From CS188, FA18, UC Berkeley: http://ai.berkeley.edu.

Neural Networks

Introduction to Data Science
Spring 1404

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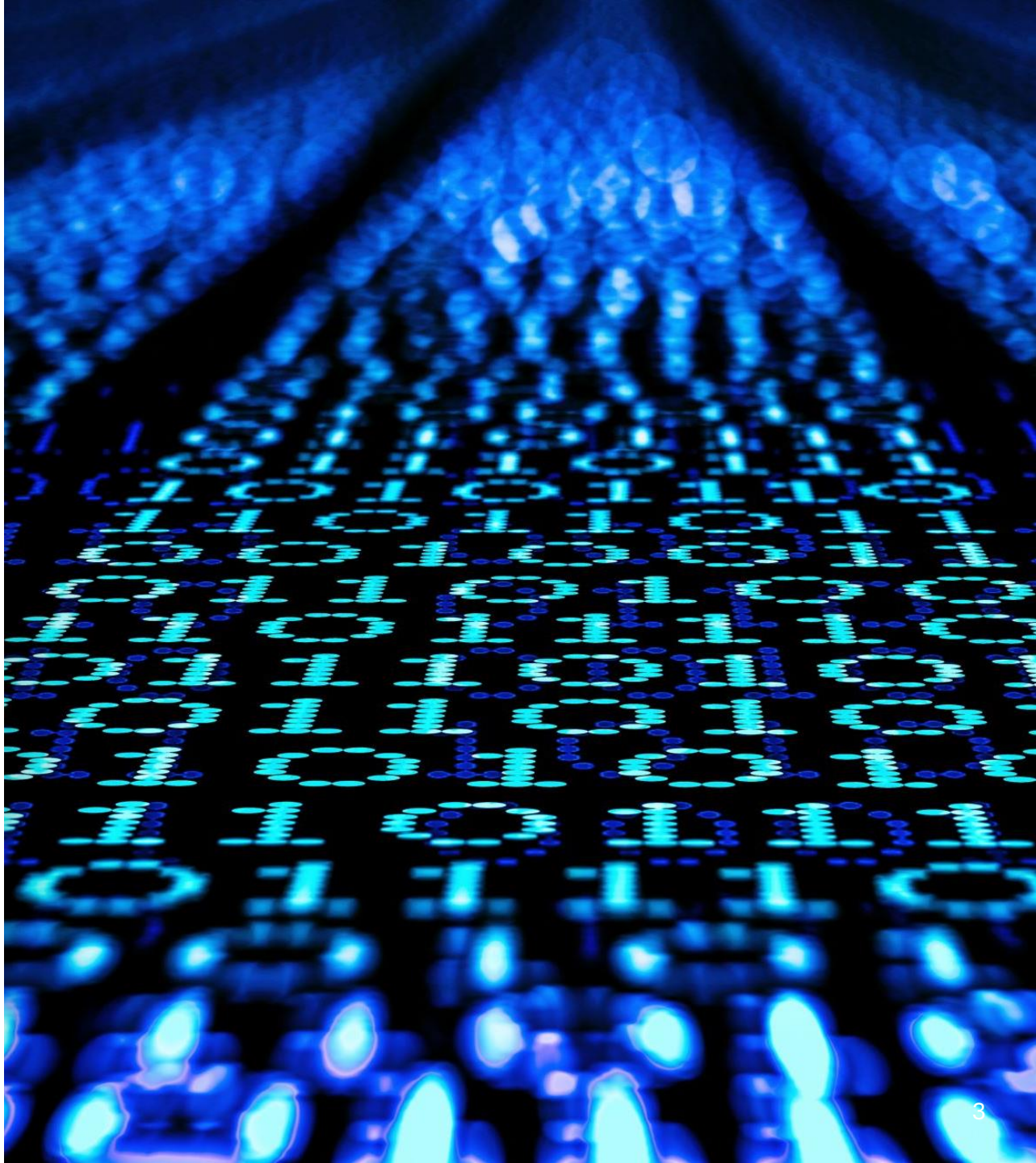
Deep Learning

Multi-layer artificial neural networks

Rise of DL

- Data
- Compute
- Algorithms



Deep learning

- What is its position wrt to ML and AI?

Key differences with other ML techniques

- It learns the features itself
- It is scalable and learn from any large data

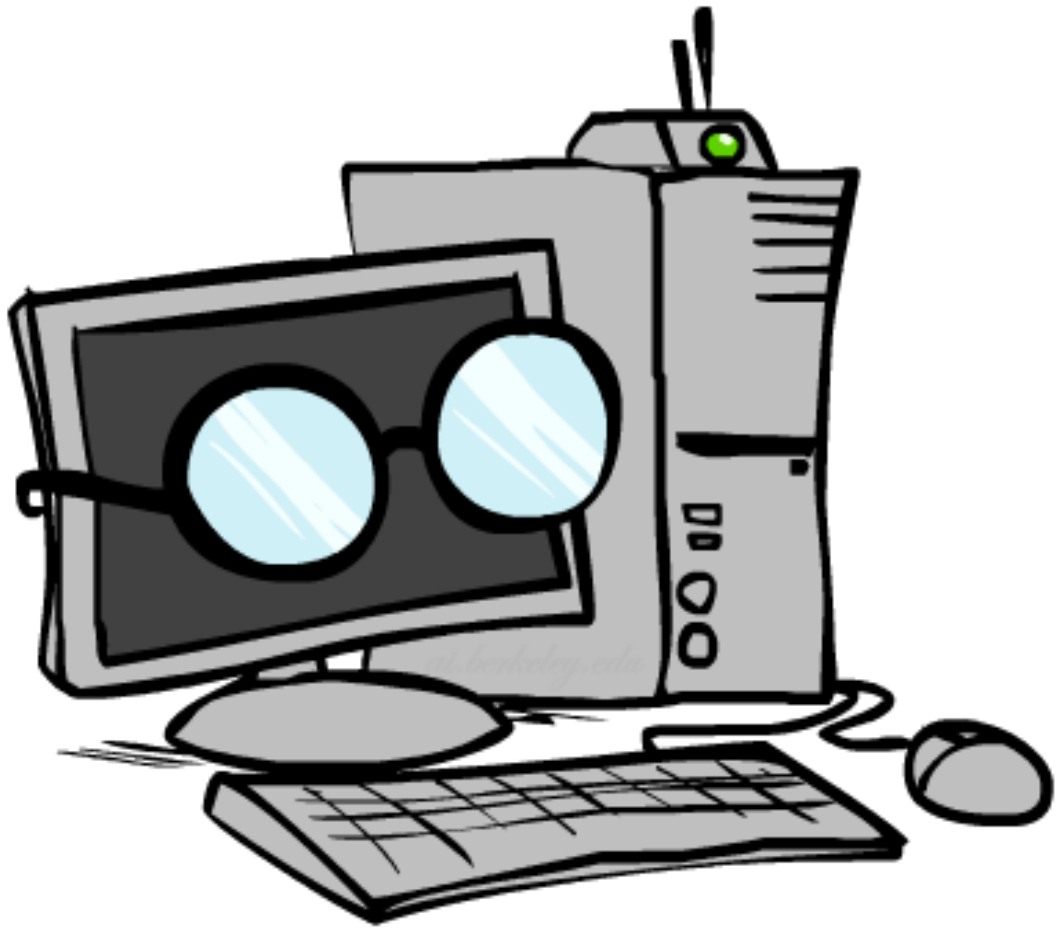
Applications

- Natural language processing
  - Machine translation
  - Search
  - Sentiment analysis

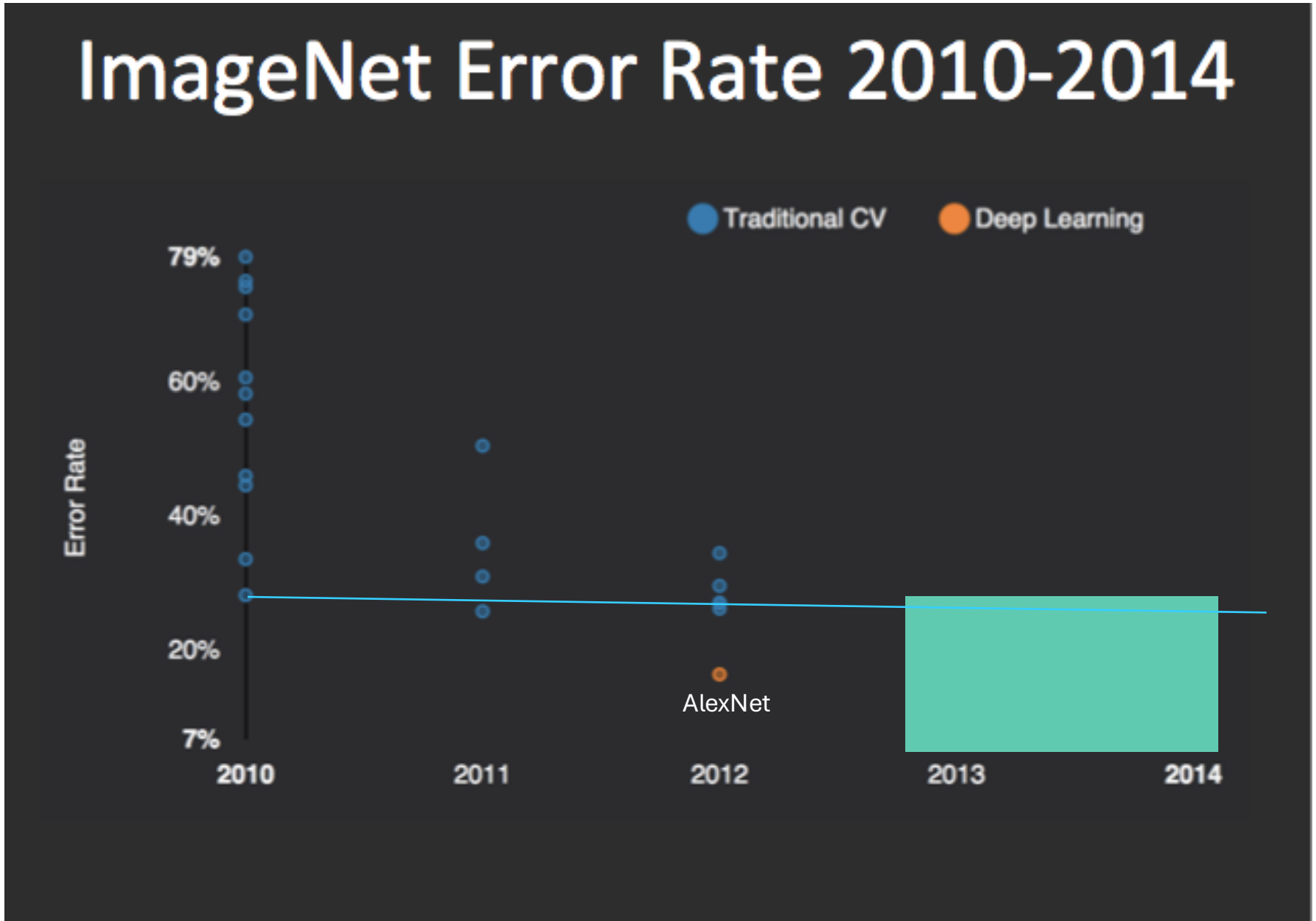
  ➔ Large language models
- Computer vision
  - Image captioning
  - Image generation
  - Image classification
  - Image segmentation
- Recommendation systems

How well does it work?

Computer Vision

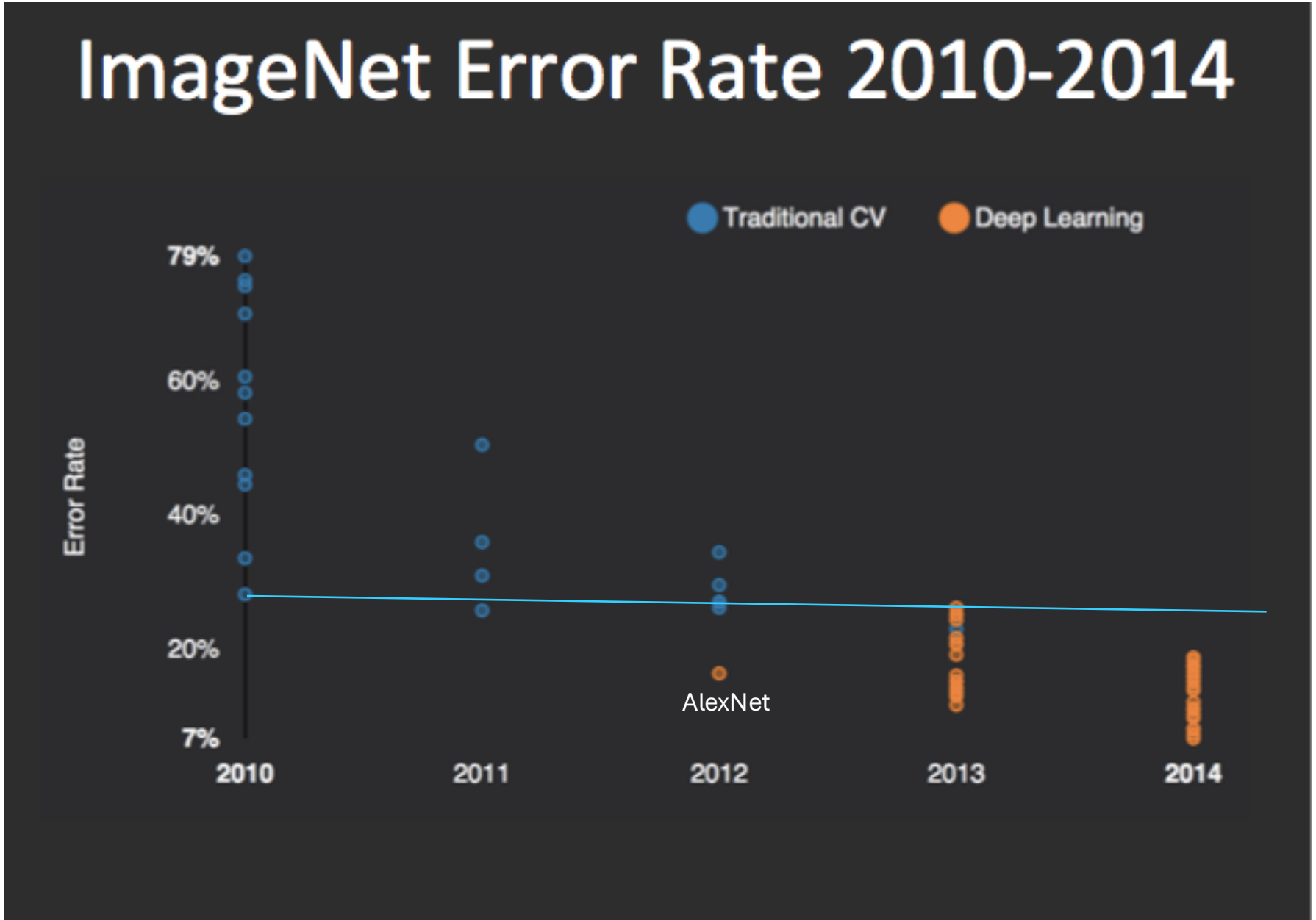


Performance



graph credit Matt Zeiler, Clarifai

Performance



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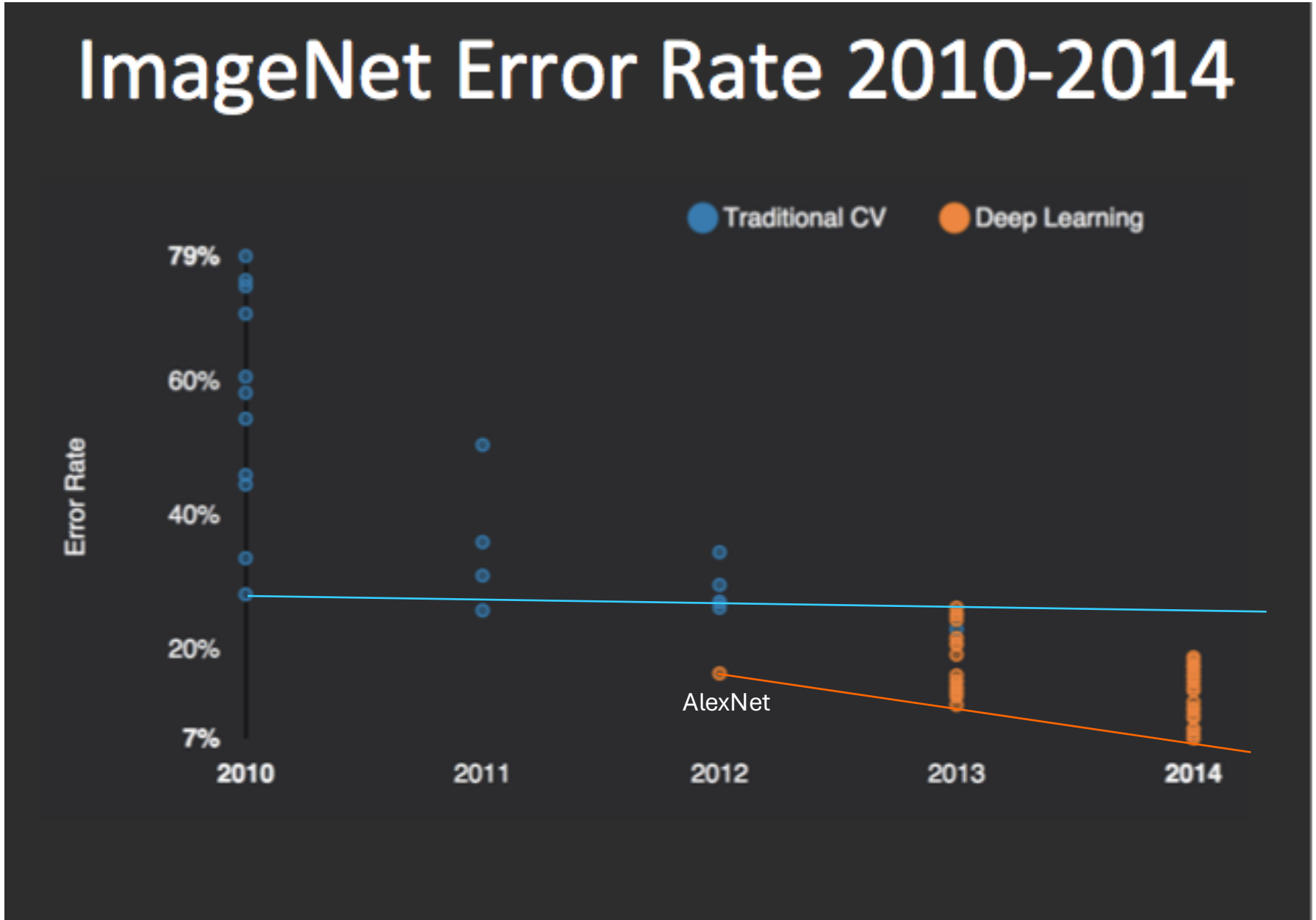
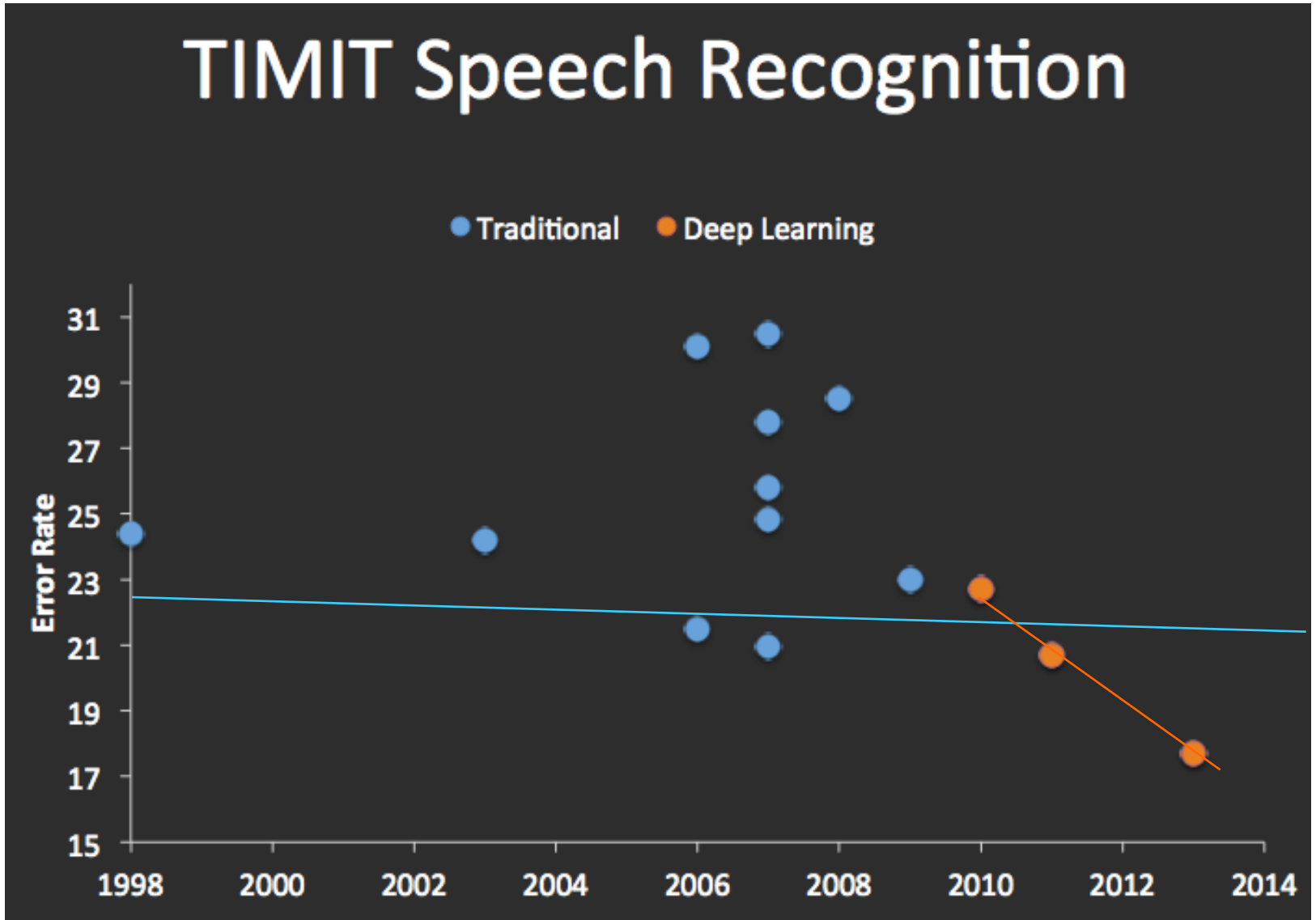
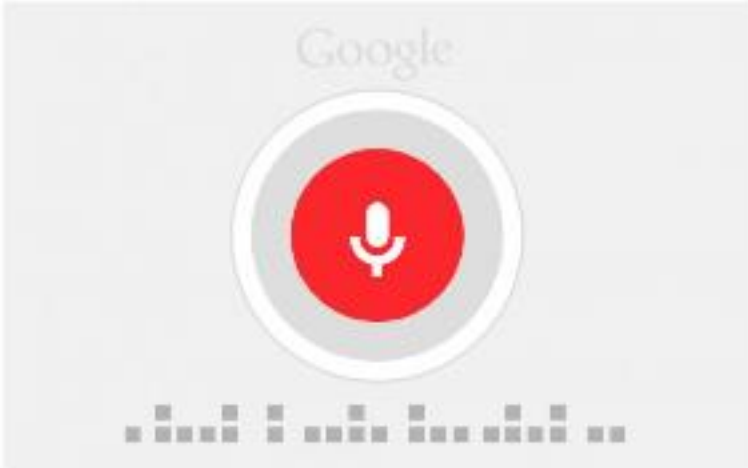
Performance



graph credit Matt Zeiler, Clarifai

Speech Recognition





graph credit Matt Zeiler, Clarifai

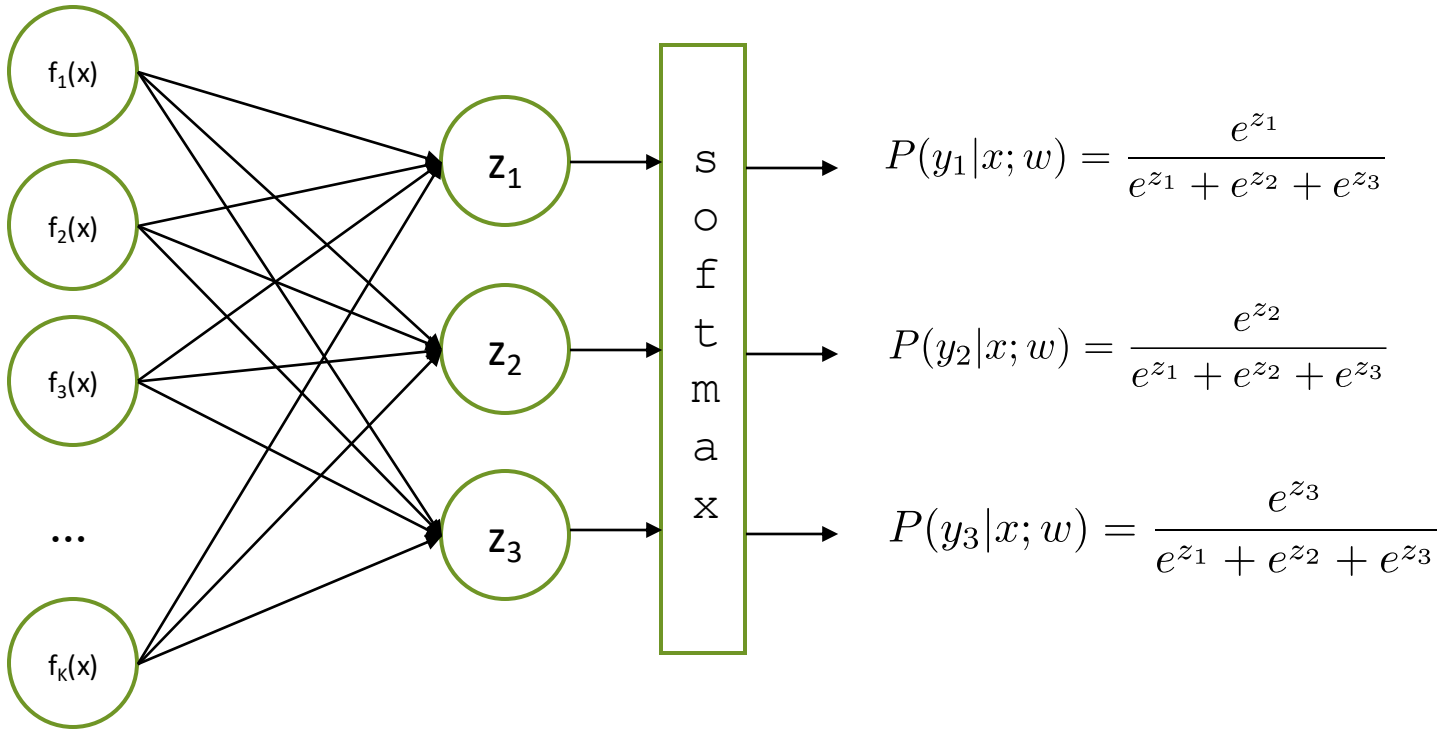
Natural language processing

- BERT (2017)
- ChatGPT (2022)

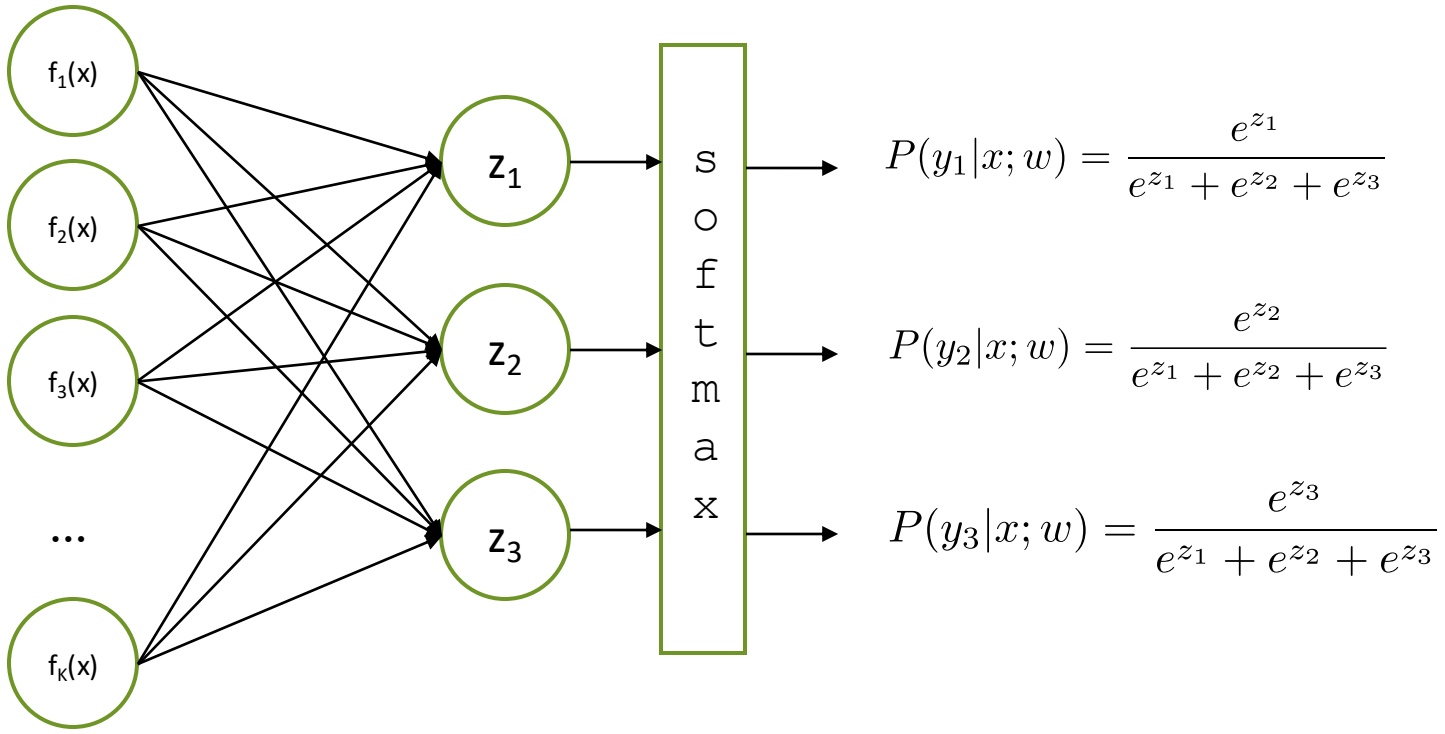
But what is ANN?

Multi-class Logistic Regression

= special case of neural network



Deep Neural Network = Also learn the features!



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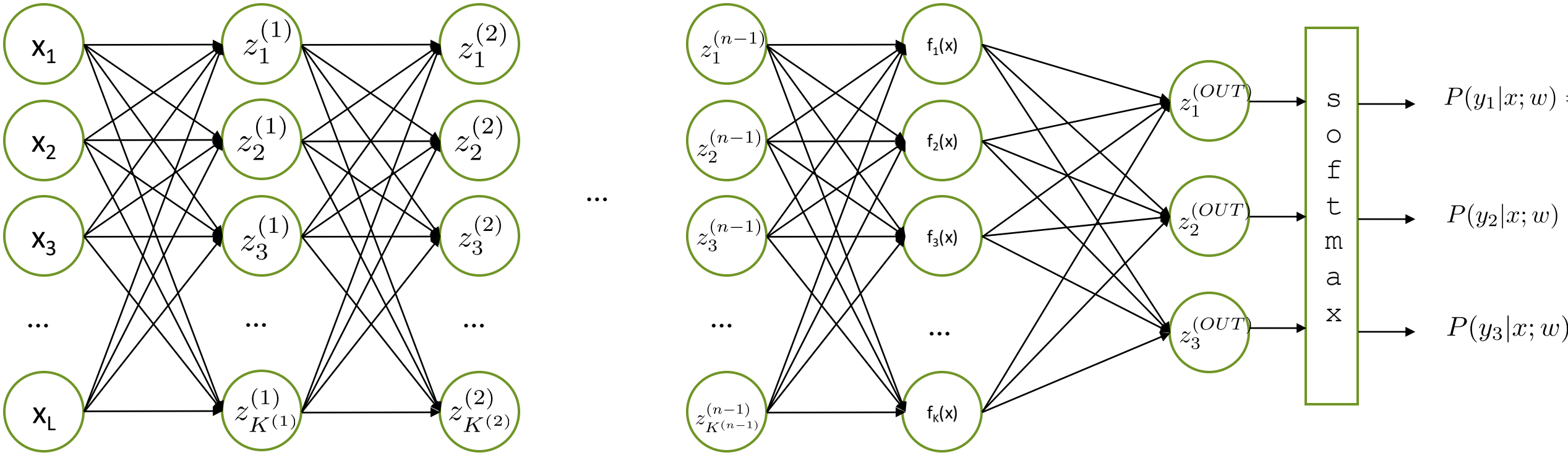
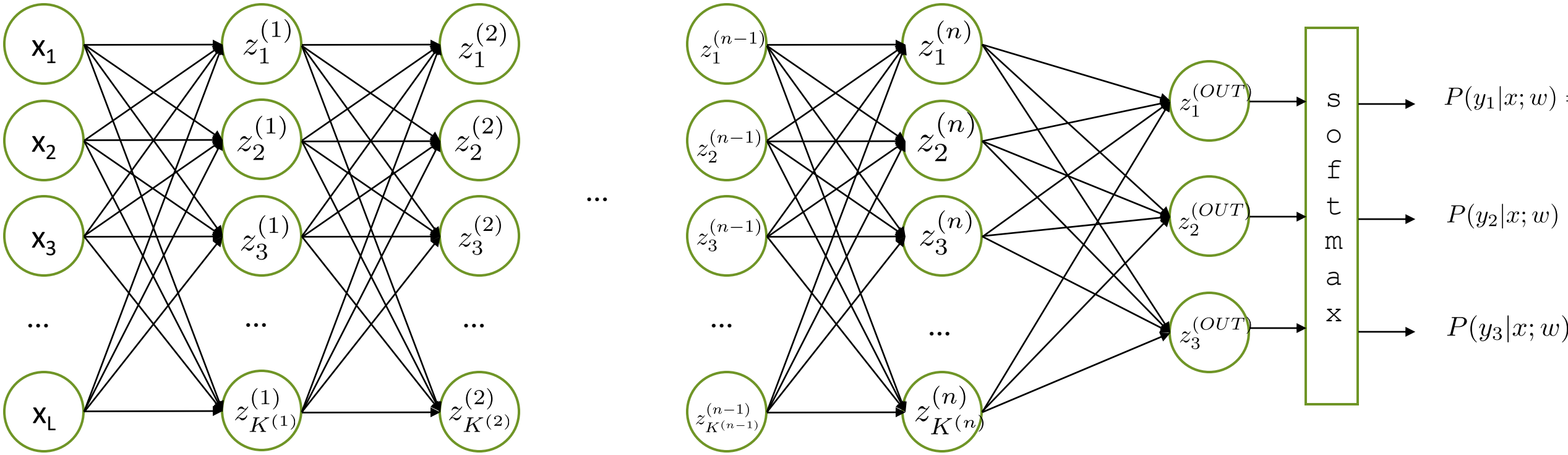


$$z_i^{(k)} = g(\sum_j W_{i,j}^{(k-1,k)} z_j^{(k-1)})$$

g = nonlinear activation function

Deep Neural Network = Also learn the features!



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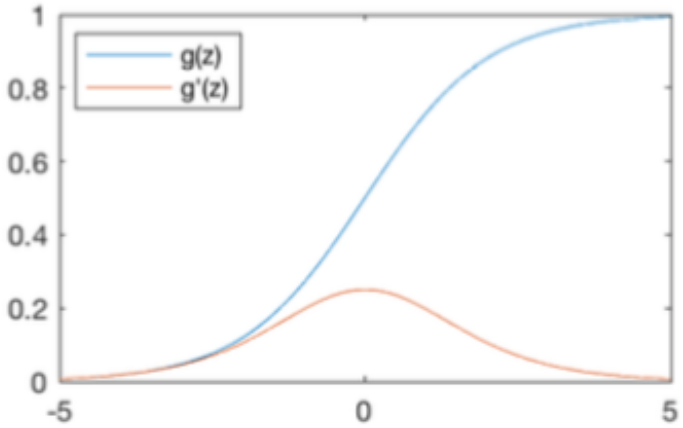
Common Activation Functions

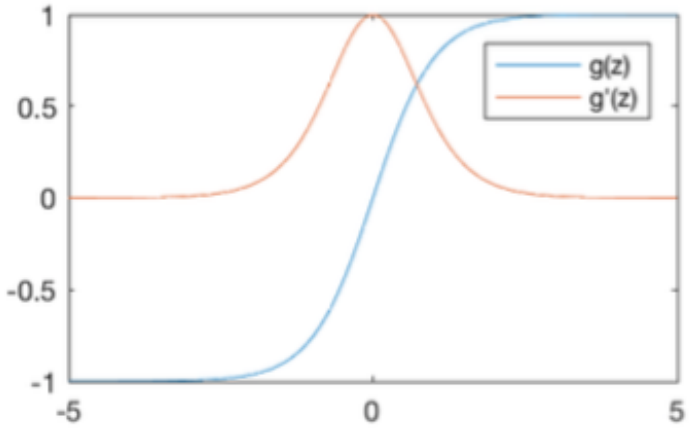
Sigmoid Function



$$g(z) = \frac{1}{1 + e^{-z}}$$

$$g'(z) = g(z)(1 - g(z))$$

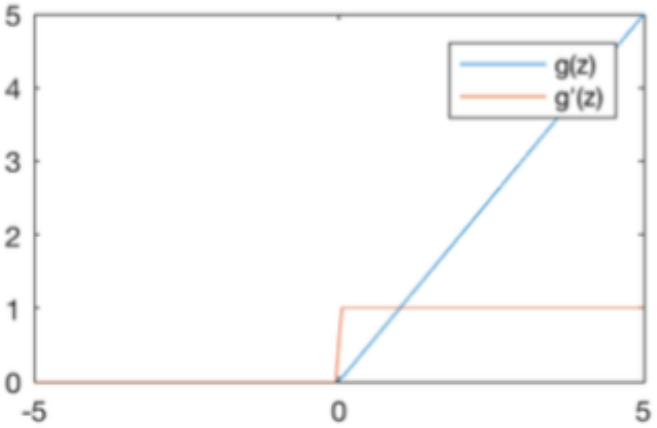
Hyperbolic Tangent



$$g(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}}$$

$$g'(z) = 1 - g(z)^2$$

Rectified Linear Unit (ReLU)



$$g(z) = \max(0, z)$$

$$g'(z) = \begin{cases} 1, & z > 0 \\ 0, & \text{otherwise} \end{cases}$$

[source: MIT 6.S191 introtodeeplearning.com]

Deep Neural Network: Also Learn the Features!

Training the deep neural network is just like logistic regression:

$$\max_w \quad ll(w) = \max_w \quad \sum_i \log P(y^{(i)}|x^{(i)}; w)$$

just w tends to be a much, much larger vector ☺

→just run gradient ascent

+ stop when log likelihood of hold-out data starts to decrease

Optimization Procedure: Gradient Ascent

- init w
- for iter = 1, 2, …

$$w \leftarrow w + \alpha * \nabla g(w)$$

- α: learning rate --- tweaking parameter that needs to be chosen carefully
- How? Try multiple choices
  - Crude rule of thumb: update changes w about 0.1 – 1 %

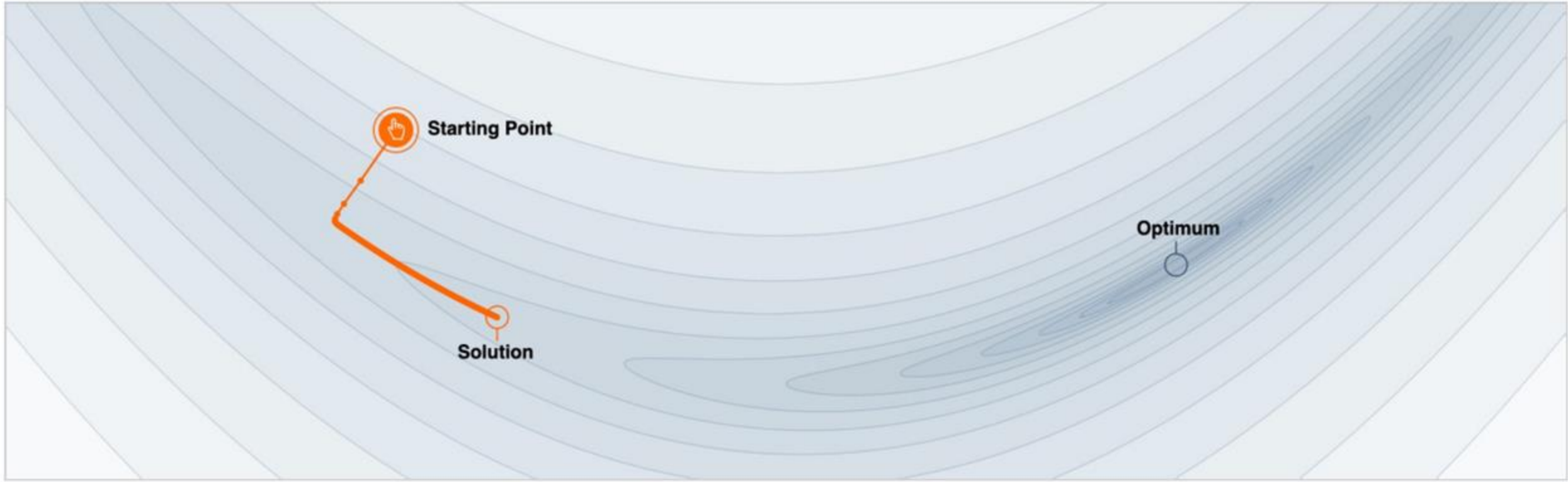
Minimizing loss functions

- In practice we minimize the loss instead of maximizing the objective function
- E.g.,
  - Cross-entropy loss for classification
  - Mean squared error for regression

Learning Rate

Choice of learning rate α is a hyperparameter

Example: α=0.001 (too small)

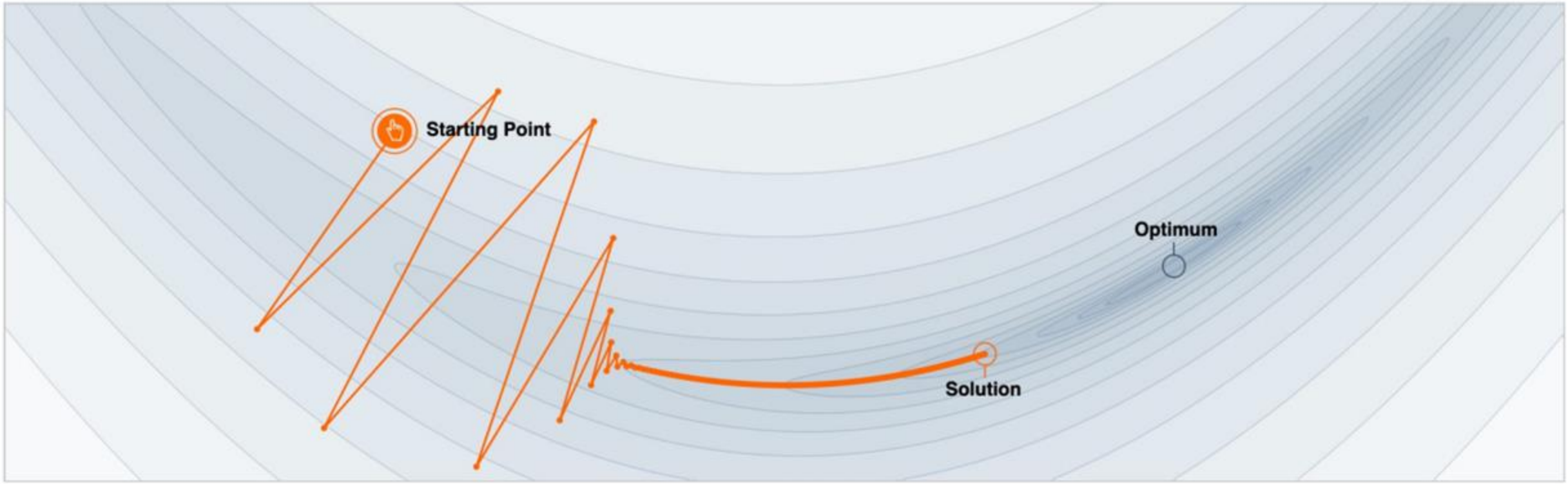


Source: https://distill.pub/2017/momentum/

Learning Rate

Choice of step size α is a hyperparameter

Example: α=0.004 (too large)



Fun Neural Net Demo Site

- Demo-site:
  - http://playground.tensorflow.org/

Backpropagation

- **Back-propagation:** gradients are computed in the direction from output to input layers and combined using chain rule

- CHAIN RULE:

  If

$$f(x) = g(h(x))$$

$$f'(x) = g'(h(x))h'(x)$$

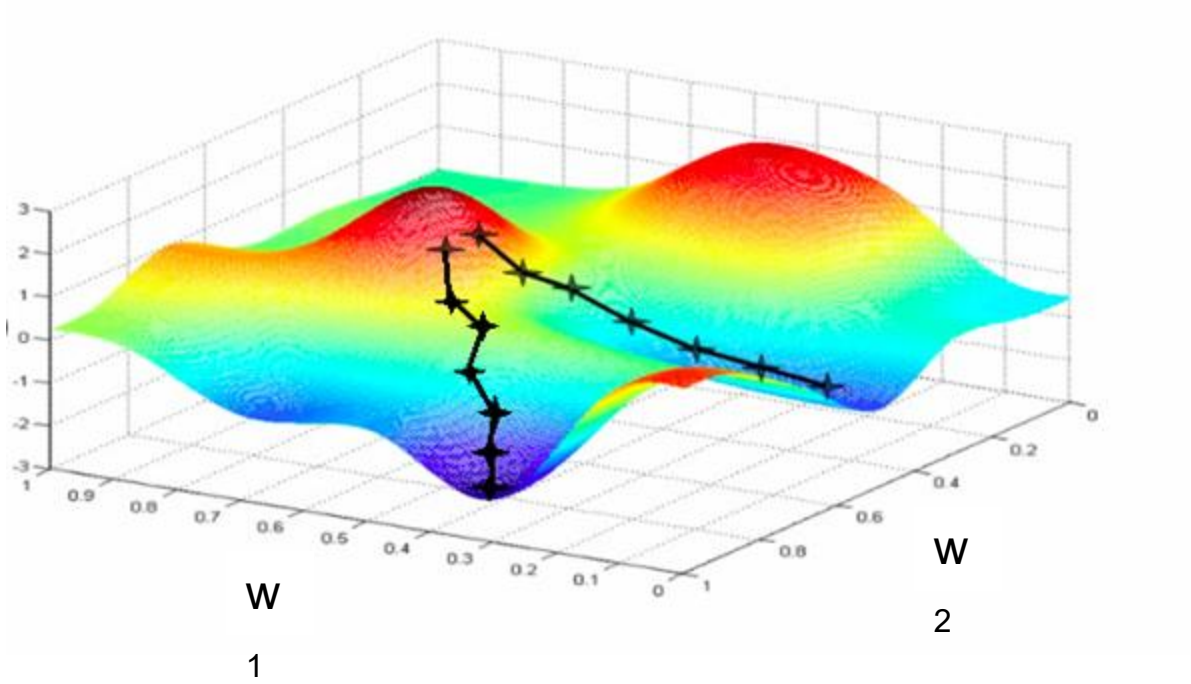
  Then

  → **Derivatives can be computed by following well-defined procedures**

Deep Neural Network: Training

- Update weights by **gradient descent:**

$$\mathbf{w} \leftarrow \mathbf{w} - \alpha \frac{\partial E}{\partial \mathbf{w}}$$



Automatic Differentiation

- Automatic differentiation software
  - e.g. Theano, TensorFlow, PyTorch, Chainer
  - Only need to program the function g(x,y,w)
  - Can automatically compute all derivatives w.r.t. all entries in w
  - This is typically done by caching info during forward computation pass of f, and then doing a backward pass = “backpropagation”
  - Autodiff / Backpropagation can often be done at computational cost comparable to the forward pass
- Need to know this exists
- How this is done? -- outside of scope of this class

Summary of Key Ideas

- Optimize probability of label given input $\max_w \; ll(w) = \max_w \; \sum_i \log P(y^{(i)}|x^{(i)}; w)$
- Continuous optimization
  - Gradient ascent:
    - Compute steepest uphill direction = gradient (= just vector of partial derivatives)
    - Take step in the gradient direction
    - Repeat (until held-out data accuracy starts to drop = "early stopping")
- Deep neural nets
  - Last layer = still logistic regression
  - Now also many more layers before this last layer
    - = computing the features
    - → the features are learned rather than hand-designed
  - Universal function approximation theorem
    - `If` neural net is large enough
    - `Then` neural net can represent any continuous mapping from input to output with arbitrary accuracy
    - But remember: need to avoid overfitting / memorizing the training data → early stopping!
  - Automatic differentiation gives the derivatives efficiently (how? = outside of scope of this class)

The Training Loop

Repeat for multiple epochs

- Get a batch of data
- Forward pass: Calculate predictions
- Calculate Loss
- Backward pass: Calculate gradients (Backprop)
- Update weights/biases (Optimizer)

- We usually have a number of hyperparameters to tune
  - Optimizer hyperparameters like learning rate
  - Batch size
  - Epochs

Connection Architecture

- Fully connected
- Convolution
- Recurrent
- Self-attention

Fully connected layers