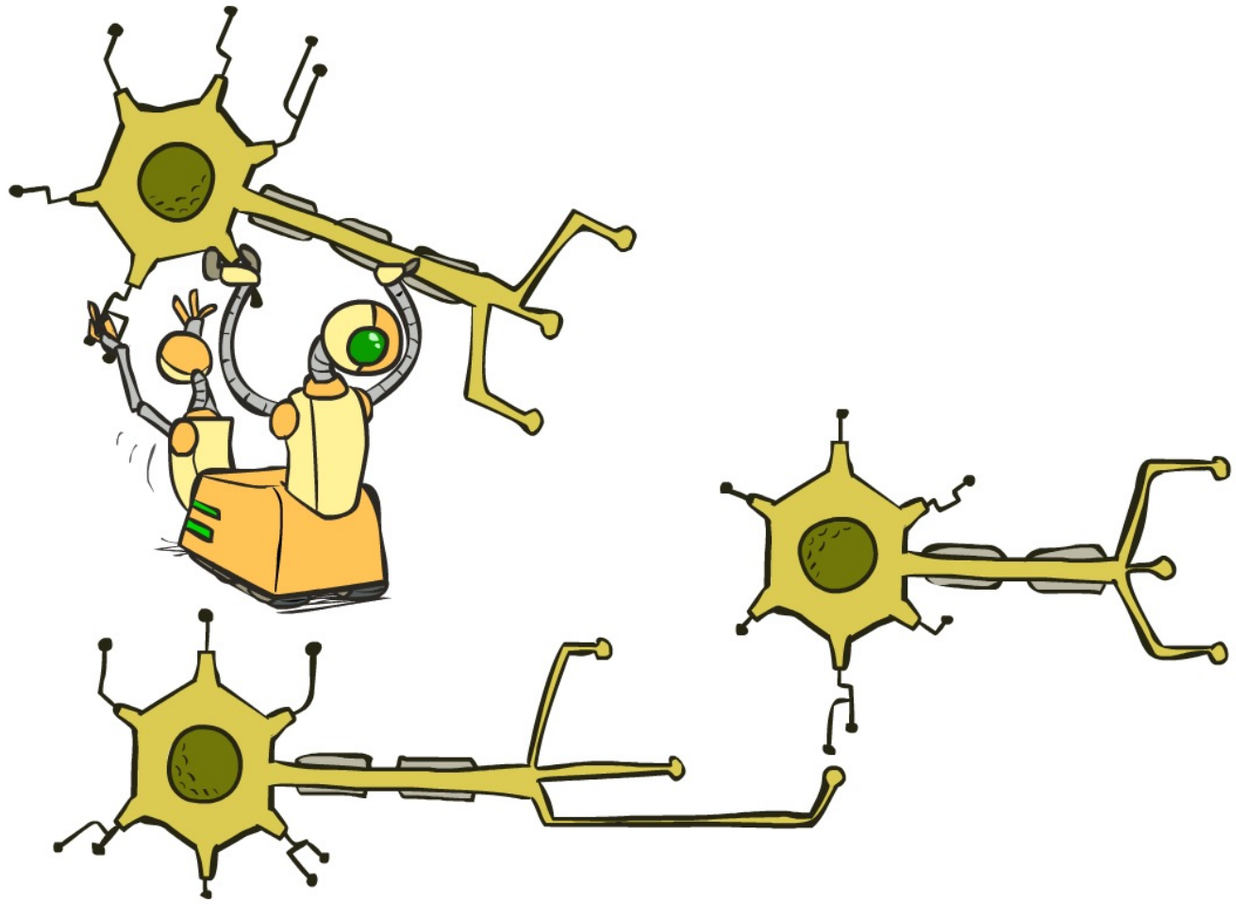
Ve492: Introduction to Artificial Intelligence

Neural Nets



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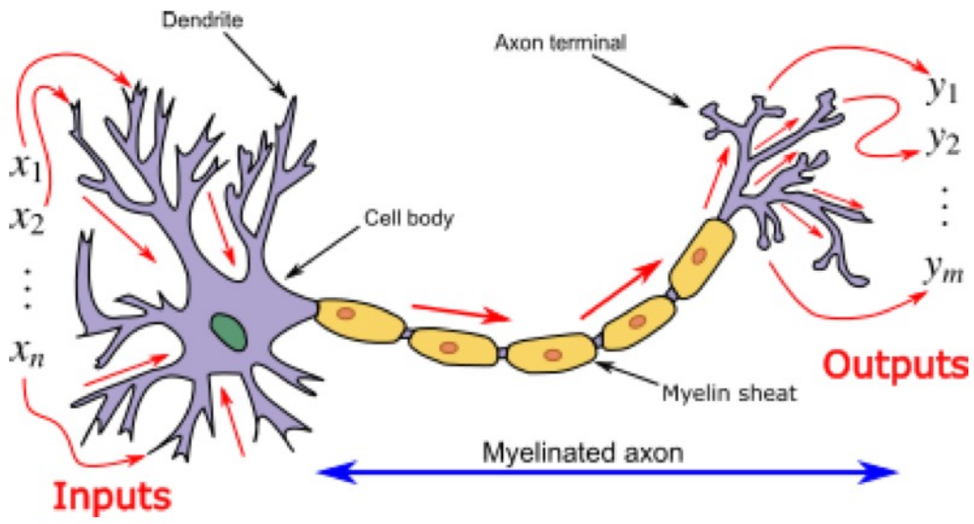
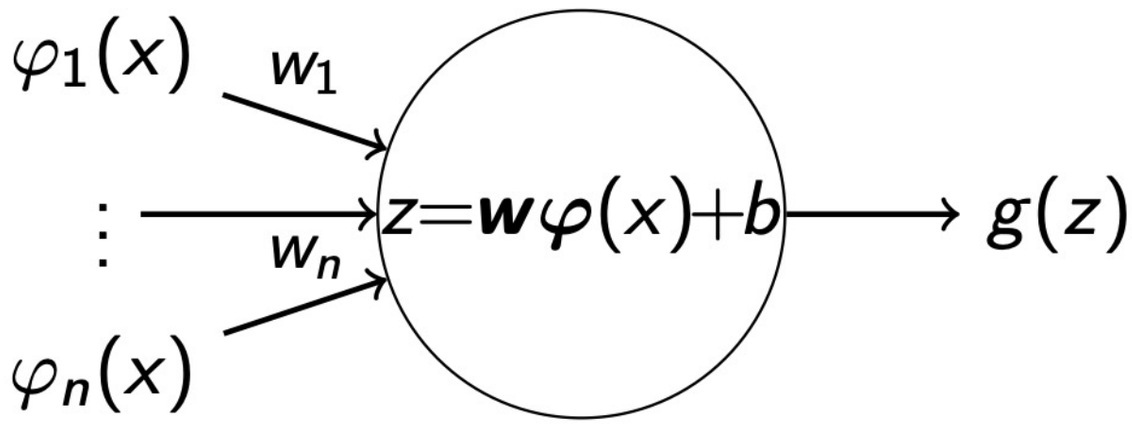
Slides adapted from http://ai.berkeley.edu, AIMA, UM

Today

- (Deep) neural network
- Applications

Artificial Neuron





- Perceptron: $g(z) = sign(z)$
- Logistic regression: $g(z) = \frac{1}{1+e^{-z}}$
- Linear regression: $g(z) = z$
- g is called activation function, usually non-linear (sub)differentiable

How to Learn the Parameters of the Model?

- Iterative method that updates unknown weights
- For perceptron:

$$w \leftarrow w + y^* \varphi(x) \mathbf{1}(w \cdot \varphi(x) \cdot y^* < 0)$$

- For logistic regression:
  - Write likelihood function: $P(X, Y|w)$
  - Maximize $\log P(X, Y|w)$ with gradient descent

$$w \leftarrow w + \alpha \nabla_w \log P(X, Y|w) \quad \text{(batch)}$$

$$w \leftarrow w + \alpha \nabla_w \log P(x, y|w) \quad \text{(stochastic)}$$

General Framework: Statistical ML

- Minimize empirical risk:

$$min_w \sum_i \ell(h_w(x^i), y^i)$$

- For perceptron:

$$\ell(\hat{y}, y) = max(0, -y\hat{y})$$

- For logistic regression:

$$\ell(\hat{y}, y) = -y\log(\hat{y}) - (1-y)\log(1-\hat{y})$$

- For linear regression:

$$\ell(\hat{y}, y) = (\hat{y} - y)^2$$

Mini-Batch Gradient Descent

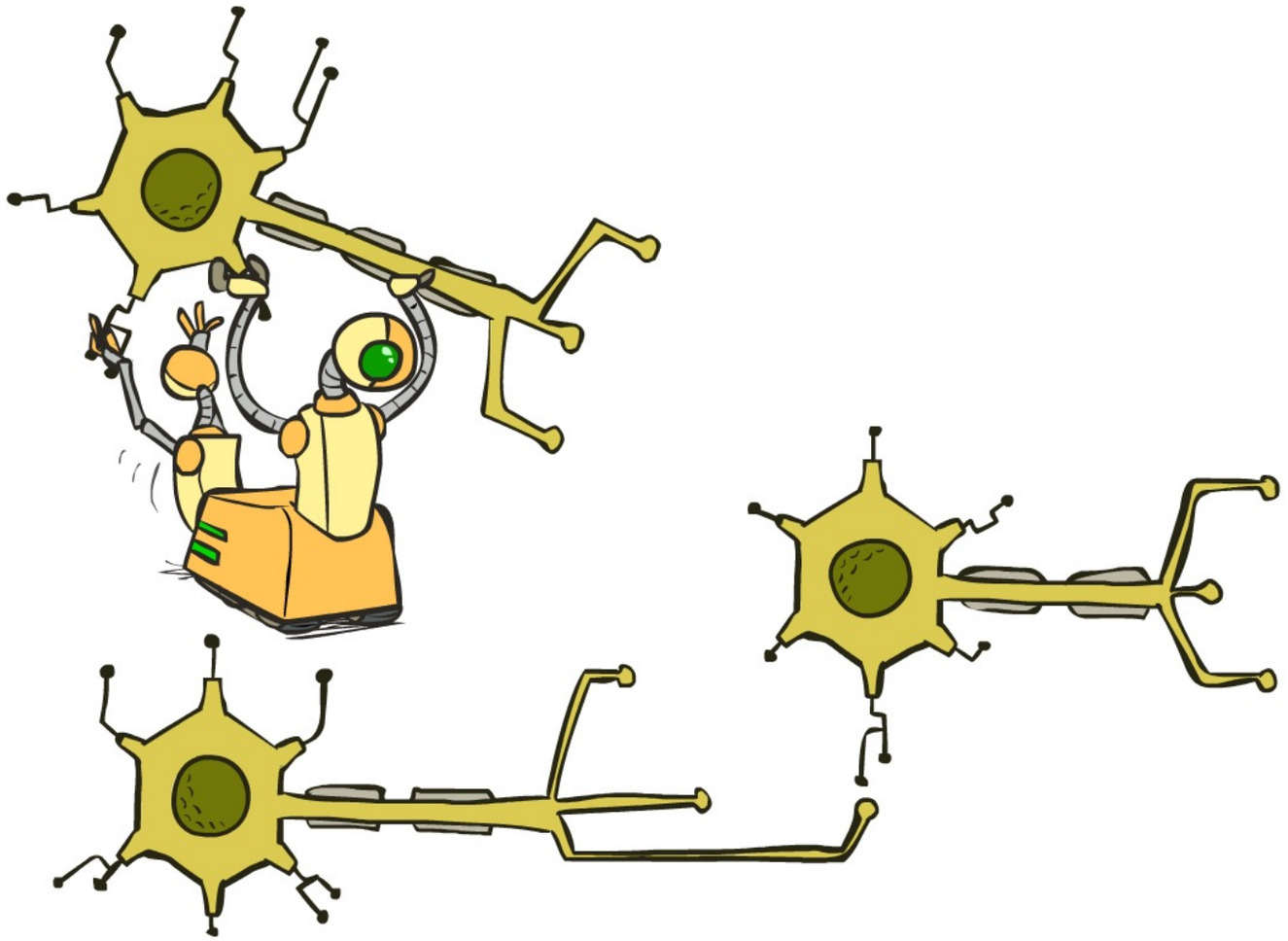
$$min_w \sum_i \ell(h_w(x^i), y^i)$$

Observation: gradient over small set of training examples (=mini-batch) can be computed in parallel, might as well do that instead of a single one

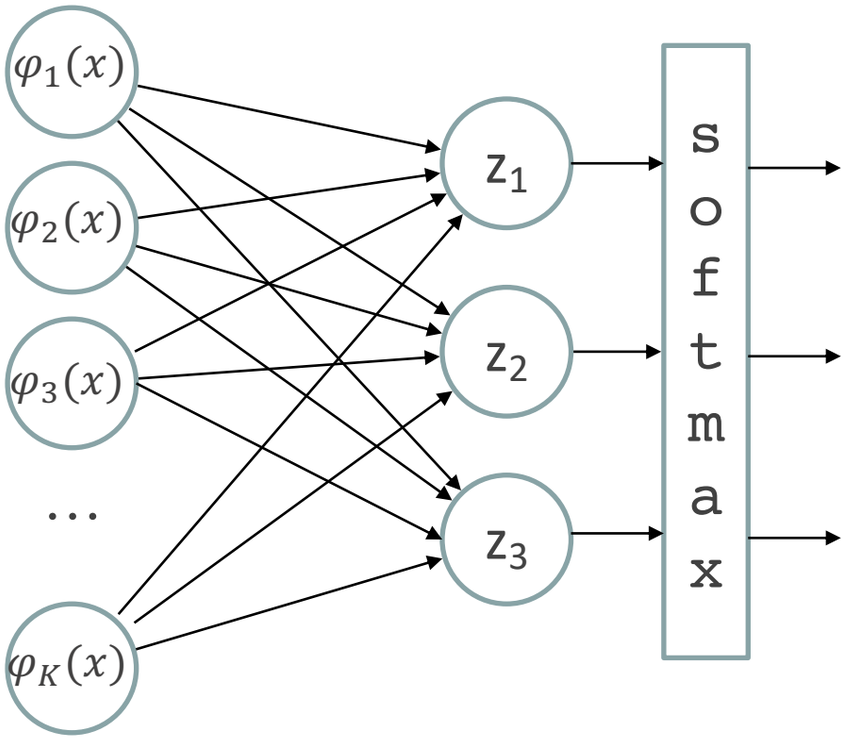
- init w
- for iter = 1, 2, …
  - pick random subset of training examples J

$$w \leftarrow w - \alpha \sum_{j \in J} \nabla_w \ell(h_w(x^j), y^j)$$

Neural Networks



Multi-class Logistic Regression



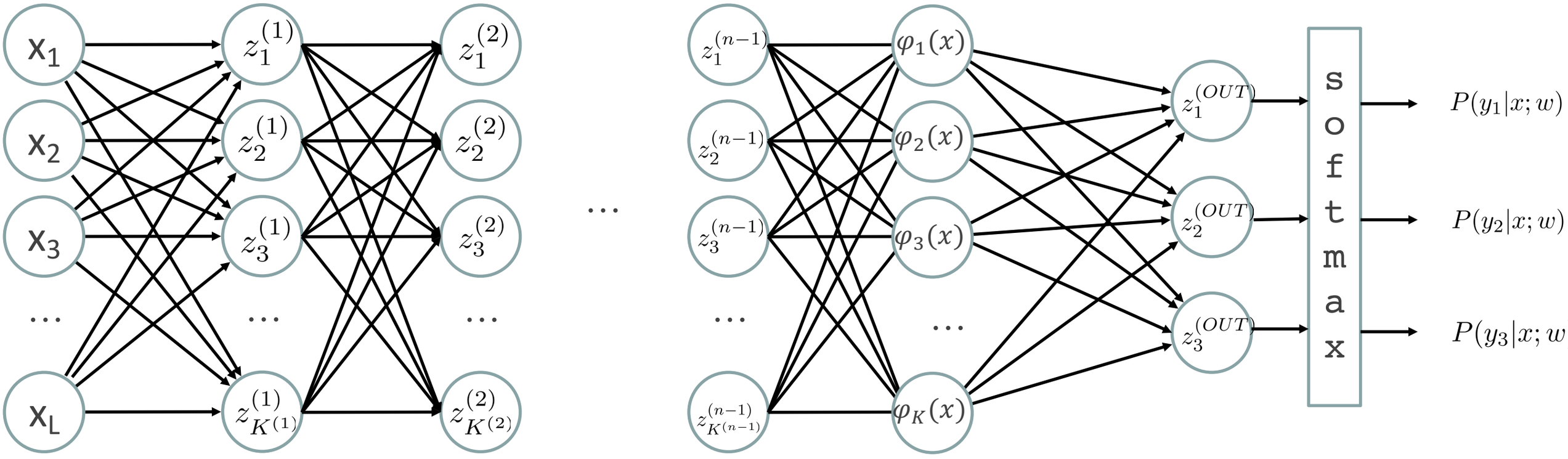
$$P(y_1|x;w) = \frac{e^{z_1}}{e^{z_1} + e^{z_2} + e^{z_3}}$$

$$P(y_2|x;w) = \frac{e^{z_2}}{e^{z_1} + e^{z_2} + e^{z_3}}$$

$$P(y_3|x;w) = \frac{e^{z_3}}{e^{z_1} + e^{z_2} + e^{z_3}}$$

(Deep) Neural Network

- Directly learns the features from data

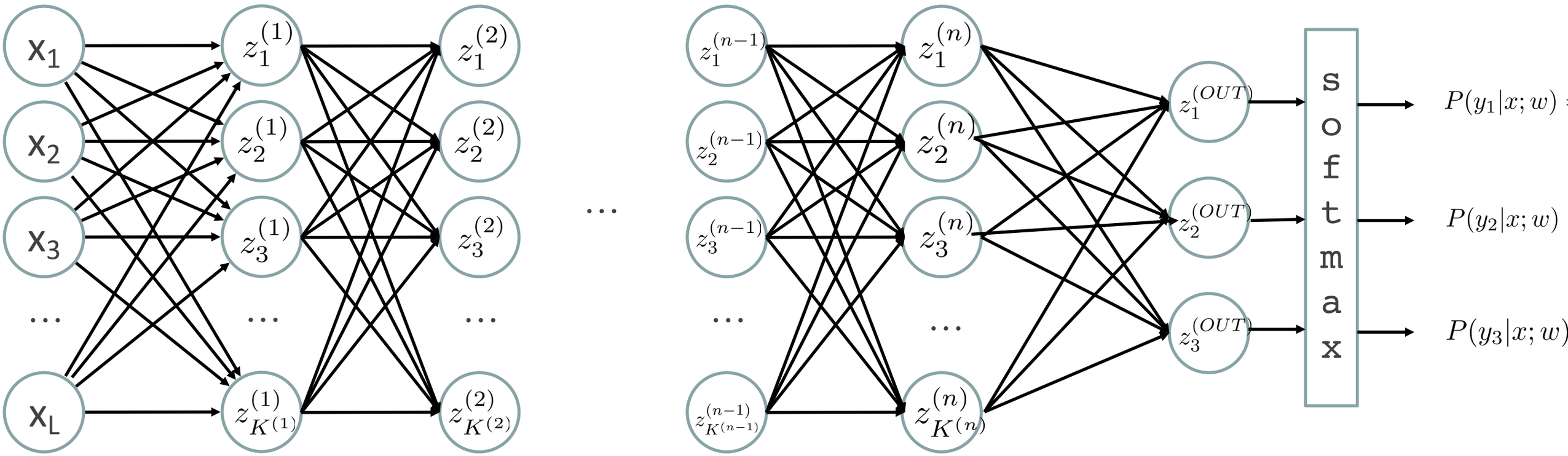


$$z_i^{(k)} = g(\sum_j W_{i,j}^{(k-1,k)} z_j^{(k-1)})$$

g = nonlinear activation function

(Deep) Neural Network

- Directly learns the features from data

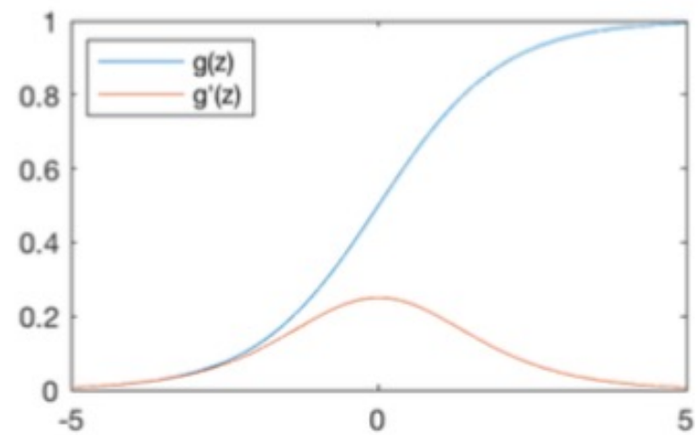


$$z_i^{(k)} = g(\sum_j W_{i,j}^{(k-1,k)} z_j^{(k-1)})$$

g = nonlinear activation function

Common Activation Functions

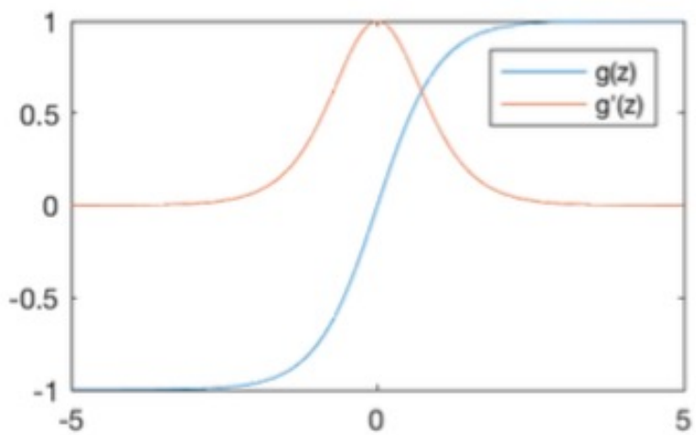
Sigmoid Function



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

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

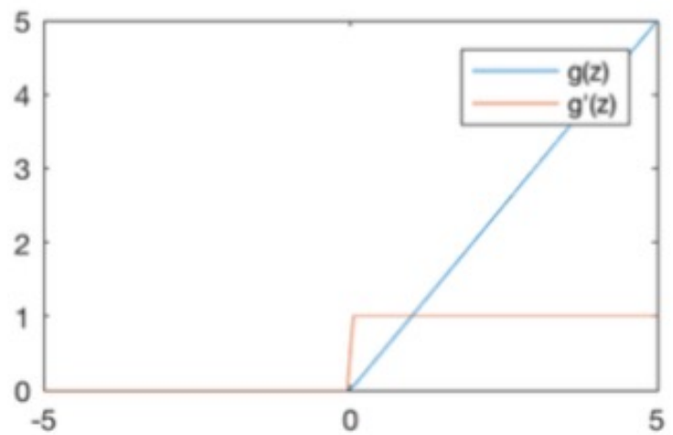
Hyperbolic Tangent



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

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

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]

Training a (Deep) Neural Network

- Training the deep neural network is just like logistic regression:

$$\min_w \; -ll(w) = \min_w \; -\sum_i \log P\left(y^{(i)} \mid x^{(i)}\,; w\right)$$

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

=> just run gradient method

+ stop when log likelihood of hold-out data starts to decrease (early stopping)

Quiz: Hyperparameter Tuning

- Can we tune the hyperparameters on the hold-out data used for early stopping?

Neural Networks Properties

- **Theorem** (Universal Function Approximators). A two-layer neural network with a sufficient number of neurons can approximate any continuous function to any desired accuracy.
- Practical considerations
  - Can be seen as learning the features
  - Large number of neurons
    - Danger for overfitting
    - (hence early stopping!)

Neural Net Demo!

https://playground.tensorflow.org/

How about computing all the derivatives?

- A neural network is just the composition of many functions: $h_w(x) = f_n(f_{n-1}(\dots f_1(x) \dots))$
- Apply chain rule:
  - $f(x) = g(h(x))$
  - $f'(x) = h'(x)g'(h(x))$
- ⇒ Derivatives can be computed by following well-defined procedures

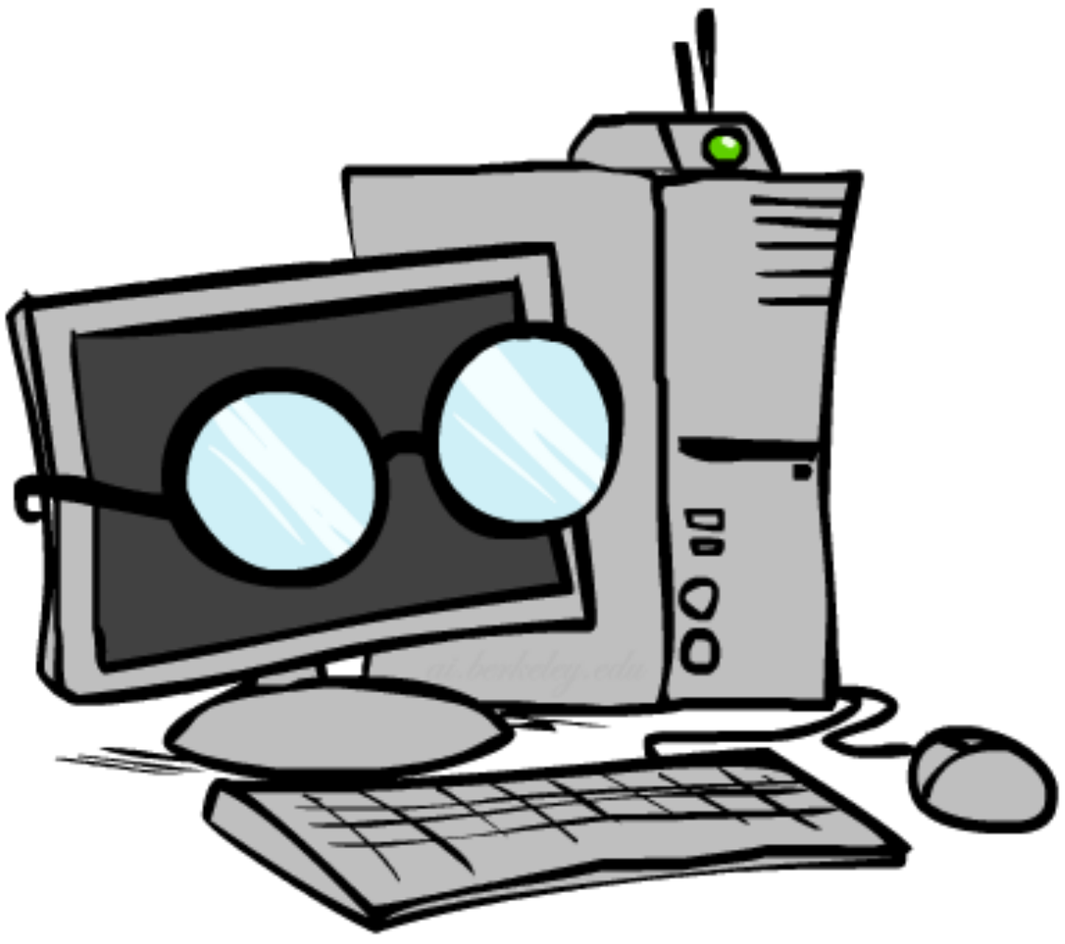
Automatic Differentiation

- Automatic differentiation software
  - e.g., Theano, TensorFlow, PyTorch
  - Only need to program the function $g(x, w)$
  - Can automatically compute all derivatives w.r.t. all entries in w
  - This is typically done by caching info during forward computation pass of g, and then doing a backward pass = "backpropagation"
- Autodiff / Backpropagation can often be done at computational cost comparable to the forward pass

Summary of Key Ideas

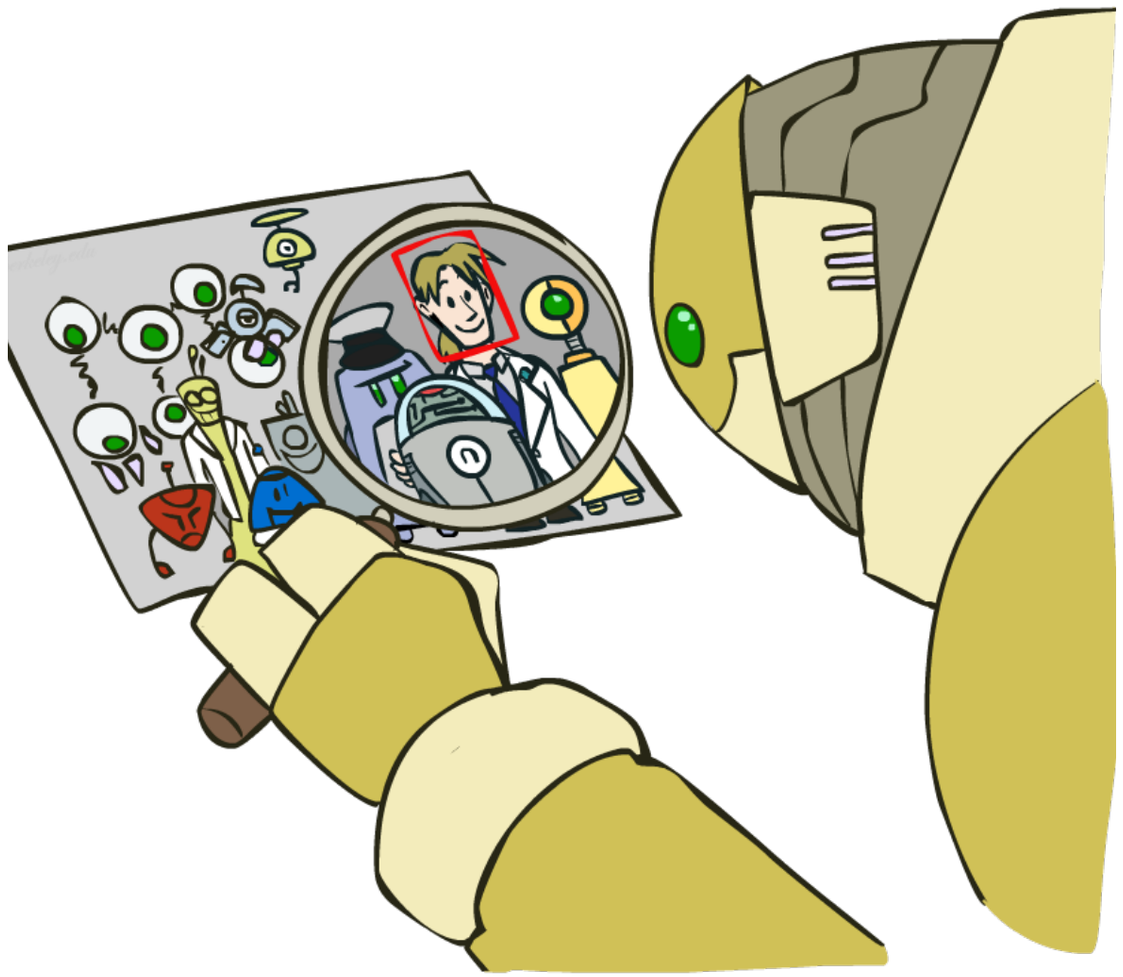
- Minimize empirical risk: $min_w \sum_i \ell(h_w(x^i), y^i)$
- Continuous optimization
  - Gradient descent:
    - Compute steepest uphill direction = gradient (= just vector of partial derivatives)
    - Take step in the opposite gradient direction
    - Repeat (until held-out data accuracy starts to drop = "early stopping")
- Deep neural nets
  - Last layer returns expected output (e.g., probability of classes)
  - 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

Applications

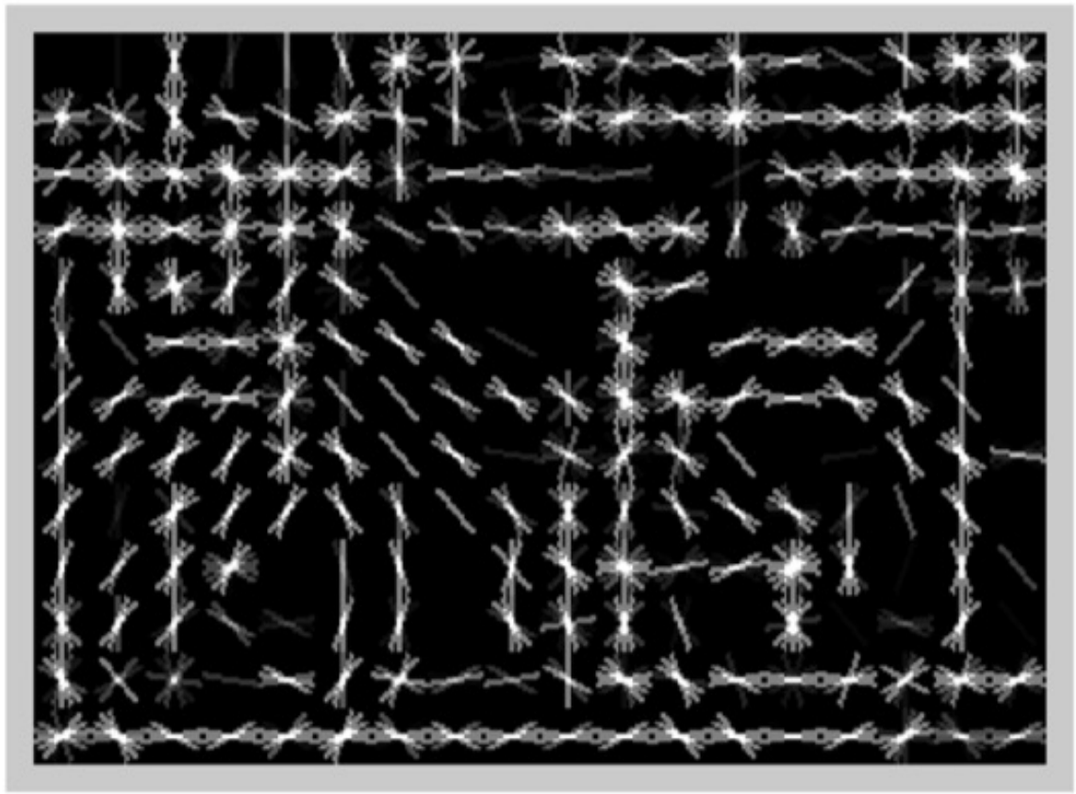


Applications

Computer Vision
Speech Recognition
Machine Translation



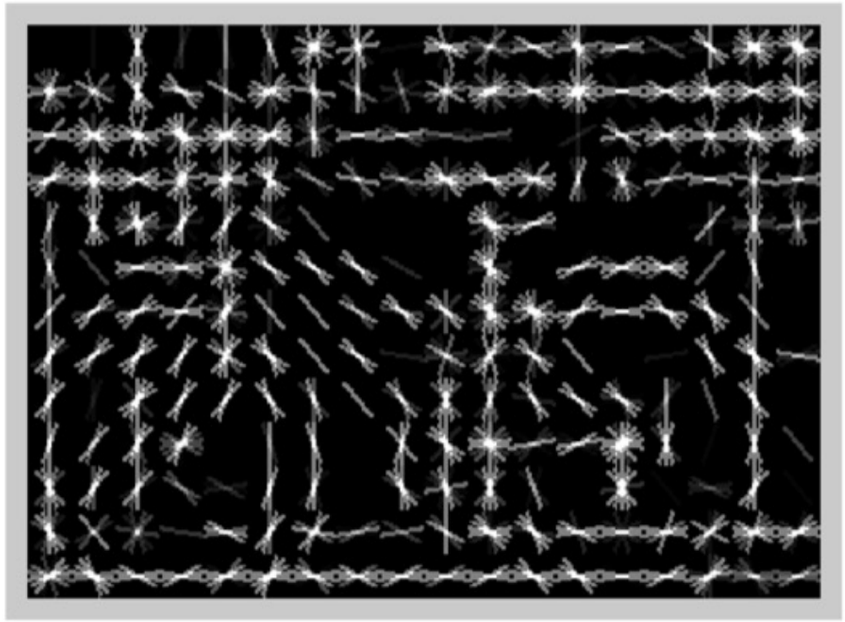
Features and Generalization



[HoG: Dalal and Triggs, 2005]

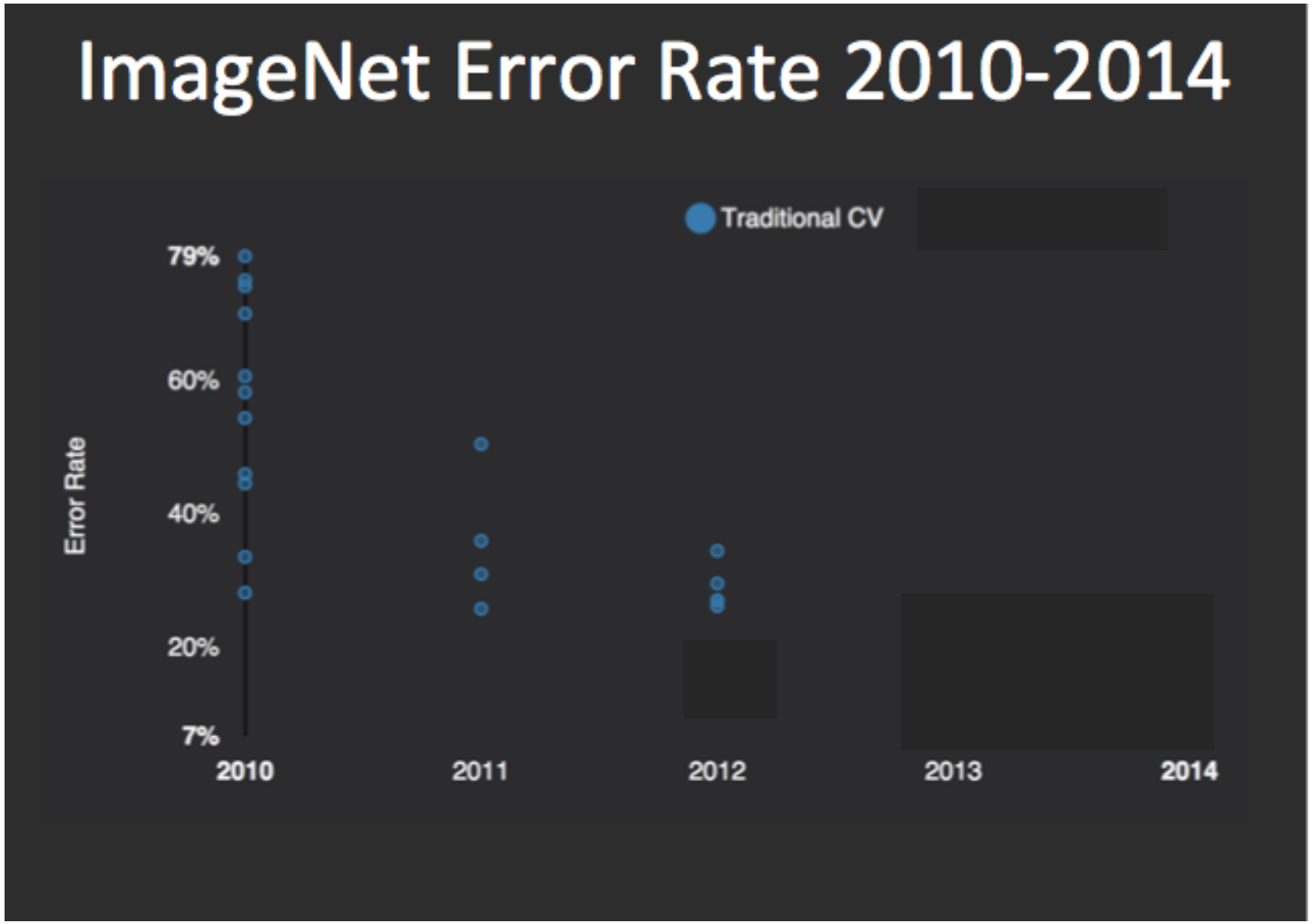
Features and Generalization

Image



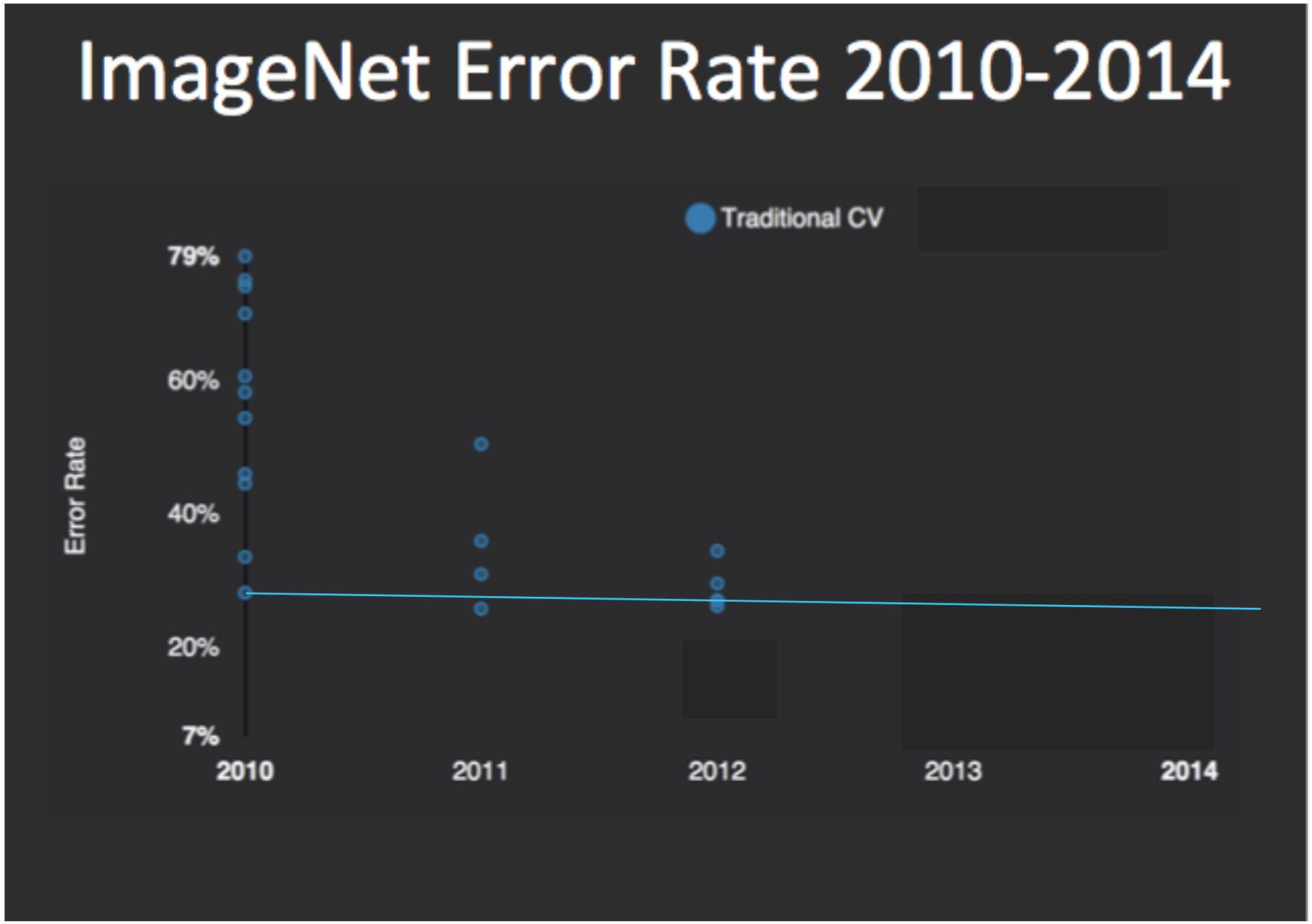
HoG

Performance



graph credit Matt Zeiler, Clarifai

Performance



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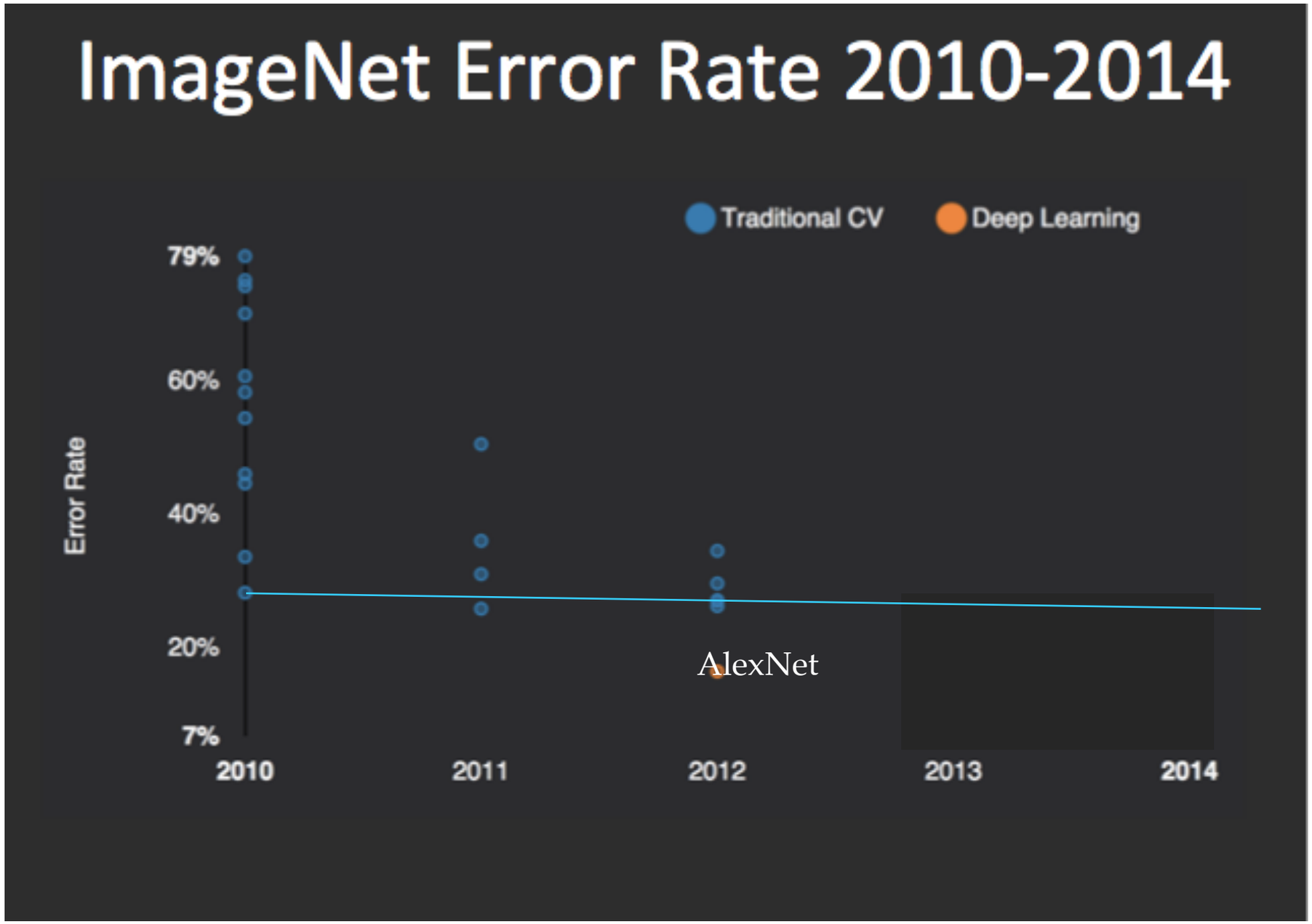

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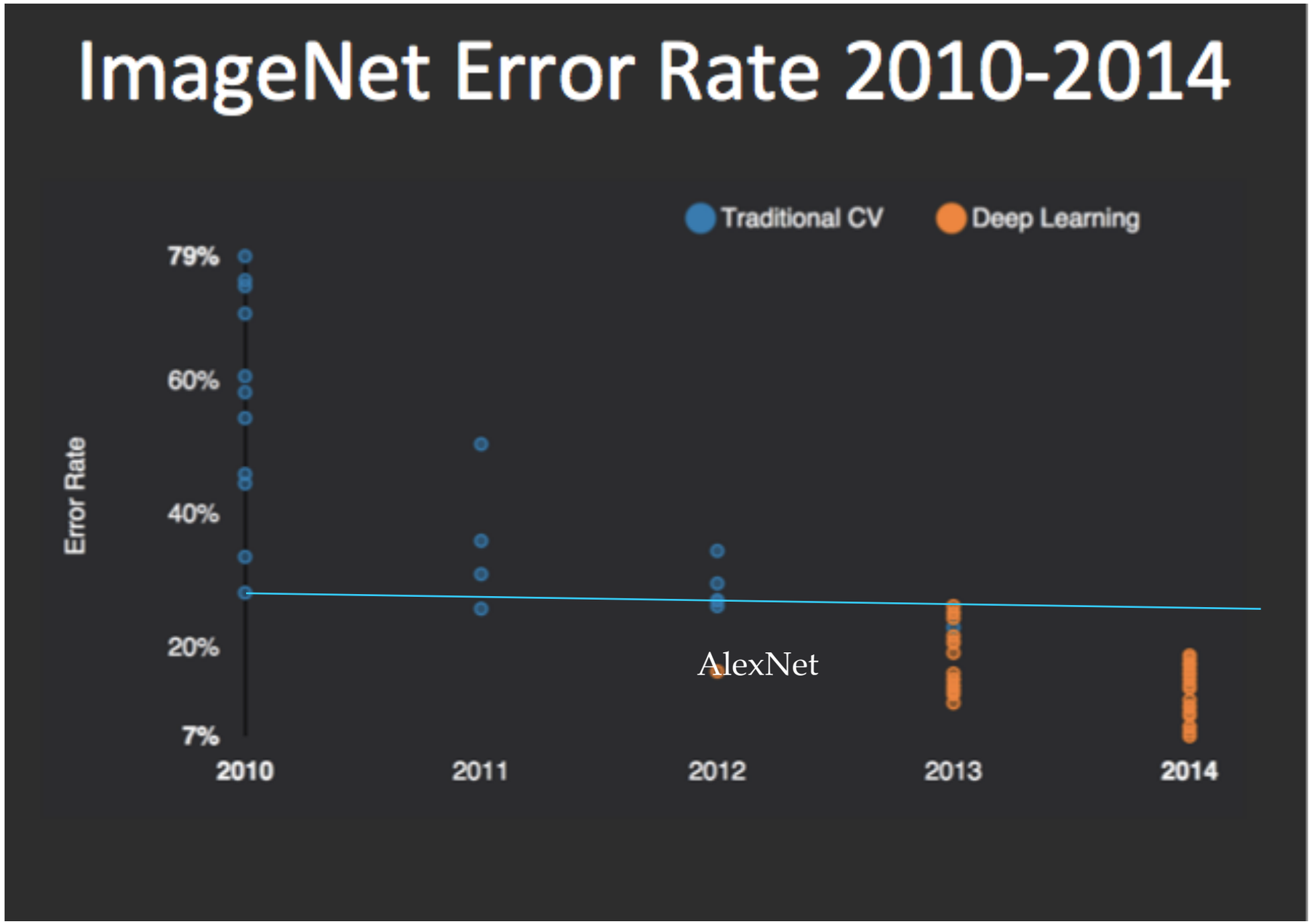

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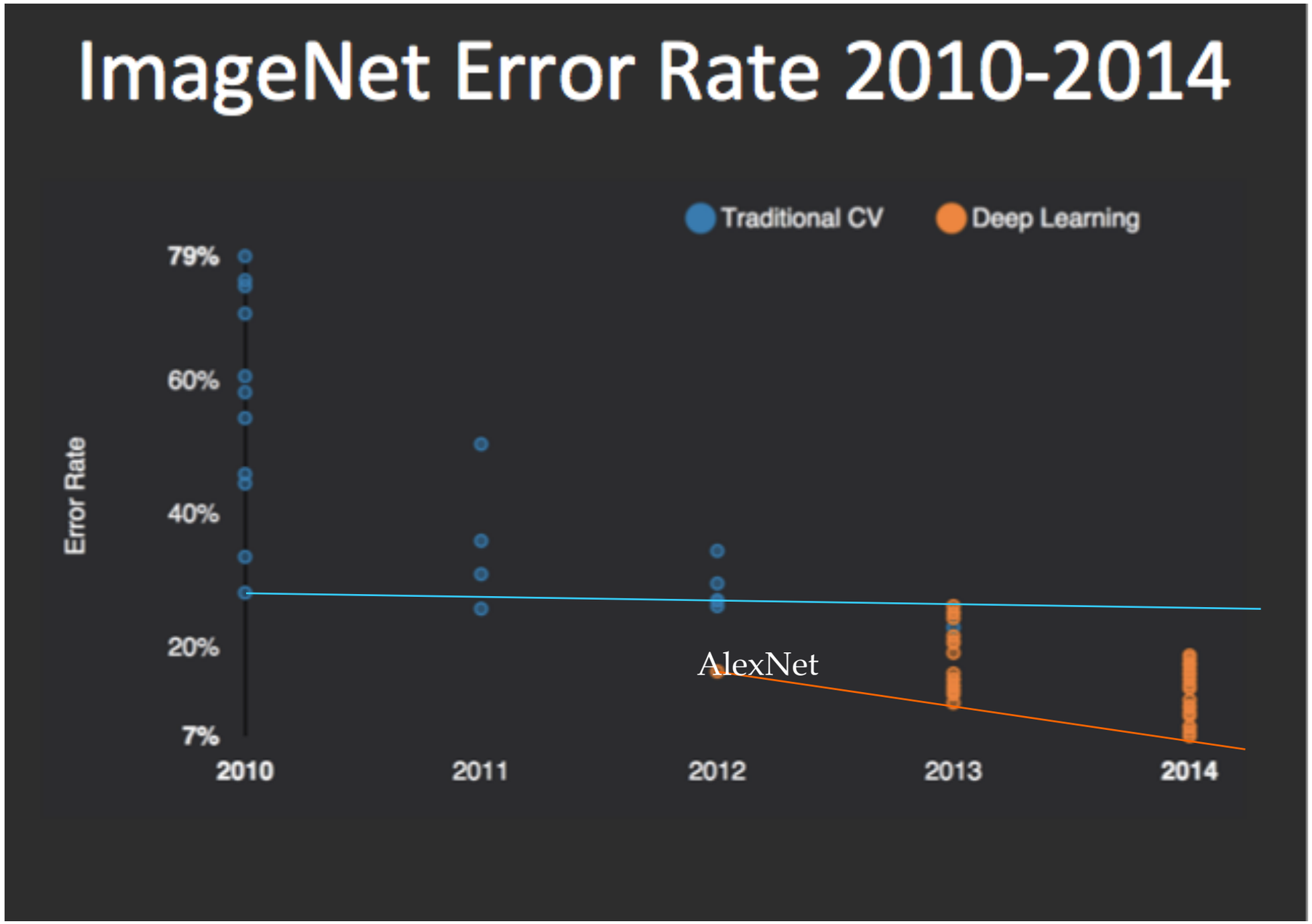


graph credit Matt Zeiler, Clarifai

MS COCO Image Captioning Challenge

"man in black shirt is playing guitar."

"construction worker in orange safety vest is working on road."

"two young girls are playing with lego toy."

"boy is doing backflip on wakeboard."

"girl in pink dress is jumping in air."

"black and white dog jumps over bar."

"young girl in pink shirt is swinging on swing."

"man in blue wetsuit is surfing on wave."

Karpathy & Fei-Fei, 2015; Donahue et al., 2015; Xu et al, 2015; many more

Visual QA Challenge

Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C. Lawrence Zitnick, Devi Parikh

What vegetable is on the plate?
Neural Net: broccoli
Ground Truth: broccoli

What color are the shoes on the person's feet ?
Neural Net: brown
Ground Truth: brown

How many school busses are there?
Neural Net: 2
Ground Truth: 2

What sport is this?
Neural Net: baseball
Ground Truth: baseball

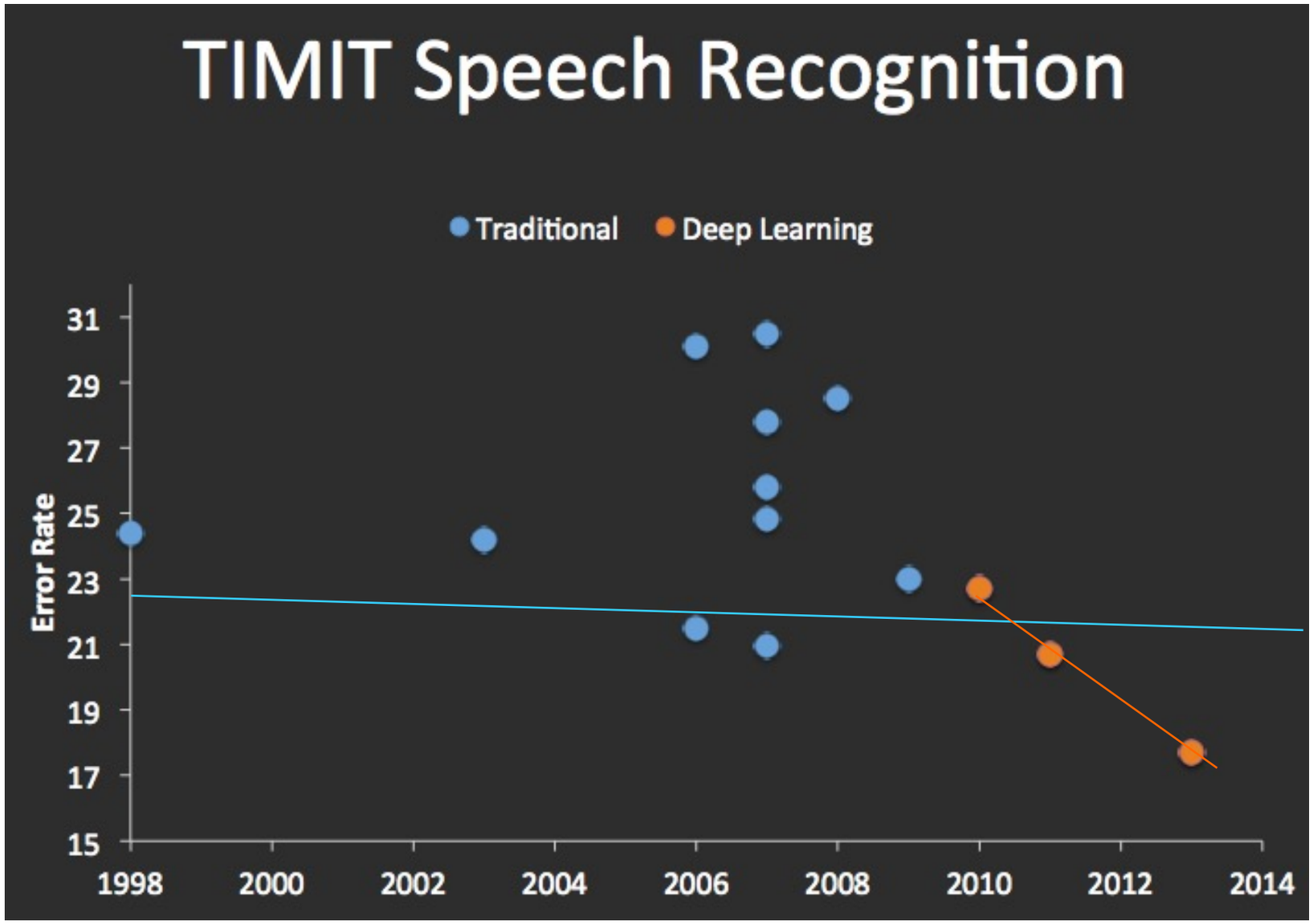
What is on top of the refrigerator?
Neural Net: magnets
Ground Truth: cereal

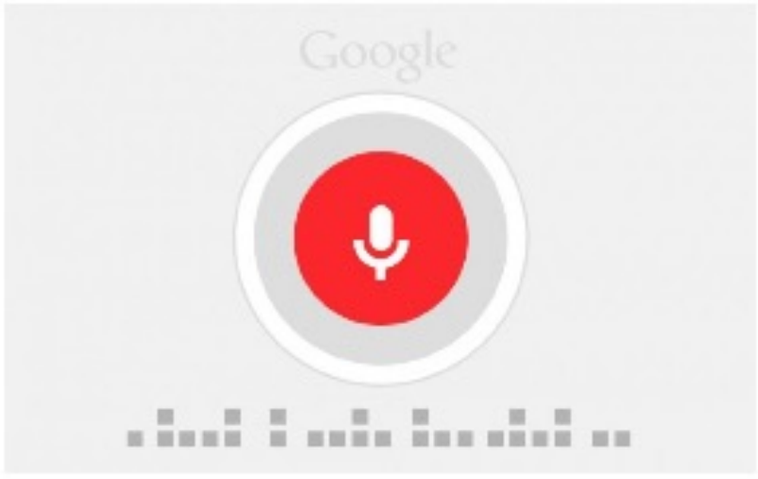
What uniform is she wearing?
Neural Net: shorts
Ground Truth: girl scout

What is the table number?
Neural Net: 4
Ground Truth:40

What are people sitting under in the back?
Neural Net: bench
Ground Truth: tent

Speech Recognition

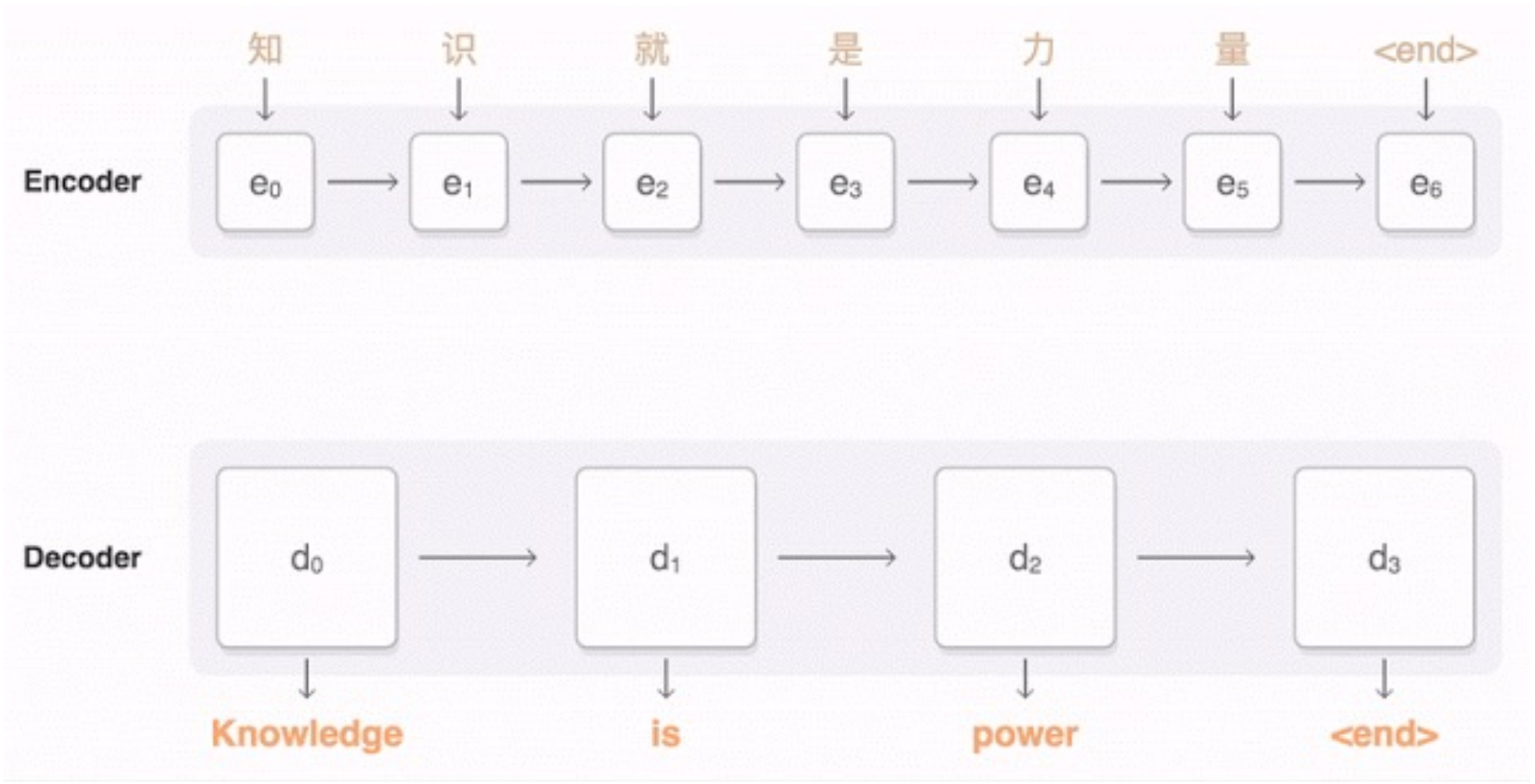




graph credit Matt Zeiler, Clarifai

Machine Translation

Google Neural Machine Translation (in production)



Combining Symbolic and Connexionist Approaches

Mastering Atari, Go, Chess and Shogi by Planning with a Learned Model

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Abstract

Constructing agents with planning capabilities has long been one of the main challenges in the pursuit of artificial intelligence. Tree-based planning methods have enjoyed huge success in challenging domains, such as chess and Go, where a perfect simulator is available. However, in real-world problems the dynamics governing the environment are often complex and unknown. In this work we present the *MuZero* algorithm which, by combining a tree-based search with a learned model, achieves superhuman performance in a range of challenging and visually complex domains, without any knowledge of their underlying dynamics. *MuZero* learns a model that, when applied iteratively, predicts the quantities most directly relevant to planning: the reward, the action-selection policy, and the value function. When evaluated on 57 different Atari games - the canonical video game environment for testing AI techniques, in which model-based planning approaches have historically struggled - our new algorithm achieved a new state of the art. When evaluated on Go, chess and shogi, without any knowledge of the game rules, *MuZero* matched the superhuman performance of the *AlphaZero* algorithm that was supplied with the game rules.