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sur le cerveau

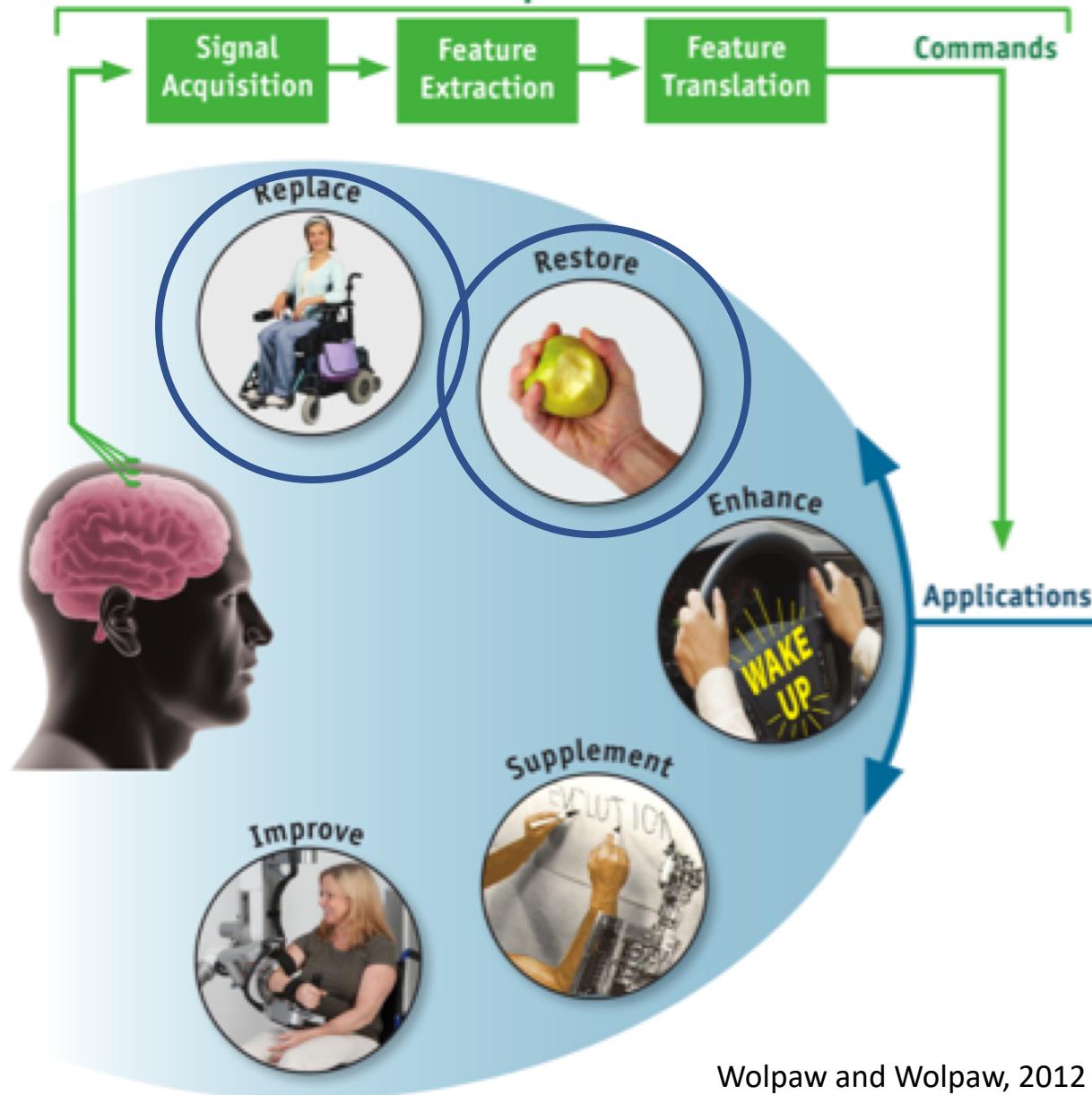
Brain and Mind
Research Institute

Workshop on Applied Deep Learning in Intracranial Neurophysiology

Part 2 – My first neural net
September 16, 2019

Presented by Chadwick Boulay, MSc, PhD
Ottawa Hospital Research Institute
University of Ottawa

Brain-Computer Interface



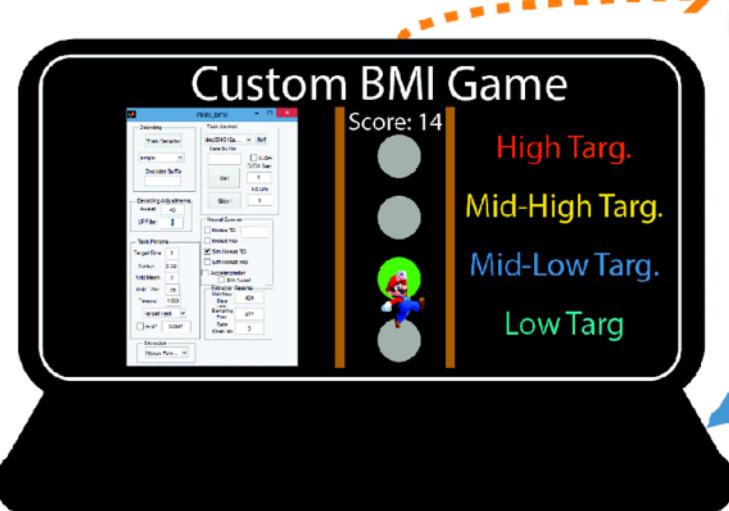
Wolpaw and Wolpaw, 2012

BCIs for Parkinson's Disease

Previous work (Starr Lab)

a

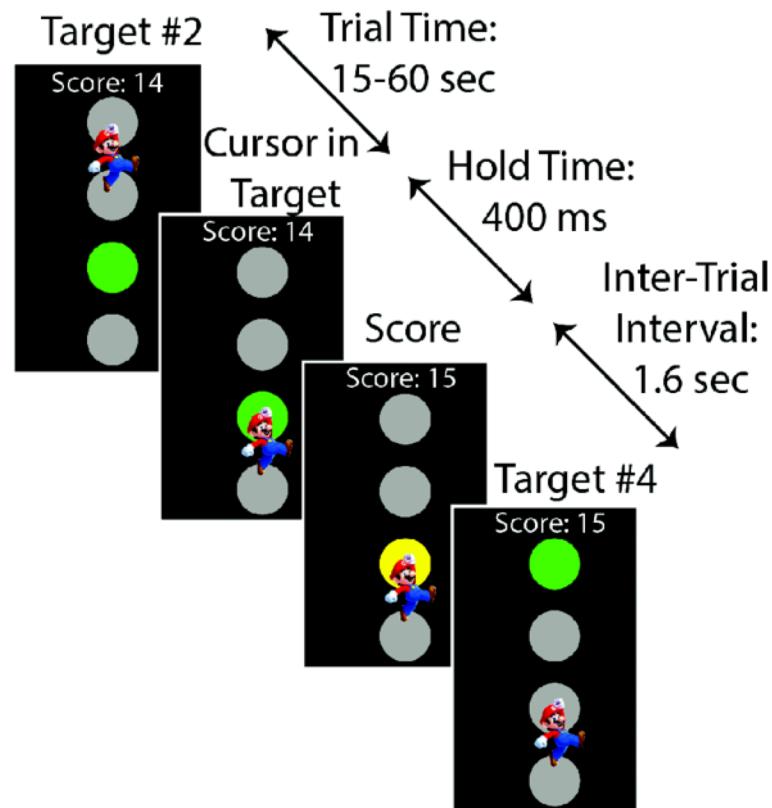
Volitional Control of Neural Activity with Visual Feedback



Cortical Recording



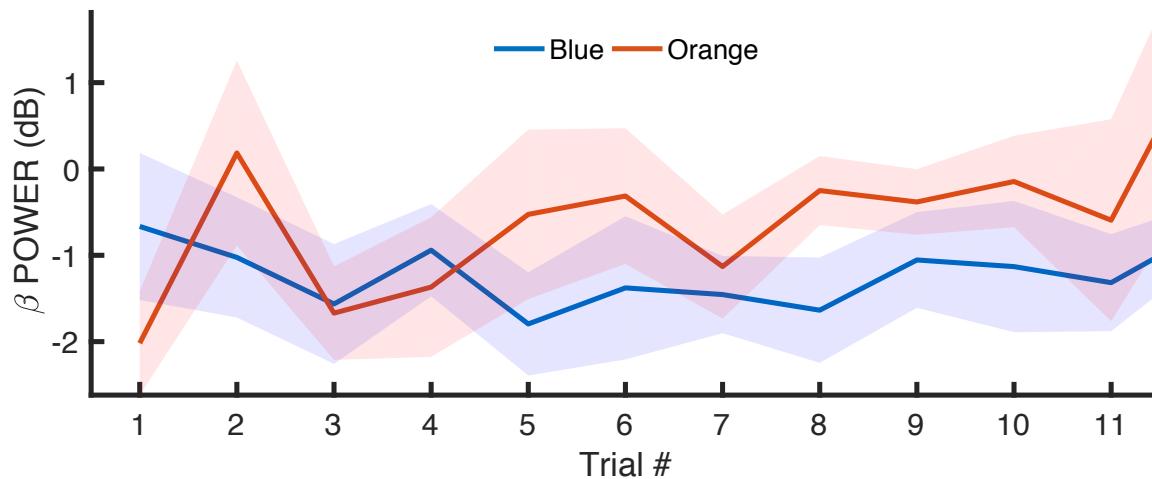
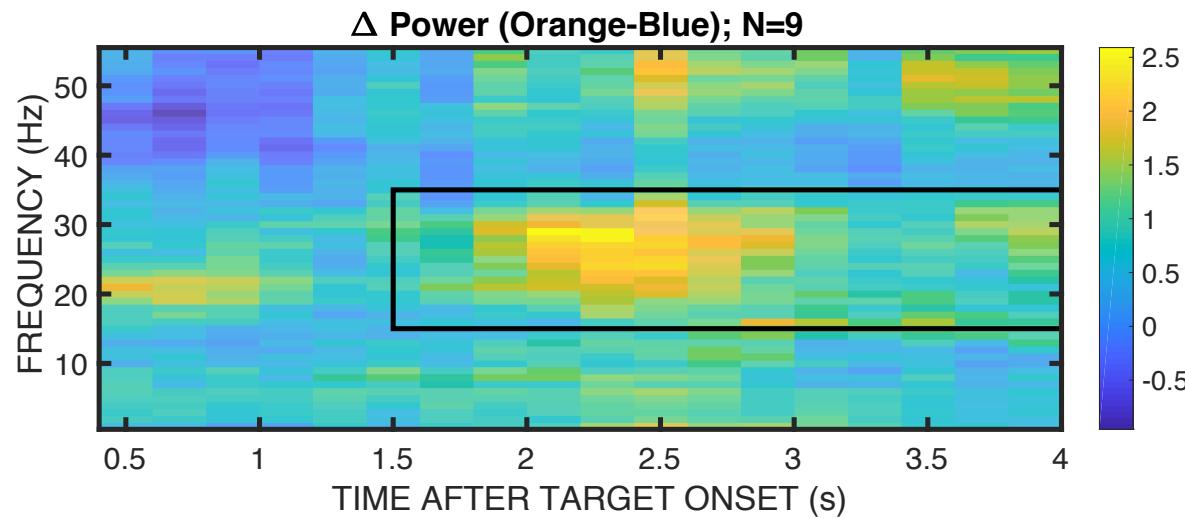
b

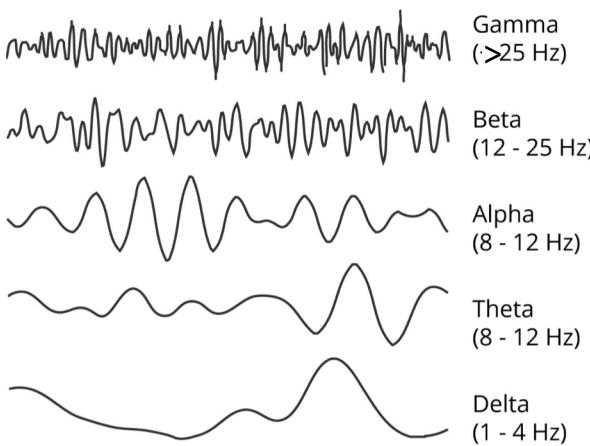
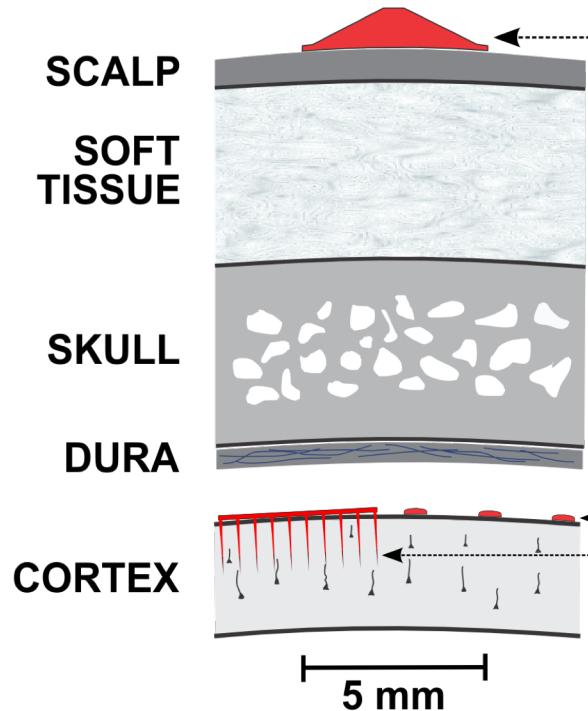




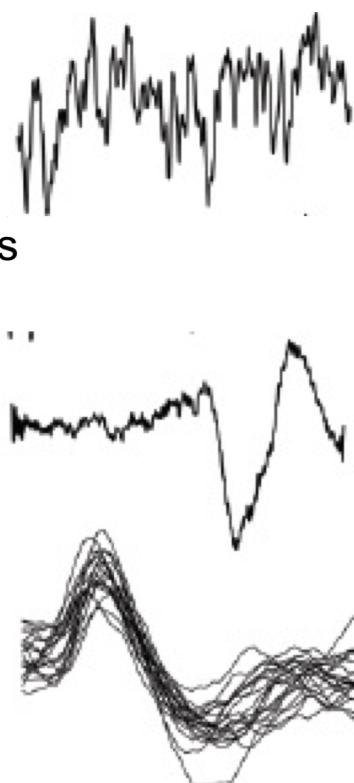
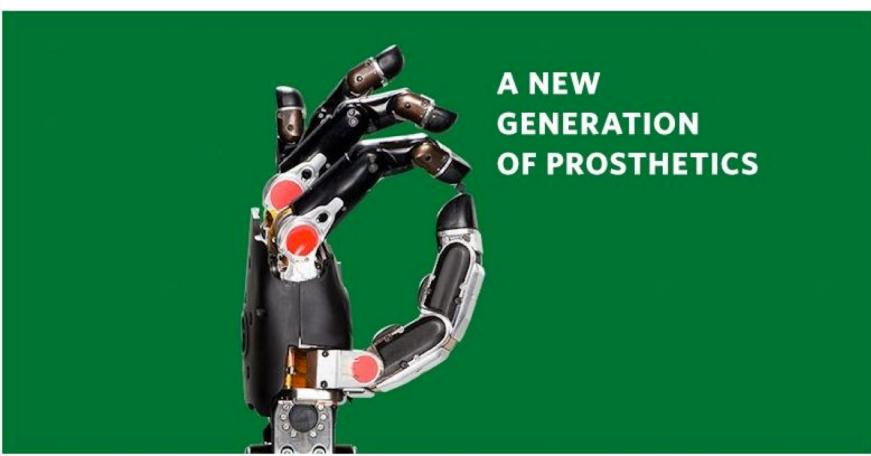
BCIs for Parkinson's Disease

Sachs Lab in uOttawa



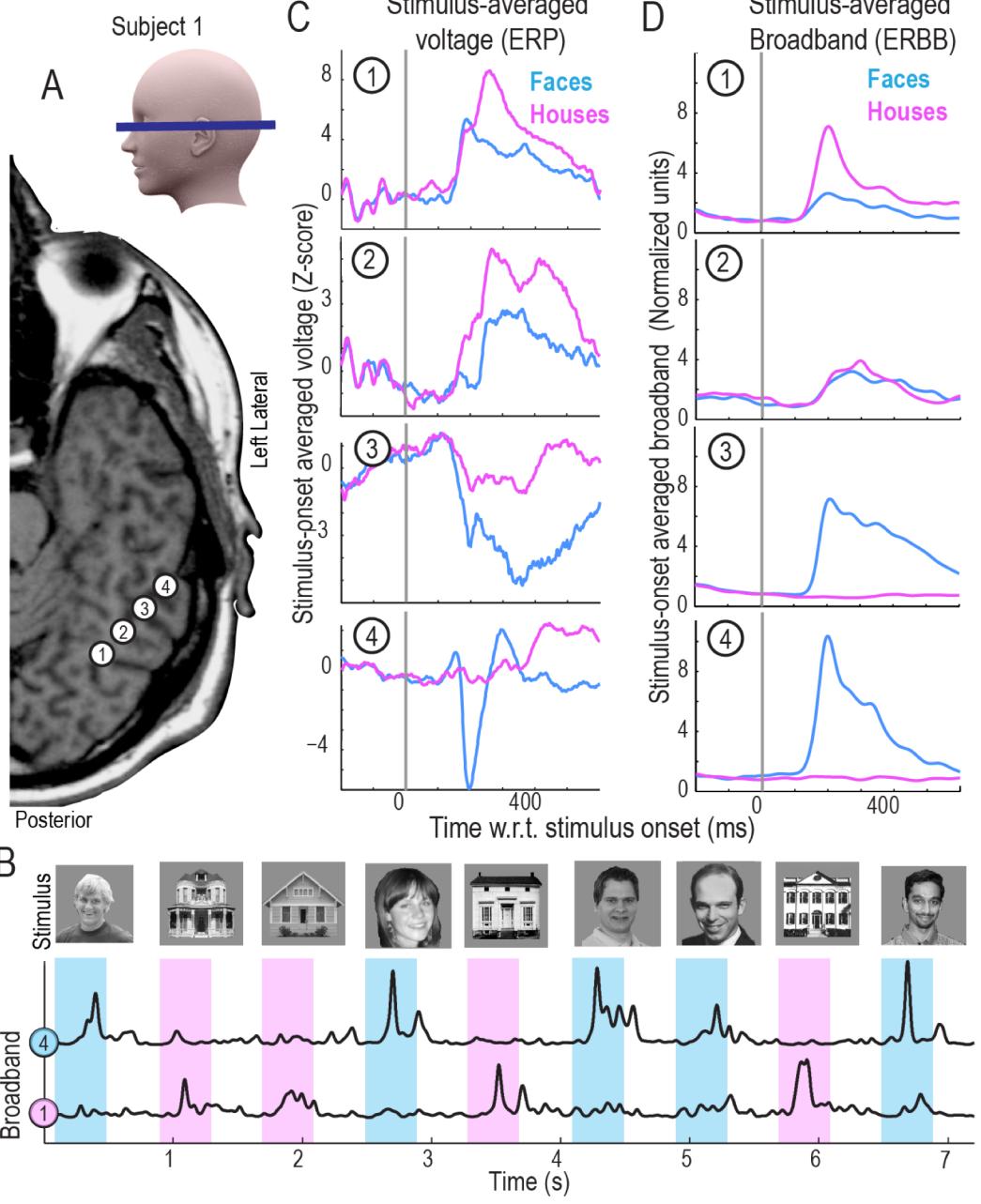


- **EEG**
 - 1 – 300 μ V
 - 10^6 neurons
 - Synchronized synaptic activity
 - < 50 Hz
- **ECoG**
 - 1 – 5000 μ V
 - 10^2 – 10^4 neurons
 - < 250 Hz
- **LFP**
 - 1 – 1000 μ V
 - 10^2 synapses
 - < 250 Hz
- **Spikes**
 - 200 – 500 μ V
 - 1-4 neurons
 - 0.1 – 7 kHz



ECoG Data Library

- Kai J Miller has made available a library of ECoG data he collected. [Link.](#)
- Today we will use one of the datasets from that library, found in the "faces_basic" folder.
 - Miller, Kai J., Gerwin Schalk, Dora Hermes, Jeffrey G. Ojemann, and Rajesh PN Rao. "Spontaneous decoding of the timing and content of human object perception from cortical surface recordings reveals complementary information in the event-related potential and broadband spectral change." *PLoS computational biology* 12, no. 1 (2016): e1004660.
 - **Ethics statement:** All patients participated in a purely voluntary manner, after providing informed written consent, under experimental protocols approved by the Institutional Review Board of the University of Washington (#12193). All patient data was anonymized according to IRB protocol, in accordance with HIPAA mandate. These data originally appeared in the manuscript "Spontaneous Decoding of the Timing and Content of Human Object Perception from Cortical Surface Recordings Reveals Complementary Information in the Event-Related Potential and Broadband Spectral Change" published in *PLoS Computational Biology* in 2016



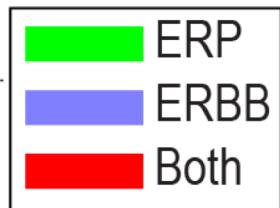
Broadband: Power in 50-300 Hz

Event-Related Potential:
Stimulus-locked time-domain signal

3 Conditions:

- * Inter-Stimulus Interval
- * face
- * house

Decoding accuracy - when timing is known



Fraction correct

1

0.8

Bar graph with non-zero y-intercept. ☺

1

2

3

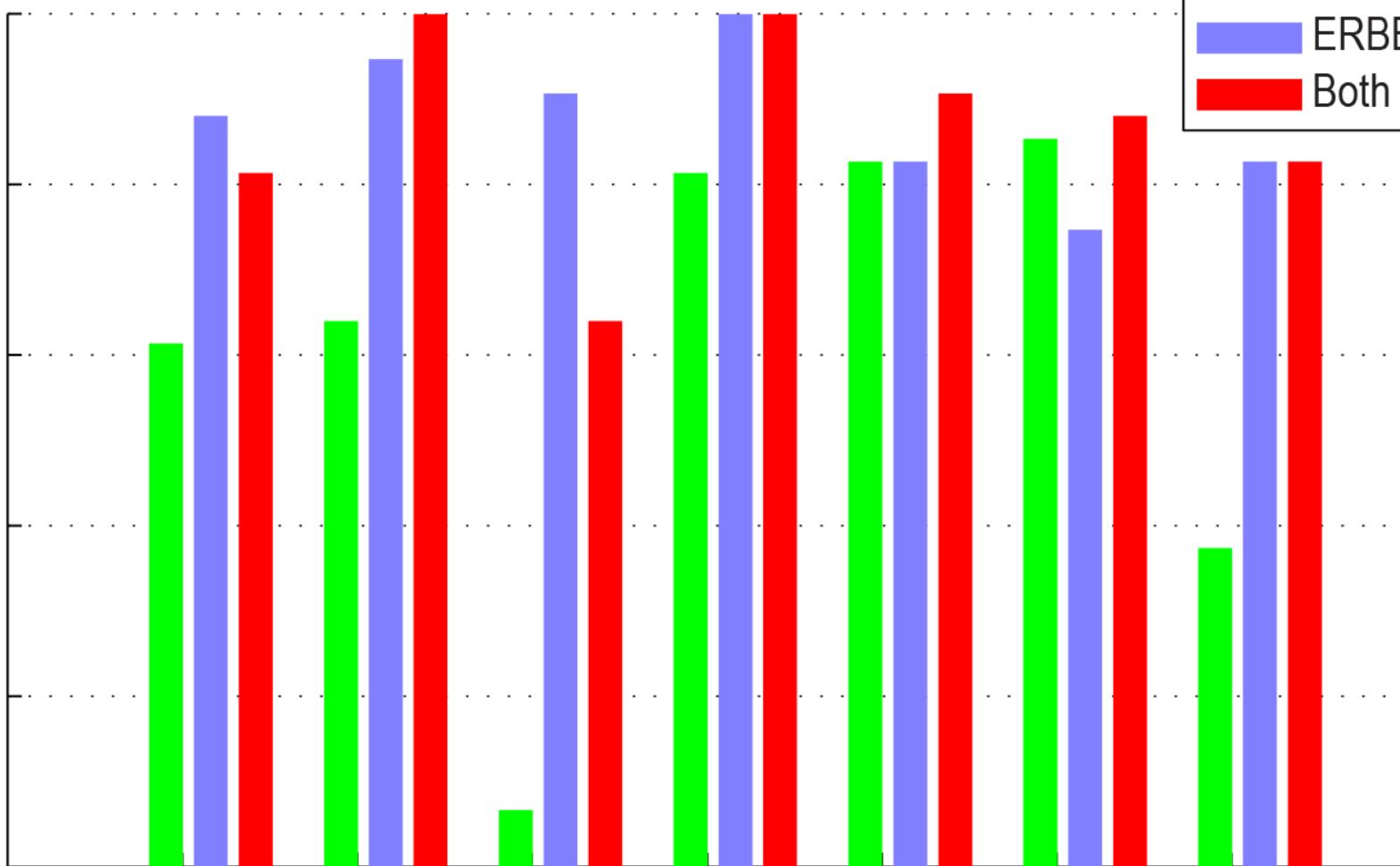
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6

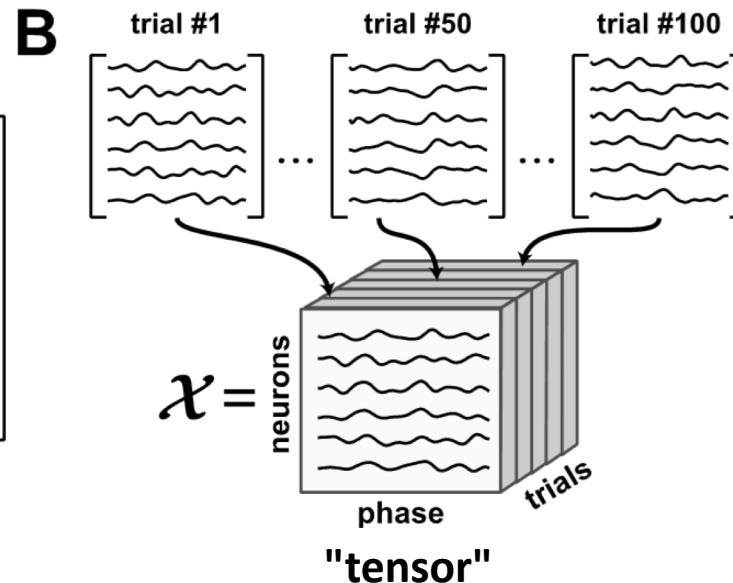
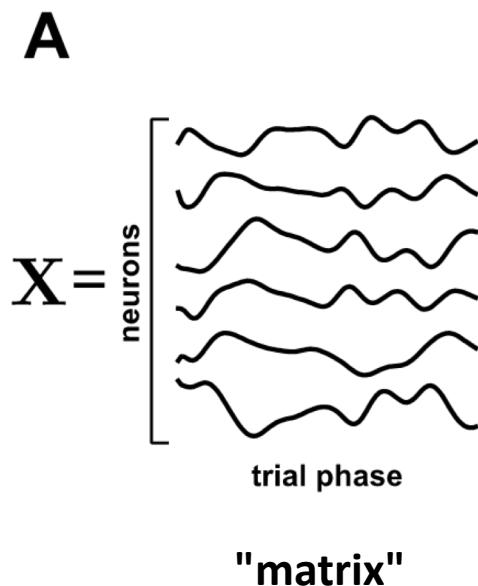
7

Subject number



Data Structure

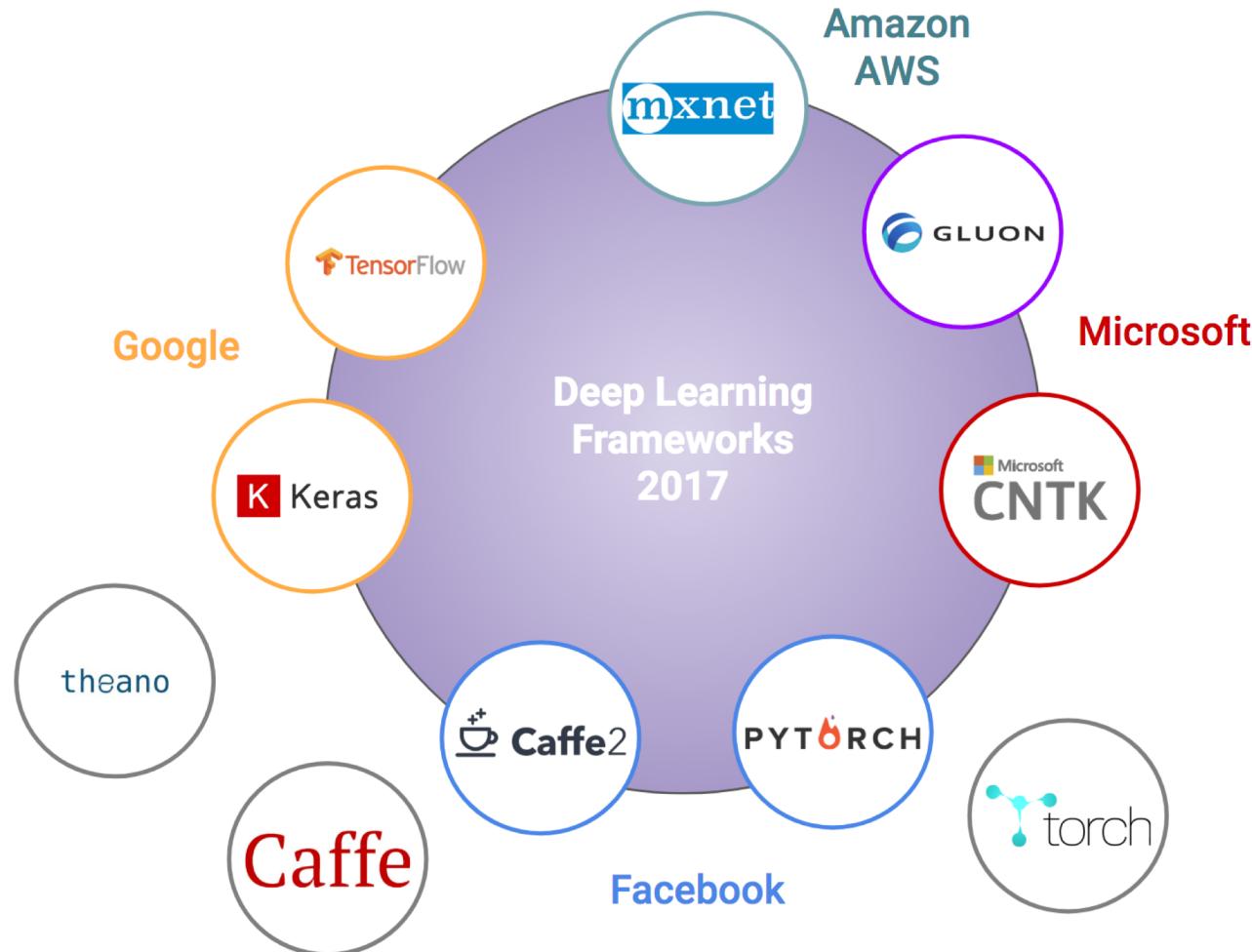
- Review 01_02_data_import.ipynb from Part 1
 - The 'signals' chunk has data with shape (603, 17, 31).
 - (trials, samples, channels)



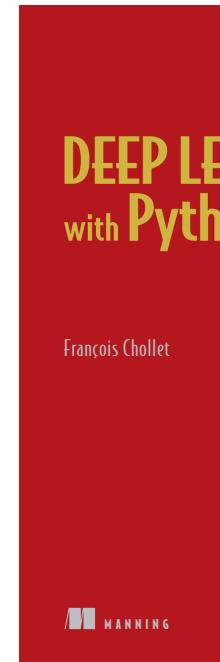
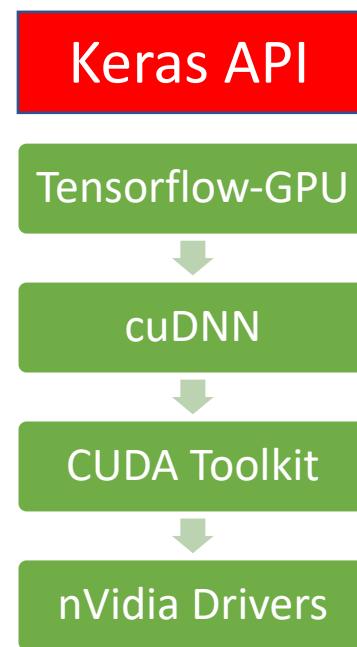
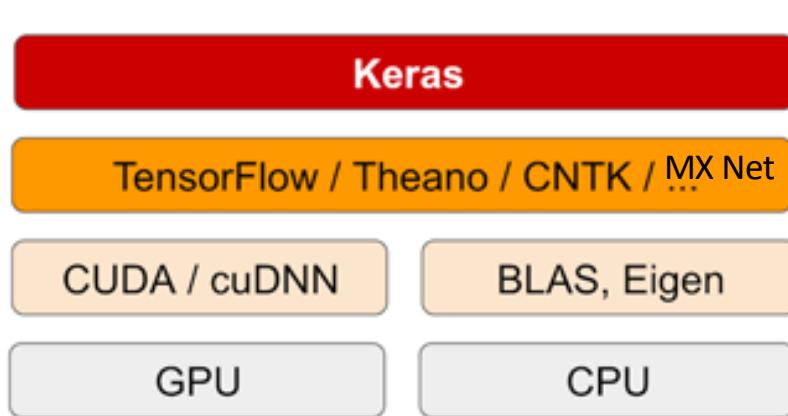
- Show preprocessing script
 - Import
 - RemoveBadTimeWindows
 - CAR
 - 1-Hz high-pass IIR
 - 60 Hz notch IIR
 - Z-Scoring
 - Segmentation (-0.2 to +0.6 seconds around stimulus)

- 02_01_basic_Ida.ipynb

Creating and training a NN model with Tensorflow and Keras



Creating and training a NN model with Tensorflow and Keras



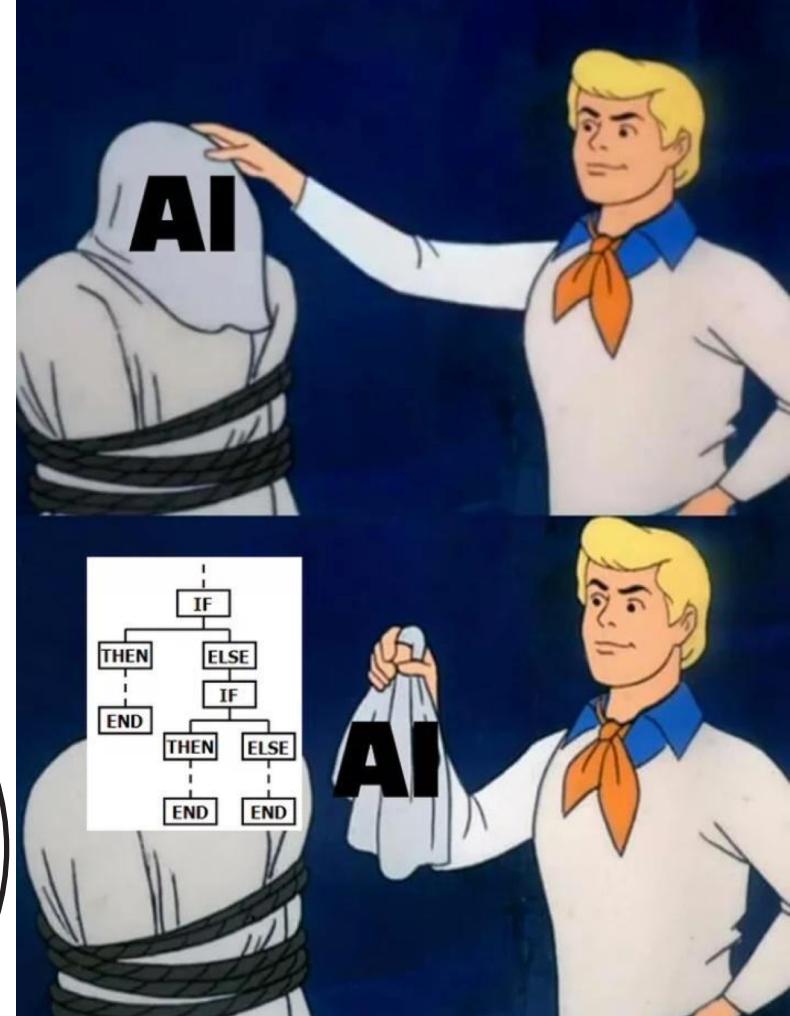
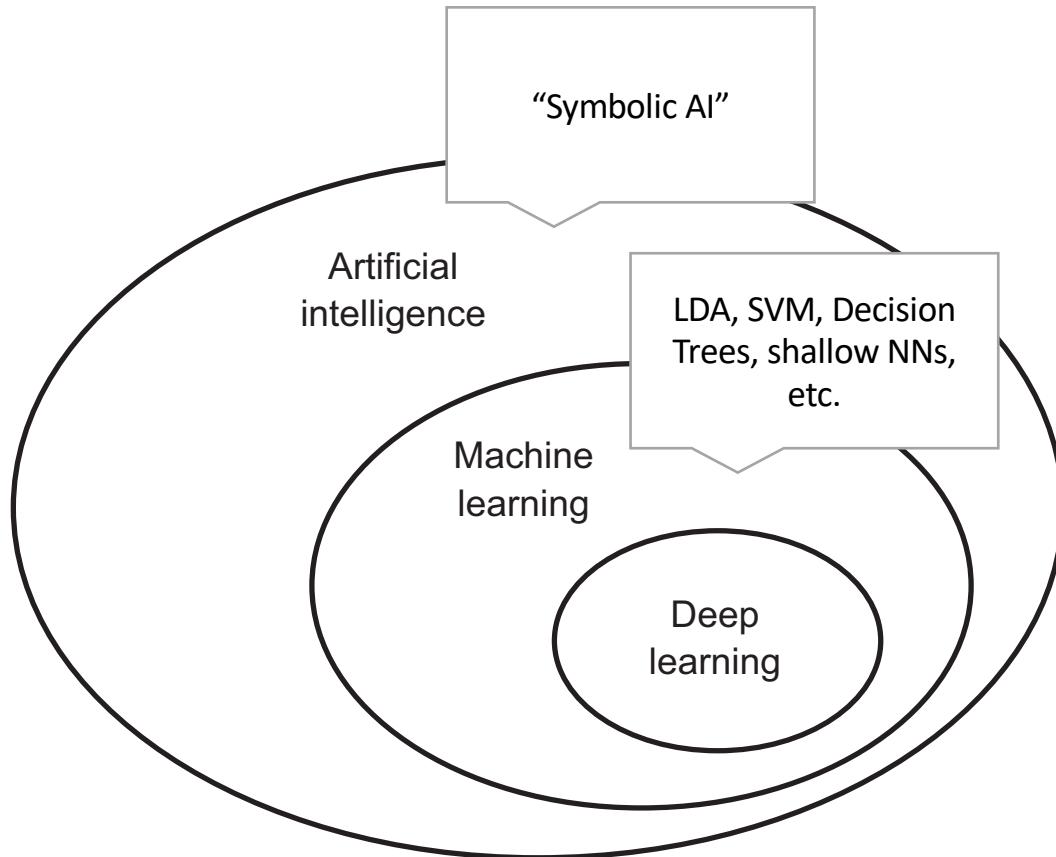


Figure 1.1 Artificial intelligence, machine learning, and deep learning

Deep Learning with Python by Chollet

Goal: finding the right values for these weights

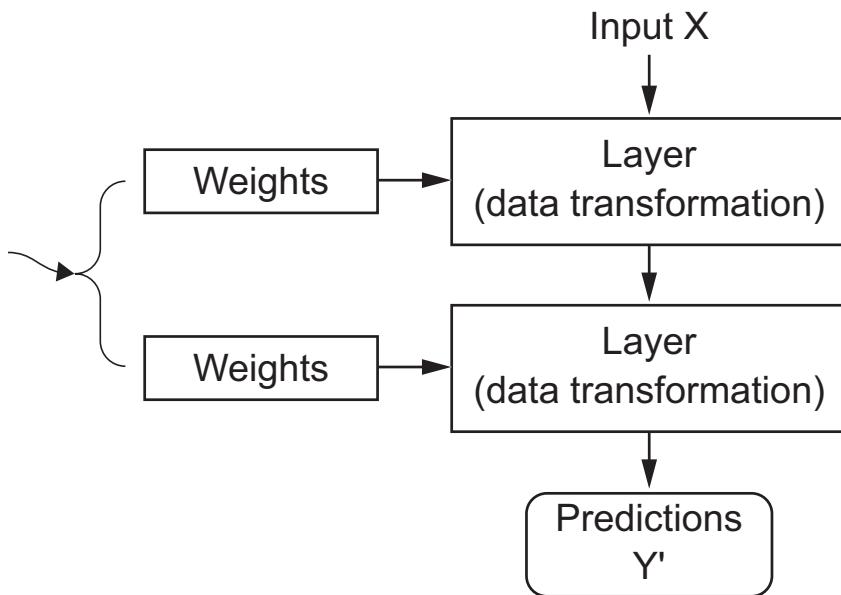


Figure 1.7 A neural network is parameterized by its weights.

Deep Learning with Python by Chollet

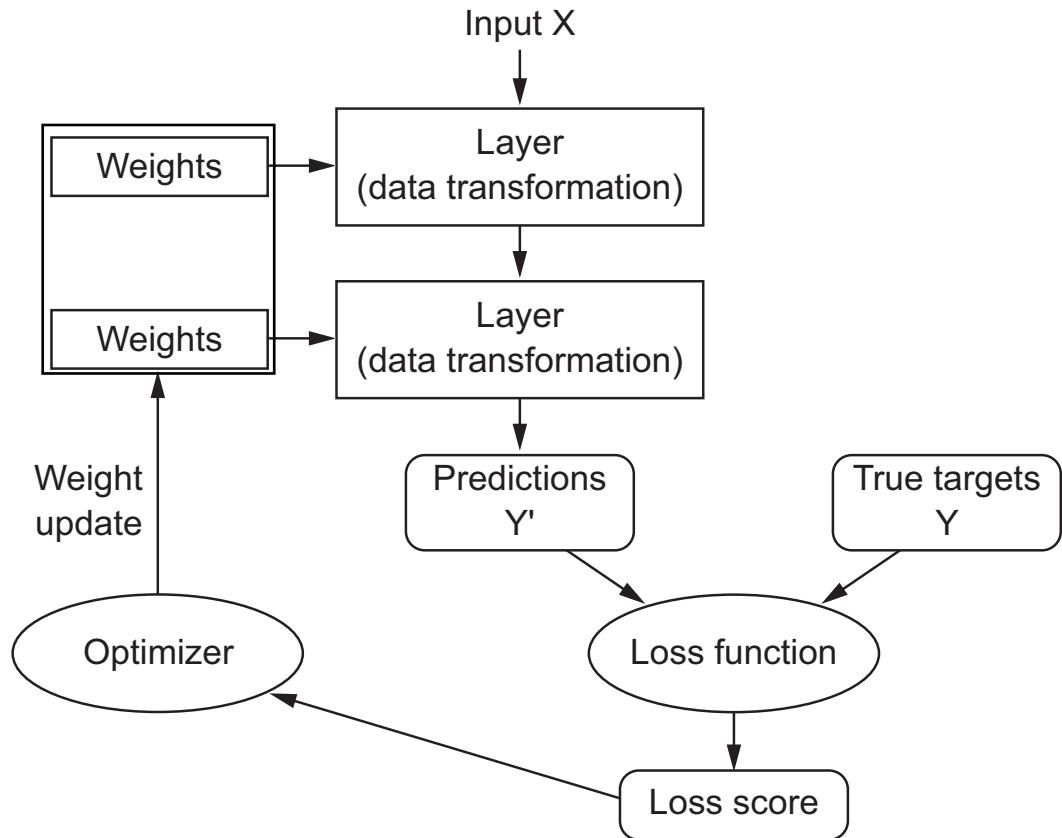
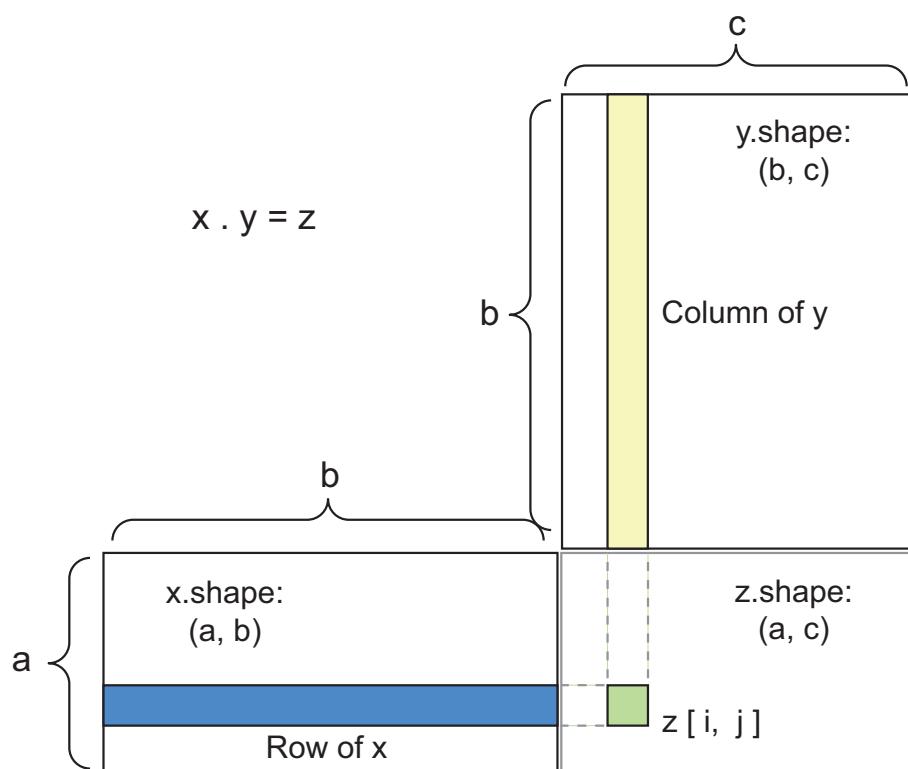


Figure 1.9 The loss score is used as a feedback signal to adjust the weights.

Deep Learning with Python by Chollet



Each transformation layer performs two operations:

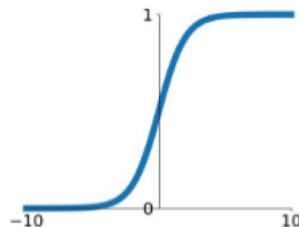
- A tensor dot product (data . Weights represented by $x \cdot y$)
- An (non-linear) activation function
 - Next slide

`x = np.arange(-10, 11, 1), y = f(x), where f is ...`

Activation Functions

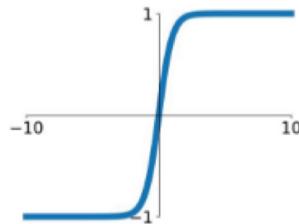
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



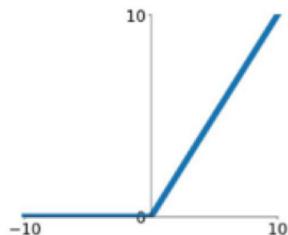
tanh

$$\tanh(x)$$



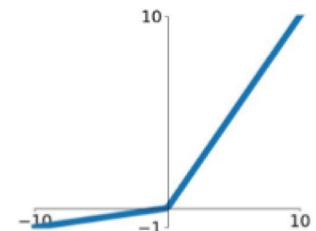
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

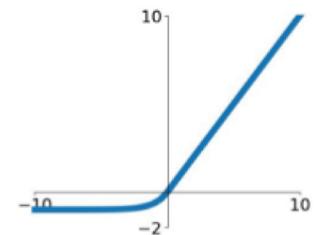


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

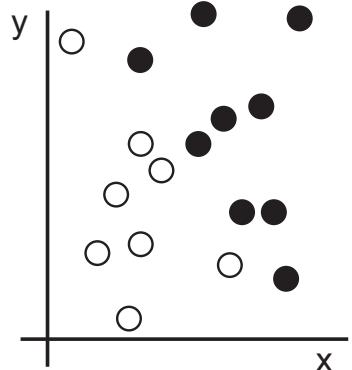
ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$

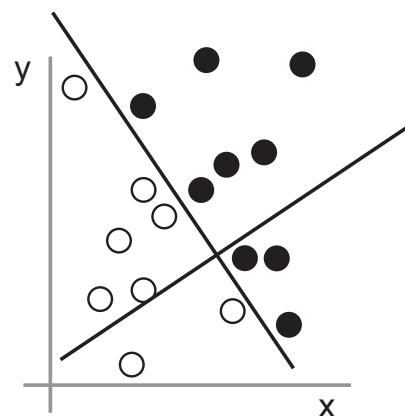


Each transformation is a geometrical operation, changing the representation of the data to something more useful (less lossy).

1: Raw data



2: Coordinate change



3: Better representation

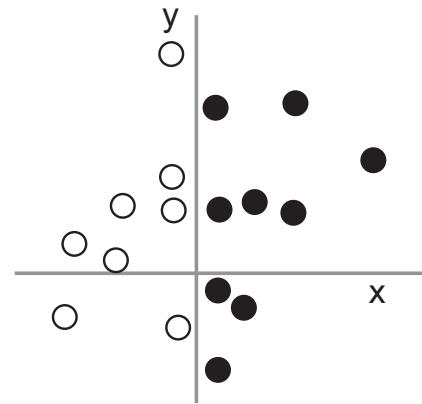


Figure 1.4 Coordinate change

Deep Learning with Python by Chollet

- Each one of many (non-linear) transformations is a step in a sequence.

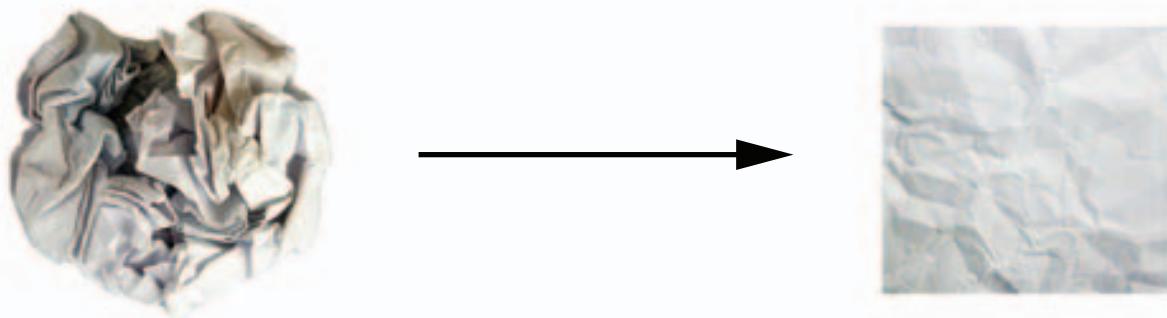
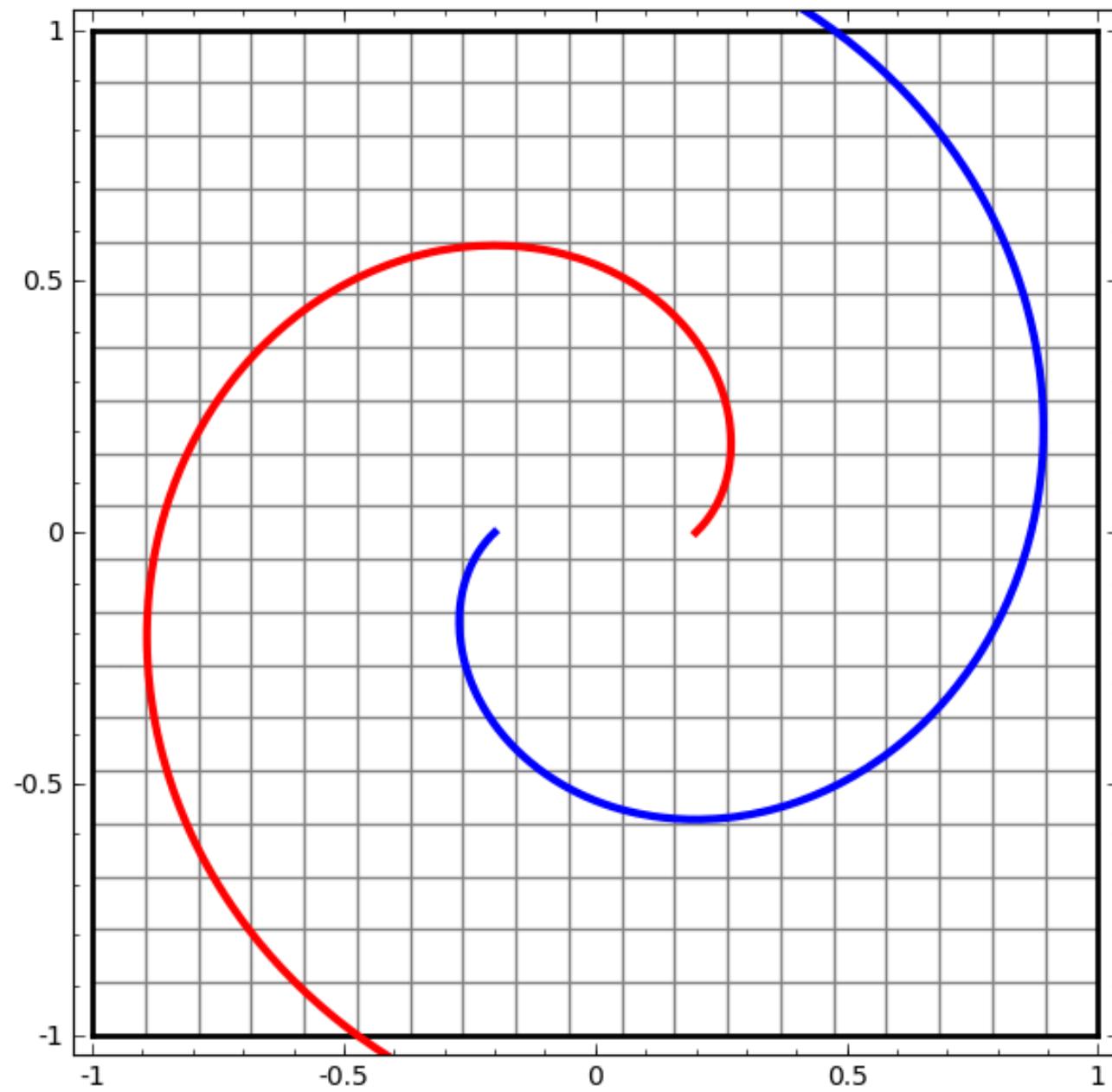


Figure 2.9 Uncrumpling a complicated manifold of data

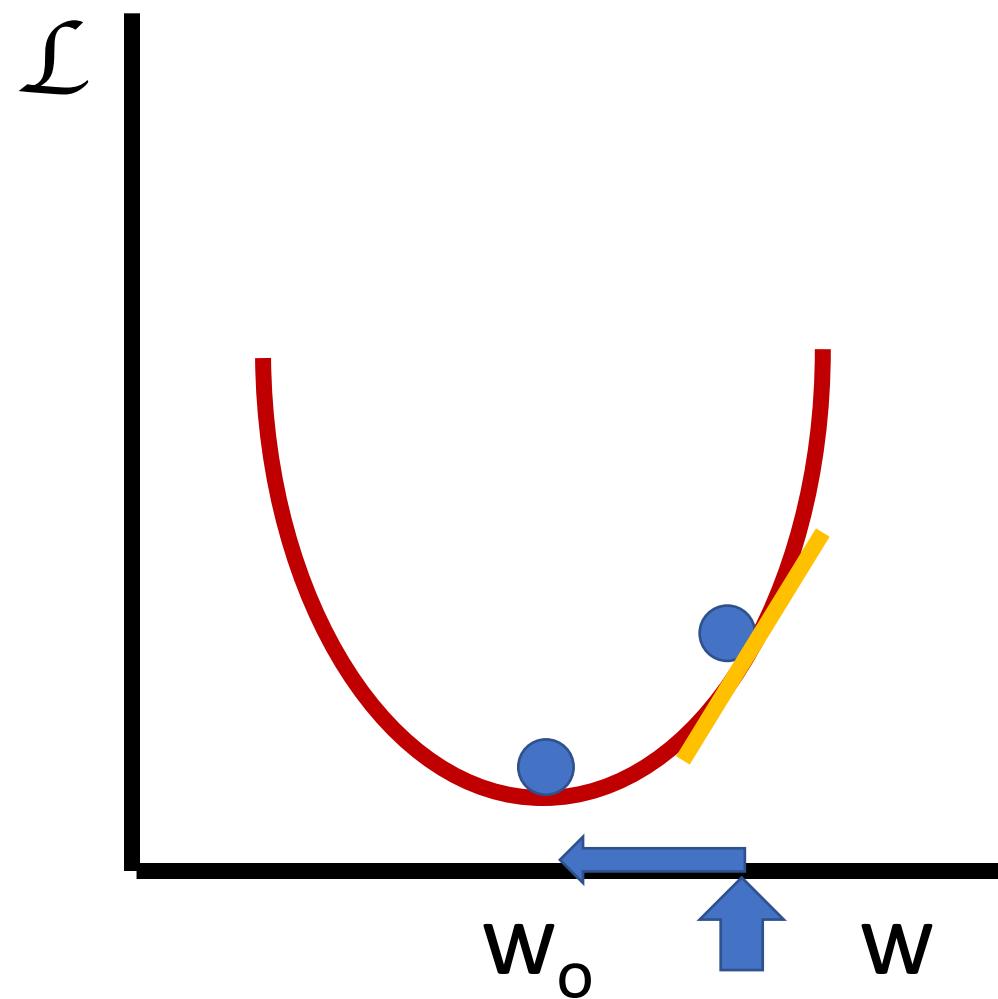
Deep Learning with Python by Chollet



[Source](#)

- 02 02 first neural net.ipynb

Loss & Gradients

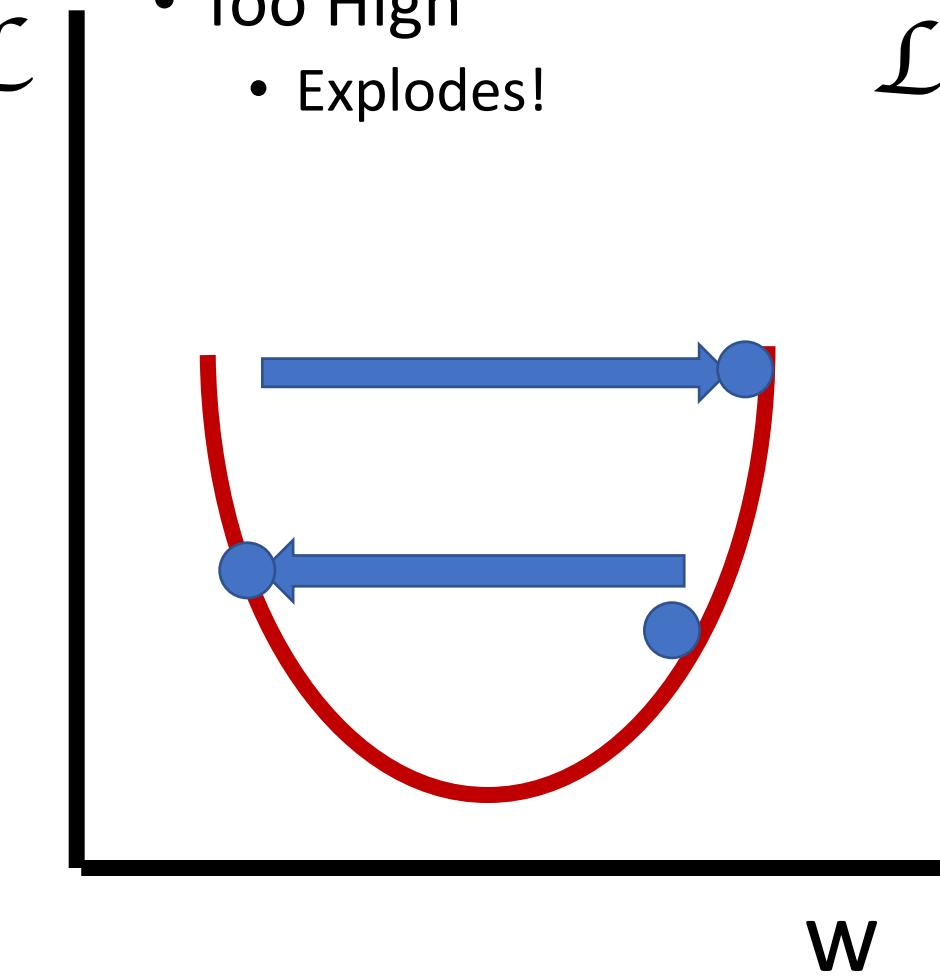


- Assume w_o is optimal value of w with minimum loss.
 - $\mathcal{L} = F(w - w_o)$
 - $\mathcal{L} = (w - w_o)^2$
- Initialize w to some random value
- Calculate loss
- Calculate weight update
 - $\text{grad} = \frac{d\mathcal{L}}{dw}$
 - $w = w - \alpha^* \text{grad}$

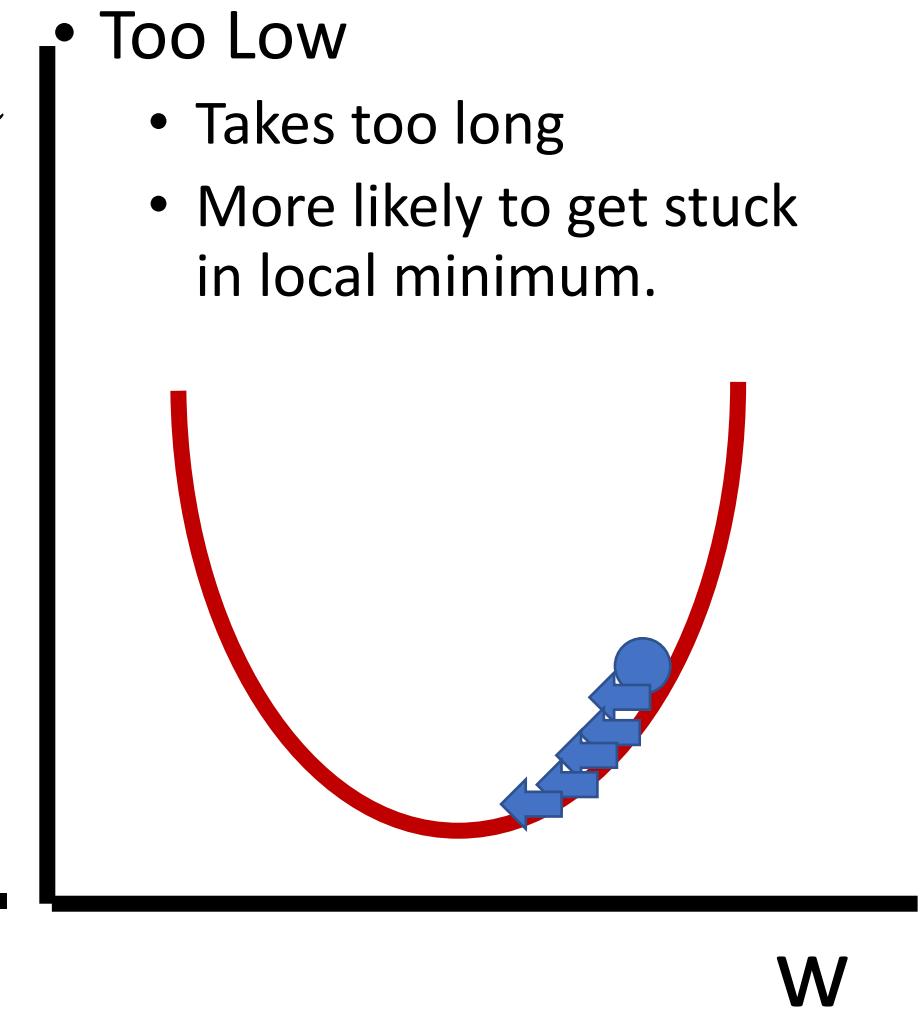
“Gradient Descent”

Learning Rate

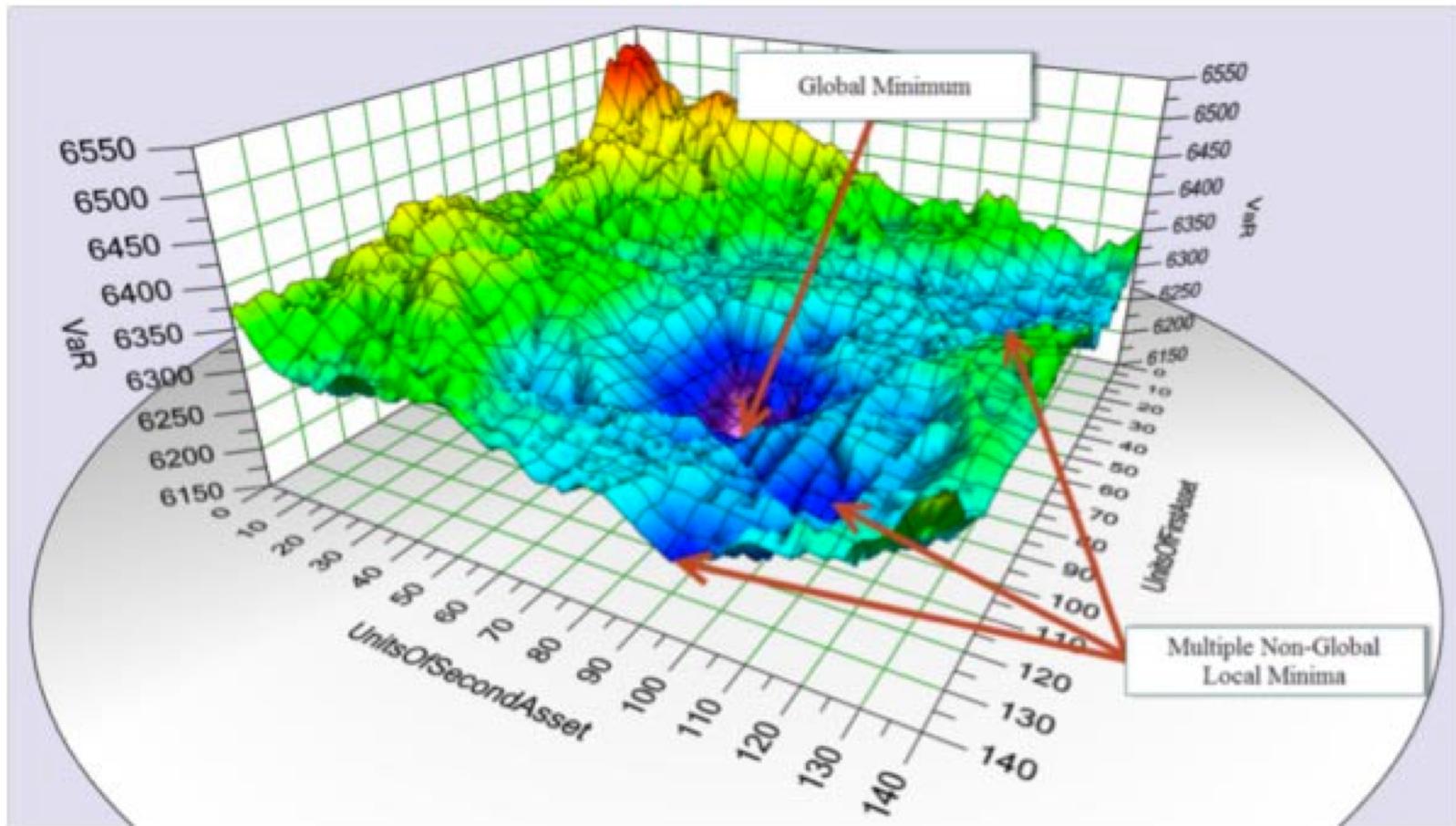
- Too High
 - Explodes!



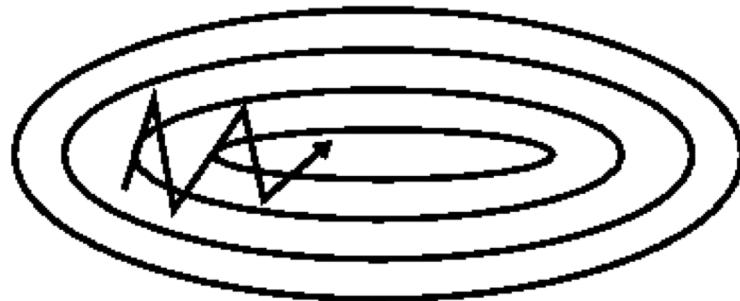
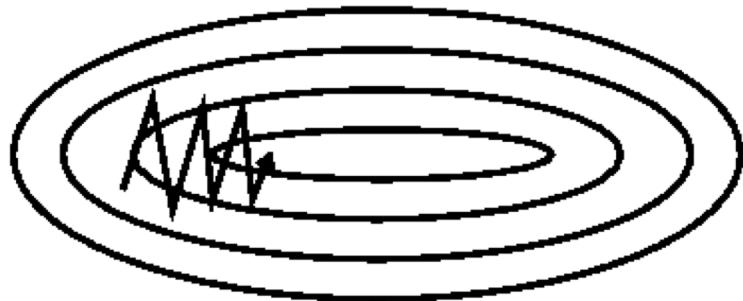
- Too Low
 - Takes too long
 - More likely to get stuck in local minimum.



Loss & Gradients



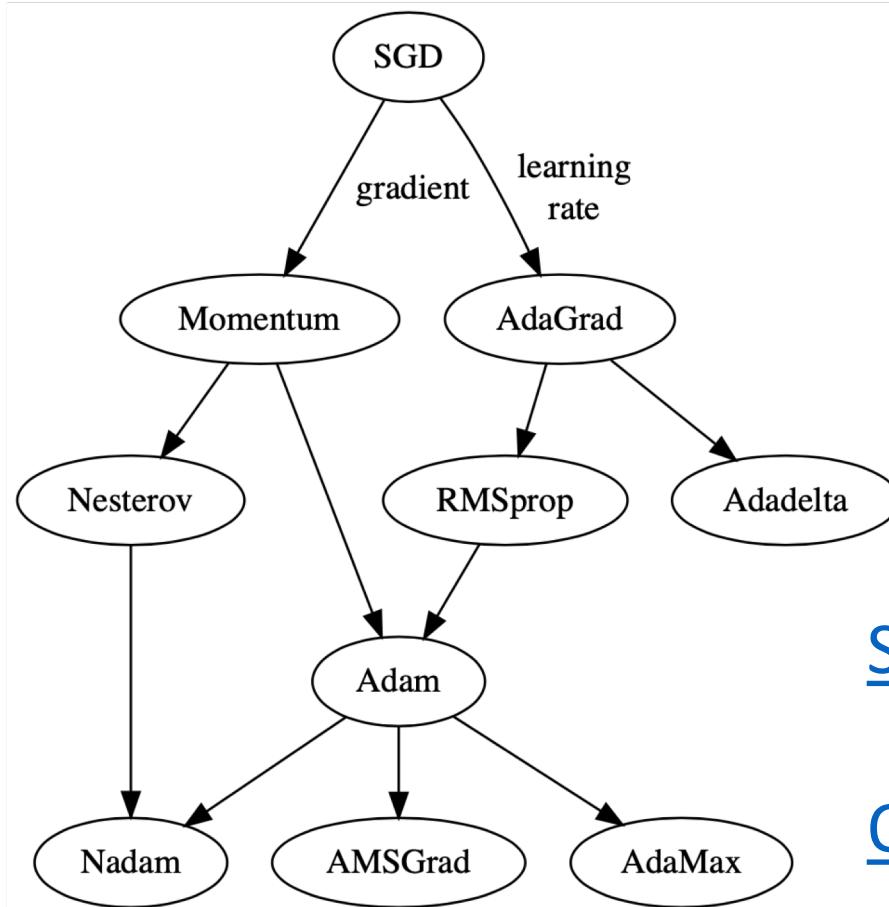
Loss & Gradients



Learning Rate and Optimizers

- Learning Rate Strategies
 - Find “Goldilocks” rate
 - Learning rate schedule
 - E.g. exponential decay
 - Optimizer
 - Combination of the above
- Optimizers
 - Update learning rate based on characteristics of loss/gradient history
$$w_{\text{new}} = w - \alpha \frac{\partial L}{\partial w}$$
 - E.g. RMSprop
$$w_{t+1} = w_t - \frac{\alpha}{\sqrt{S_t + \epsilon}} \cdot \frac{\partial L}{\partial w_t}$$
$$S_t = \beta S_{t-1} + (1 - \beta) \left[\frac{\partial L}{\partial w_t} \right]^2$$

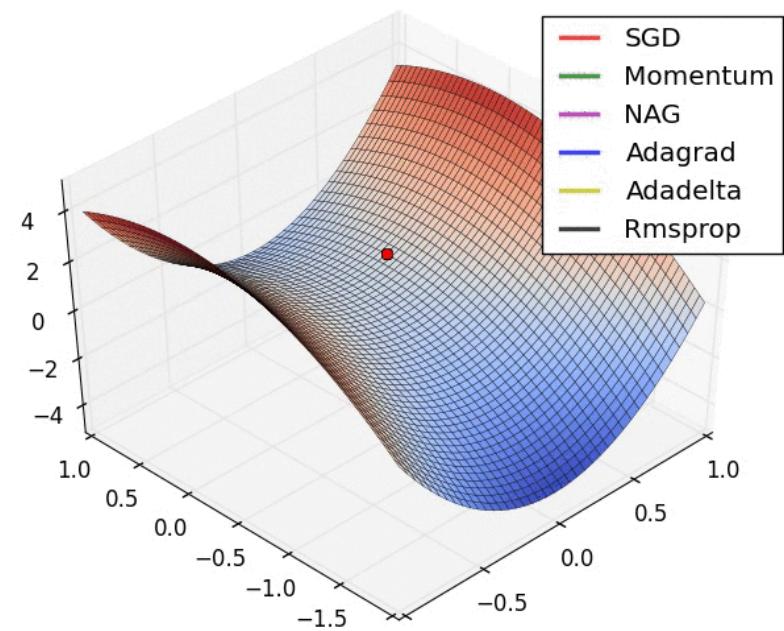
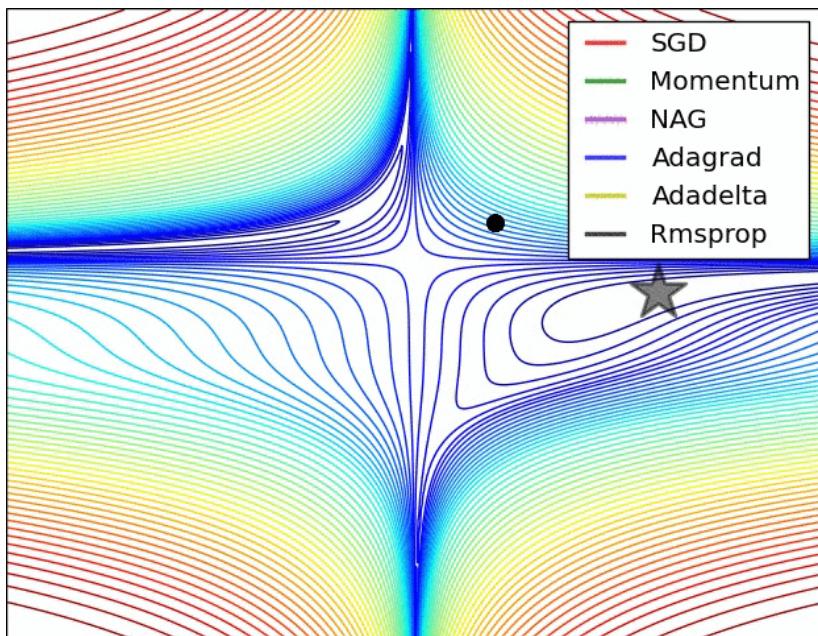
Optimizers



[Source](#)

[Other useful ref](#)

Optimizers



Back propagation

- How do we calculate gradients for middle layers in a deep model?
- [See this](#)
- Optional:
 - [Also this](#)
 - [This video](#)
 - [And this](#)