 0.86 | 0.87 | 0.87 | 56182 |
| weighted avg | 0.91 | 0.91 | 0.91 | 168587 |

**Test Set # 50000**

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| EQ | 0.98 | 0.85 | 0.91 | 16799 |
| RN | 0.87 | 0.93 | 0.90 | 16677 |
| NRN | 0.80 | 0.86 | 0.83 | 16524 |
| weighted avg | 0.89 | 0.88 | 0.88 | 50000 |

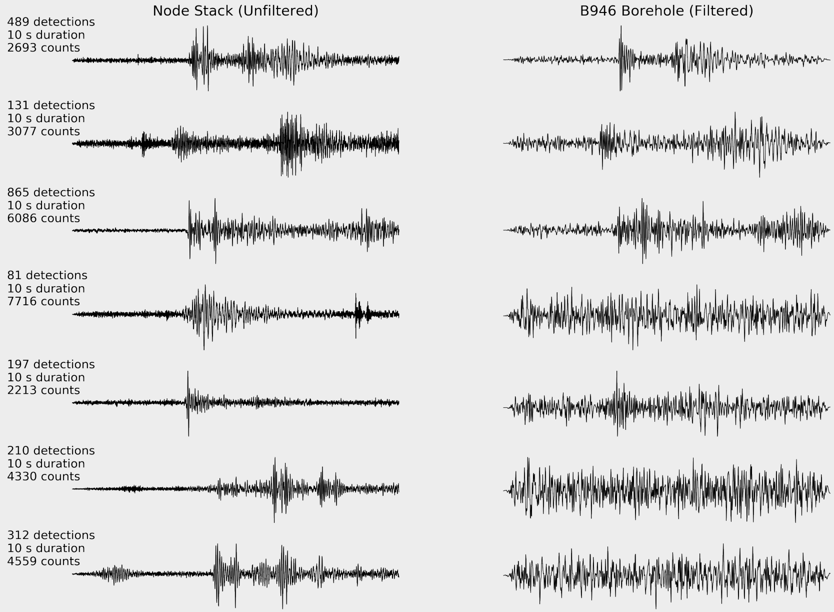
# Deep learning model - Training

- Earthquakes
  - High precision ~99%
  - Recall ~93%
    - Not-random noise expected to have mislabeled input
- Random noise
  - Precision ~88%
  - Recall ~93%
- Non-random noise
  - Precision ~86%
  - Recall ~87%



# Deep learning model – Eq Detections

- 1.5 minutes to classify 1 s interval for entire daily record
- Results for J-day 149
  - 19 catalog events
  - 64 CNN detections
  - 10 node minimum for detection
  - Node stack average
    - Time shifted to max cc
  - Borehole seismometer comparison
    - Filtered 5-30 Hz
- Similar results for all days processed
- Comparable to RF model but faster



# Remarks

- CNN can classify subtle variations in waveforms
  - Used spectrogram here
  - Time domain waveforms also will perform well if trained correctly
- Advantages
  - Trained model can classify waveforms more efficiently
  - Potential to discover new observations
- Other possible directions
  - Recurrent Neural Networks
    - Incorporate time information
  - Denoise with autoencoders