Neural Networks (INLP ch. 3)

CS 490A, Fall 2020

Applications of Natural Language Processing

https://people.cs.umass.edu/~brenocon/cs490a_f20/

Brendan O'Connor

College of Information and Computer Sciences

University of Massachusetts Amherst

some slides adapted from Mohit Iyyer, Jordan Boyd-Graber, Richard Socher, Eisenstein (2019)

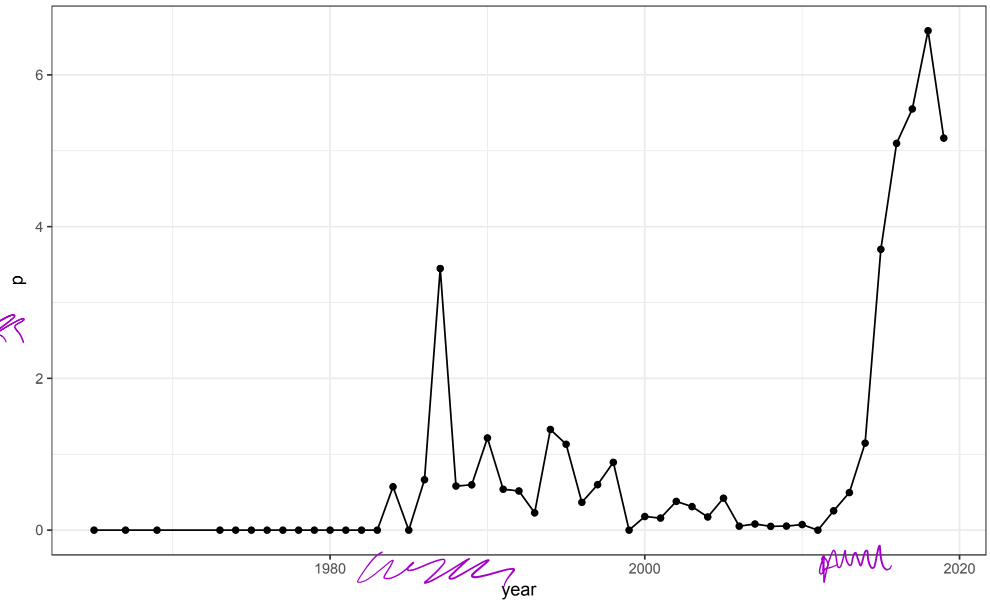
Neural Networks in NLP

- Motivations:
  - Word sparsity => denser word representations
  - Nonlinearity
- Models
  - BoE / Deep Averaging
  - *Convolutional NN*
- Learning
  - Backprop
  - Dropout

Recurrent NN
Transformer

The Second Wave: NNs in NLP

- % of ACL paper titles with “connectionist/connectionism”, “parallel distributed”, “neural network”, or “deep learning”
  - https://www.aclweb.org/anthology/



1984	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	2000	2001	2002
1	2	6	2	2	6	3	3	1	8	3	2	3	9	3	1	4
2003	2004	2005	2006	2007	2008	2009	2010	2012	2013	2014	2015	2016	2017	2018	2019	2020
3	3	4	1	1	1	1	2	8	13	39	99	199	184	296	245	46
2021																
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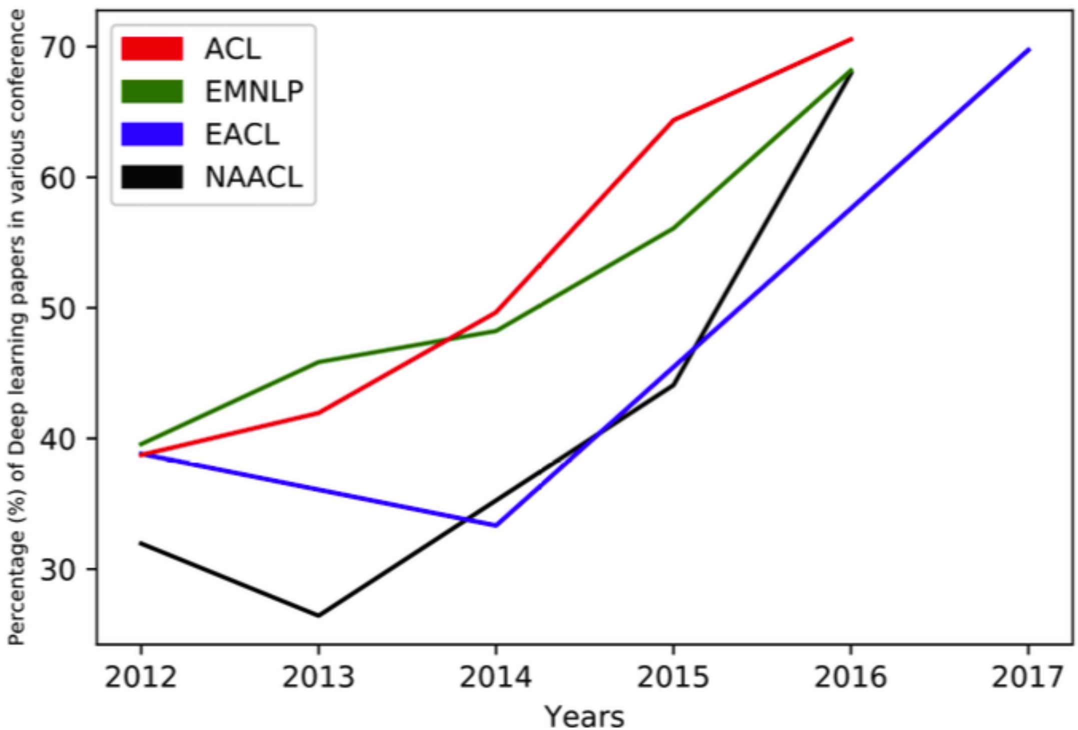
The Second Wave: NNs in NLP



NN Text Classification

- Goals:
  - Avoid feature engineering
  - Generalize beyond individual words — word embeddings
- General model architectures that work well for many different datasets (and tasks!)
- For medium-to-large labeled training datasets, deep learning methods generally outperform feature-based LogReg

- Pretraining on unlabeled corpora – and/or Transfer learning

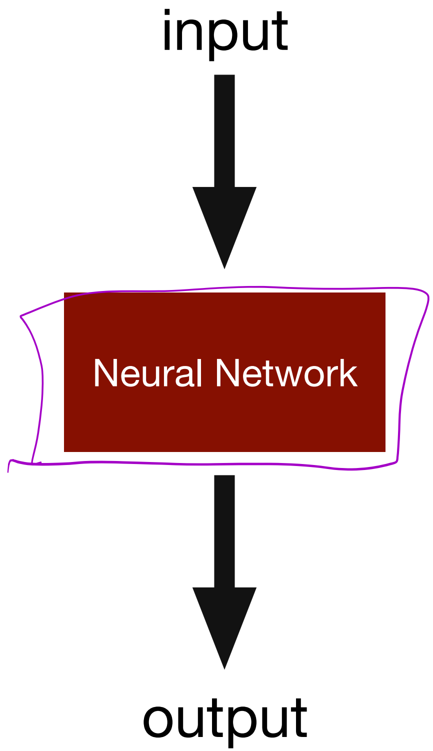
composing embeddings

- neural networks **compose** word embeddings into vectors for phrases, sentences, and documents

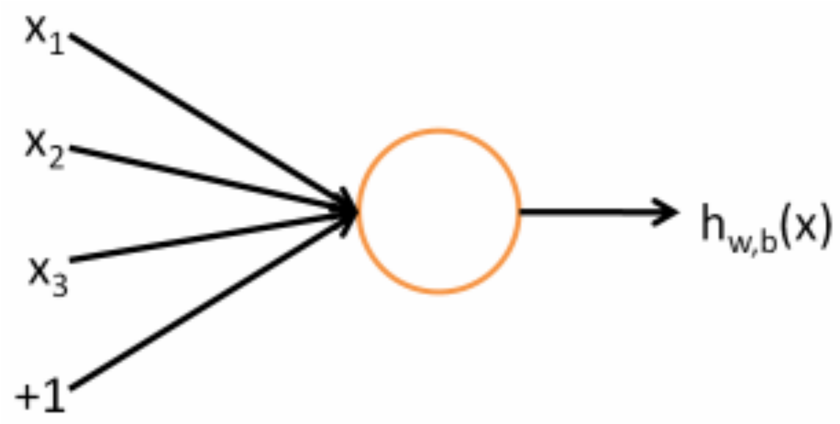
what is **deep learning**?

f(input) = output

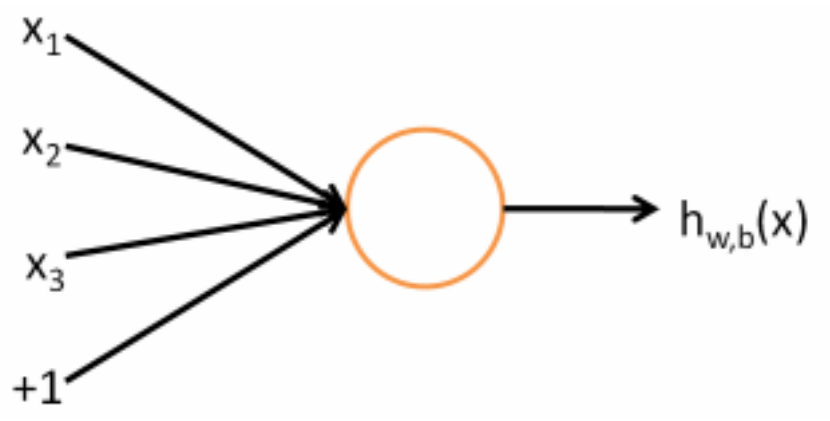
what is **deep learning?**



Logistic Regression by Another Name: Map inputs to output



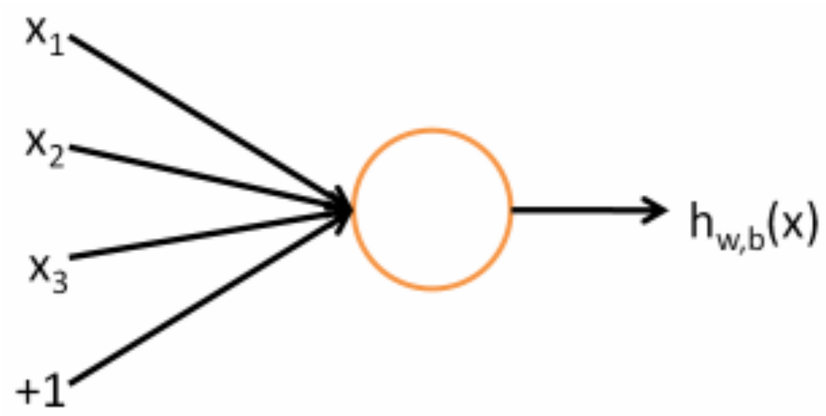
Logistic Regression by Another Name: Map inputs to output



Input
Vector $x_1 \ldots x_d$

inputs encoded as real numbers

Logistic Regression by Another Name: Map inputs to output



Output

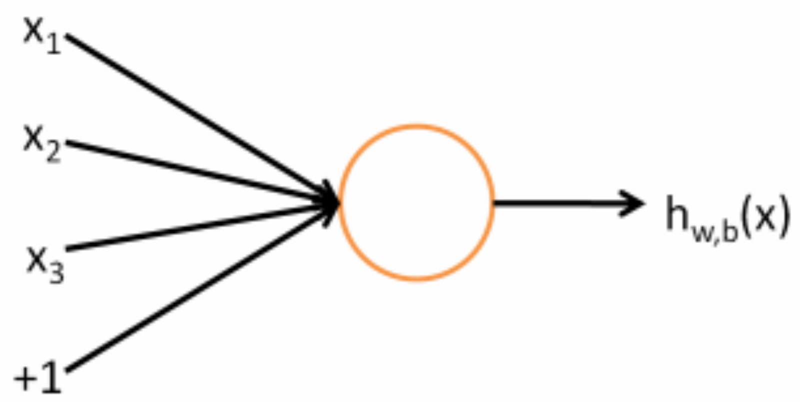
$$f\left(\sum_i W_i x_i + b\right)$$

Input

Vector $x_1 \ldots x_d$

multiply inputs

Logistic Regression by Another Name: Map inputs to output



Output

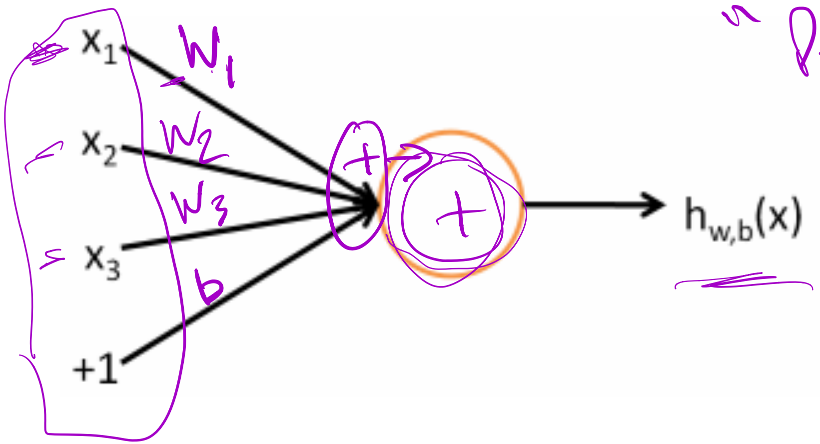
$$f\left(\sum_i W_i x_i + b\right)$$

Input

Vector $x_1 \ldots x_d$

add bias

Logistic Regression by Another Name: Map inputs to output



Input

Vector $x_1 \dots x_d$

Output

$$f\left(\sum_i W_i x_i + b\right)$$

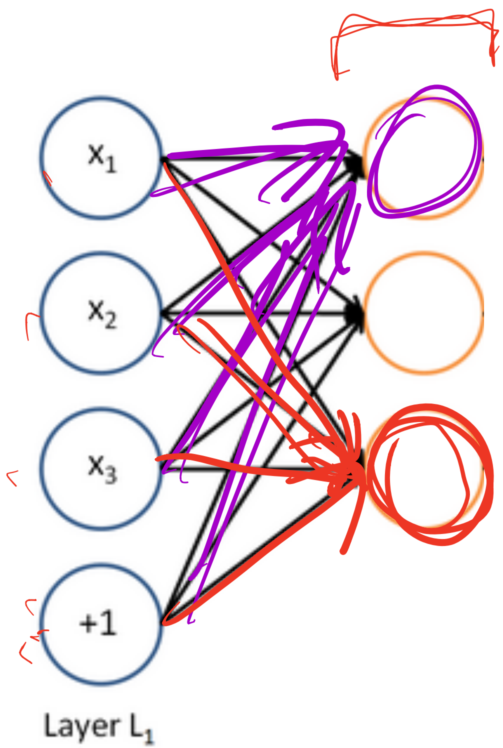
Activation

$$f(z) \equiv \frac{1}{1+\exp(-z)}$$

pass through nonlinear sigmoid

NN: kind of like several intermediate logregs

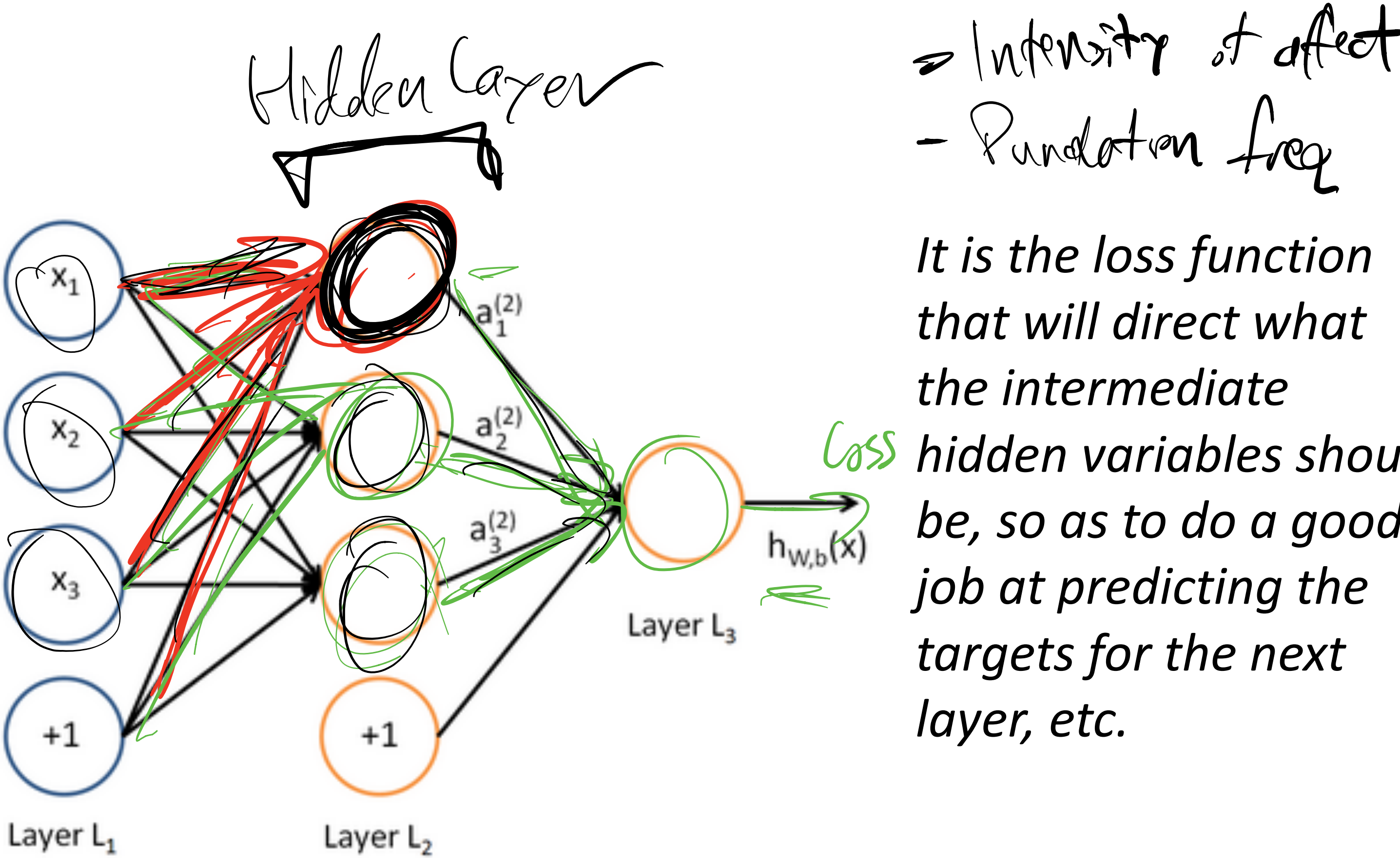
If we feed a vector of inputs through a bunch of logistic regression functions, then we get a vector of outputs …



But we don't have to decide ahead of time what variables these logistic regressions are trying to predict!

NN: kind of like several intermediate logregs

… which we can feed into another logistic regression function

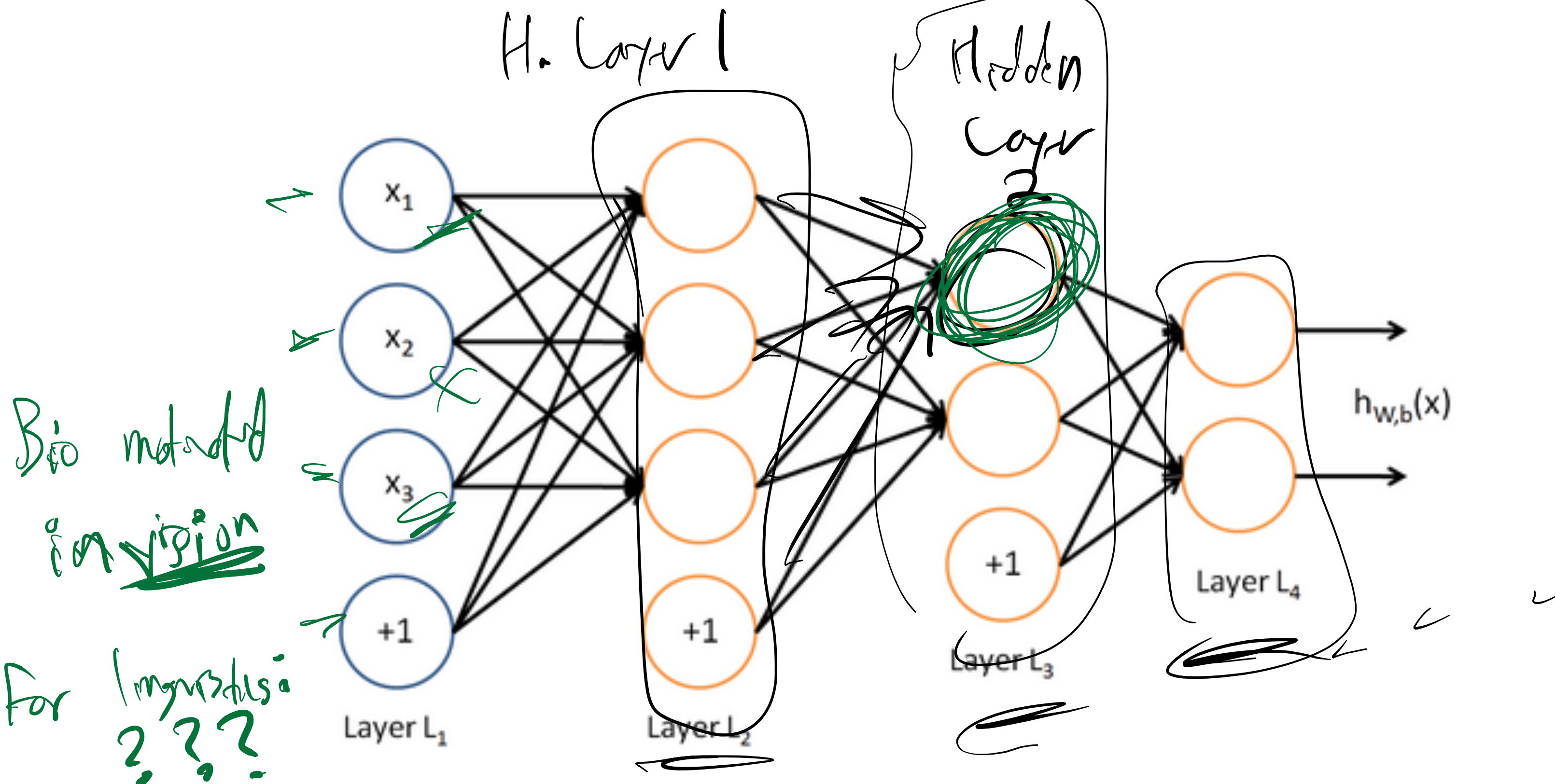


It is the loss function that will direct what the intermediate hidden variables should be, so as to do a good job at predicting the targets for the next layer, etc.

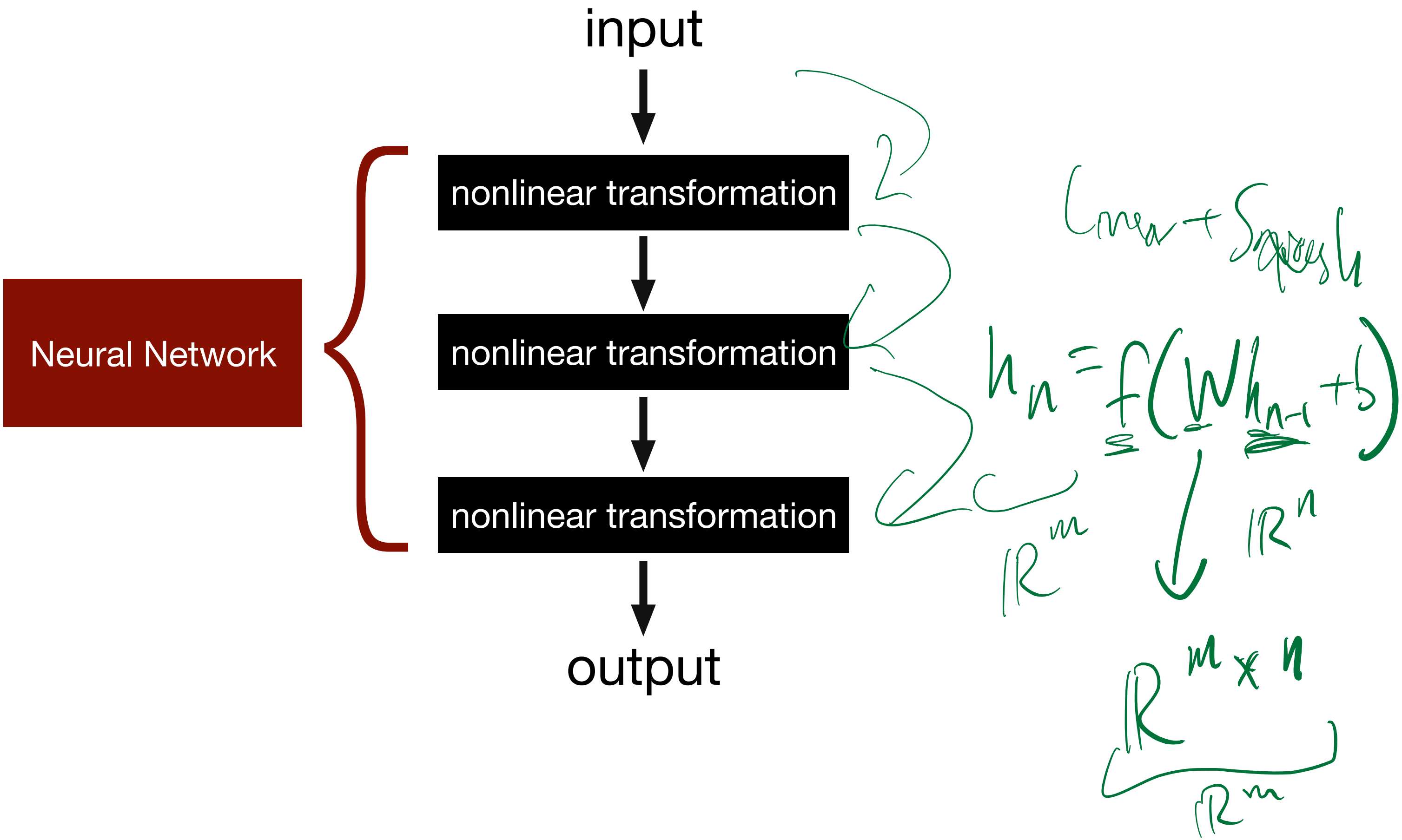
NN: kind of like several intermediate logregs

Before we know it, we have a multilayer neural network....

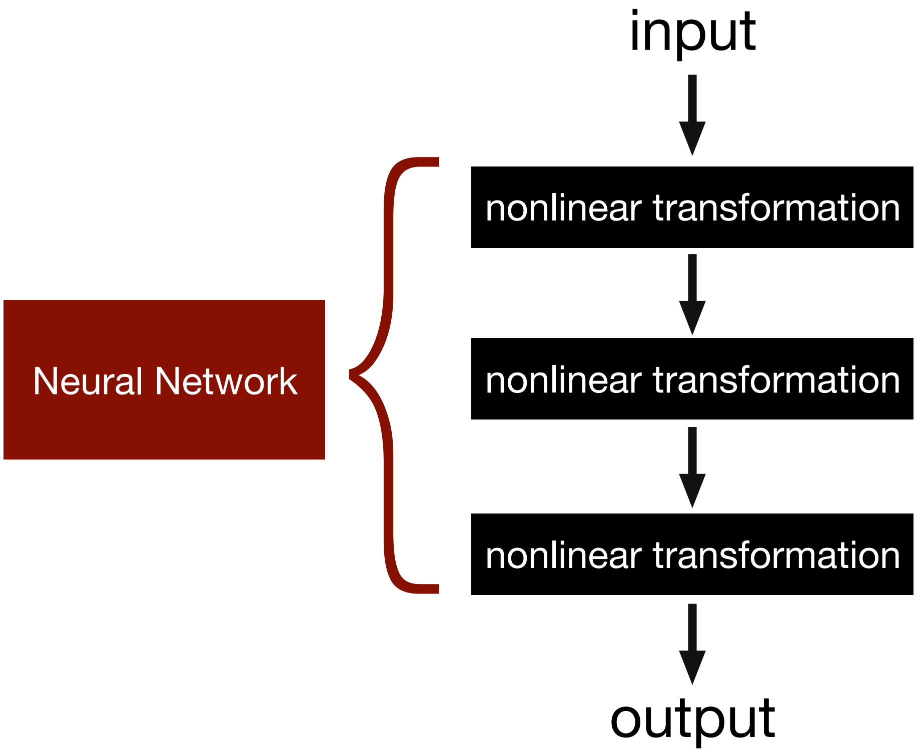
a.k.a. **feedforward network** (see INLP on terminology)



what is deep learning?



what is deep learning?



$$h_n = f(Wh_{n-1} + b)$$

Nonlinear activations

- "Squash functions"!
  - Logistic / Sigmoid

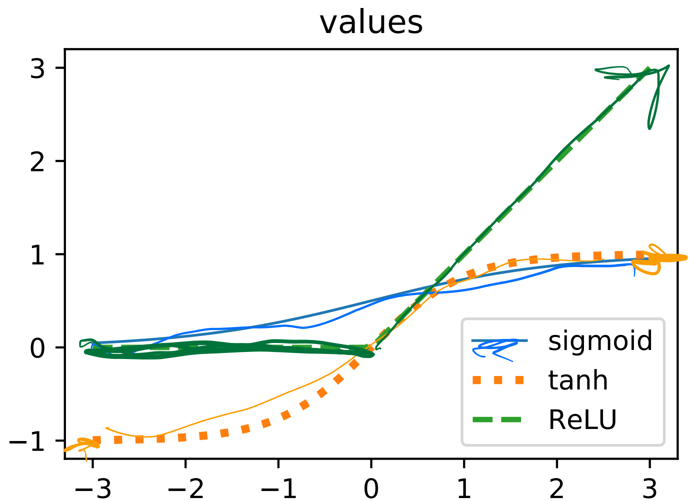
$$f(x) = \frac{1}{1+e^{-x}} \quad (1)$$

  - tanh

$$f(x) = \tanh(x) = \frac{2}{1+e^{-2x}} - 1 \quad (2)$$

  - ReLU

$$f(x) = \begin{cases} 0 & \text{for} \quad x < 0 \\ x & \text{for} \quad x \geq 0 \end{cases} \quad (3)$$

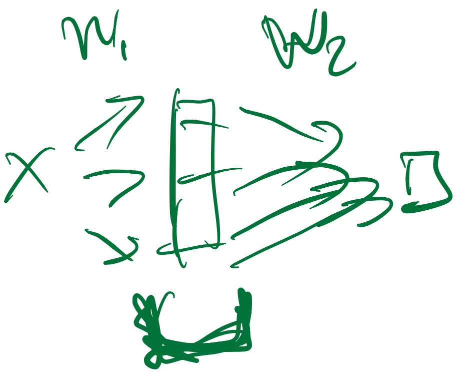


is a multi-layer neural network with no nonlinearities
(i.e., f is the identity $f(\mathbf{x}) = \mathbf{x}$)
more powerful than a one-layer network?

$$y = f(W_2 f(W_1 x)) = W_2 W_1 x$$

one matrix

"W"



with nonlinear $f(\cdot)$

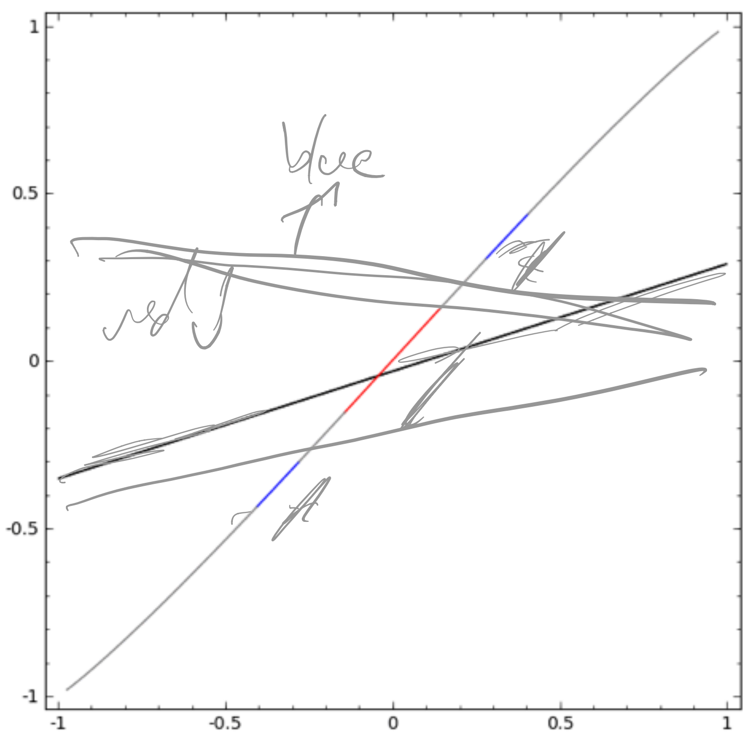
$\Rightarrow$ NN can learn any function

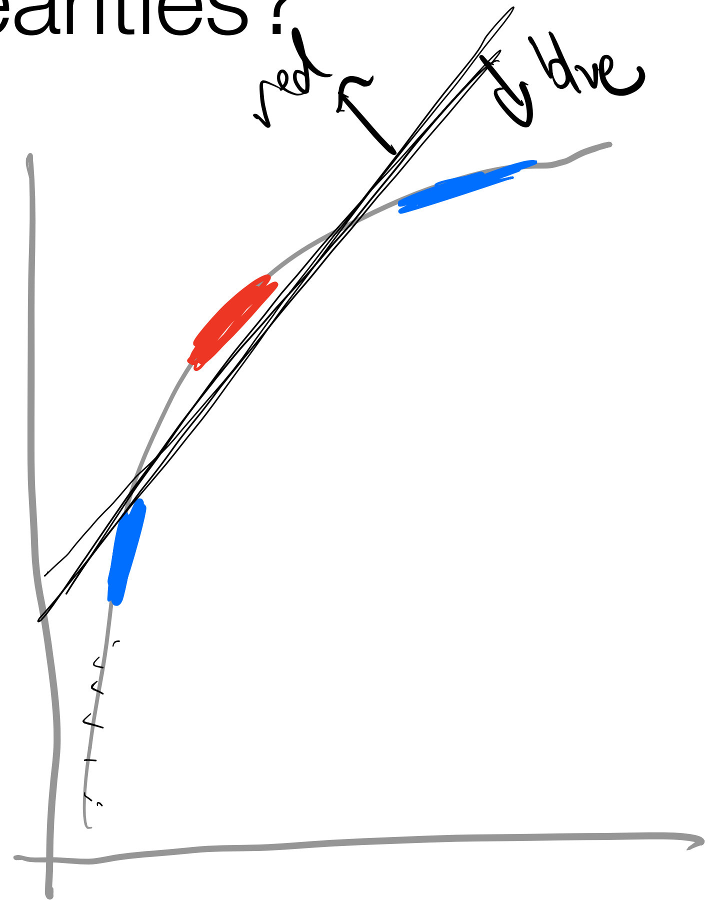
is a multi-layer neural network with no nonlinearities
(i.e., *f* is the identity *f*(**x**) = **x**)
more powerful than a one-layer network?

No! You can just compile all of the layers into a single transformation!

$$y = f(W_3 f(W_2 f(W_1 x))) = Wx$$

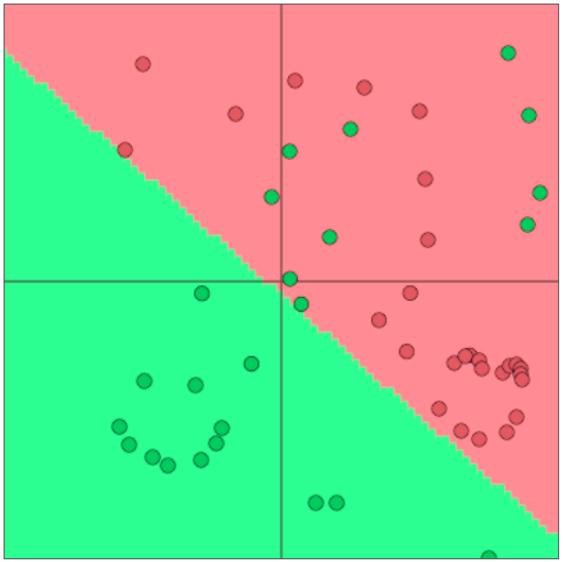
why nonlinearities?

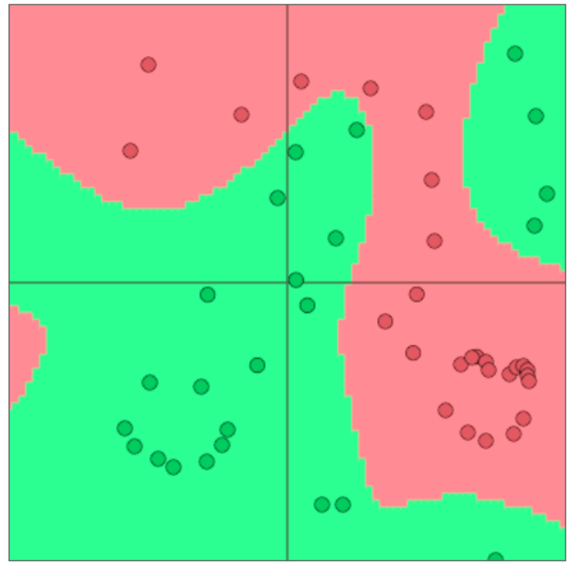


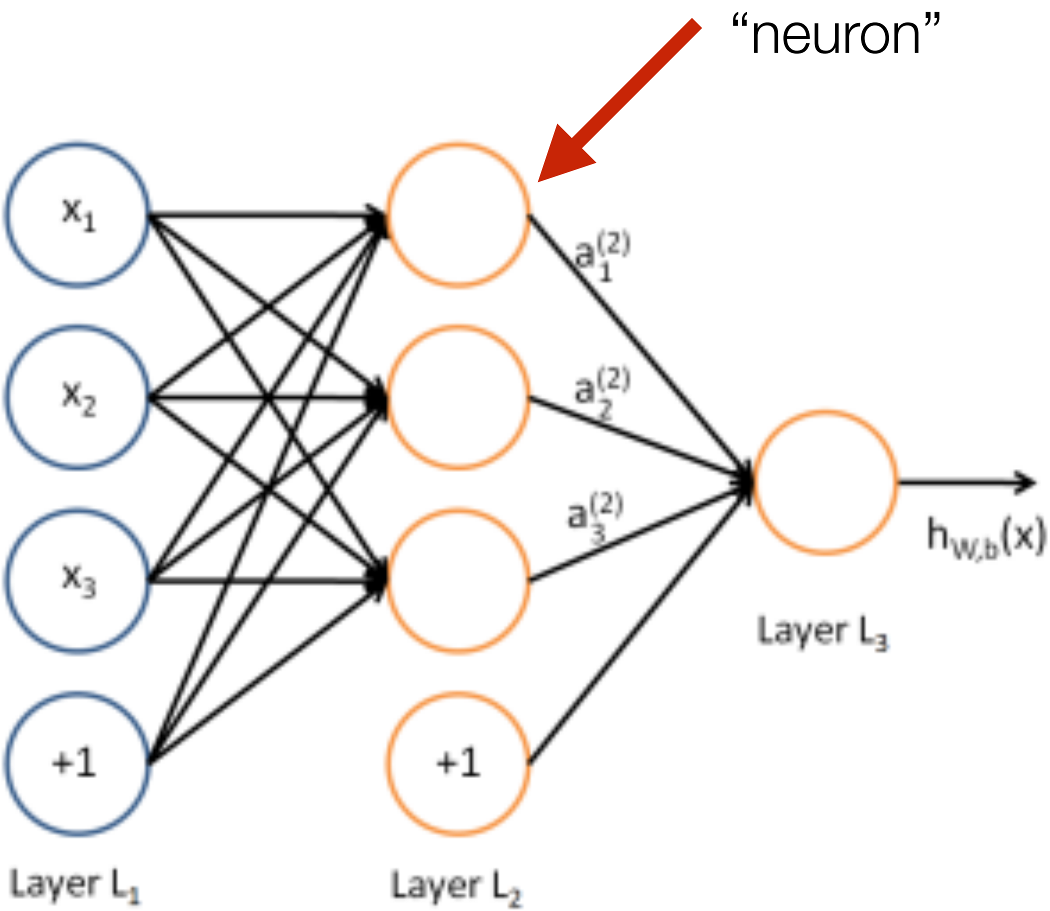


credit for figure:
Christopher Olah

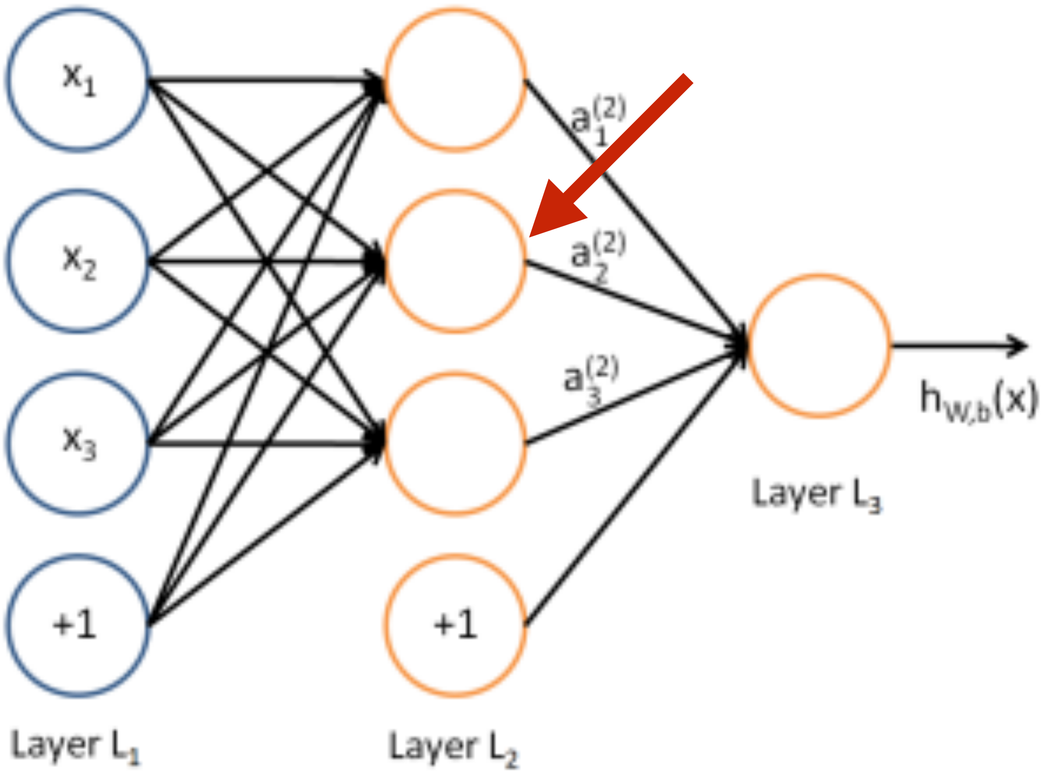
why nonlinearities?



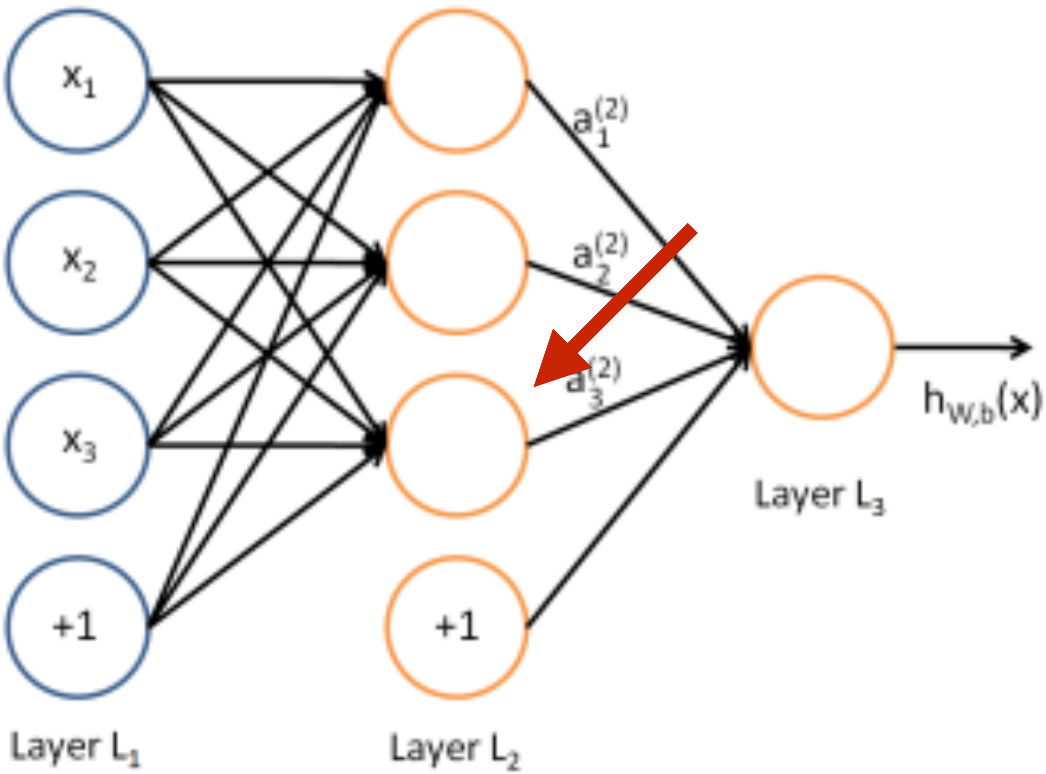




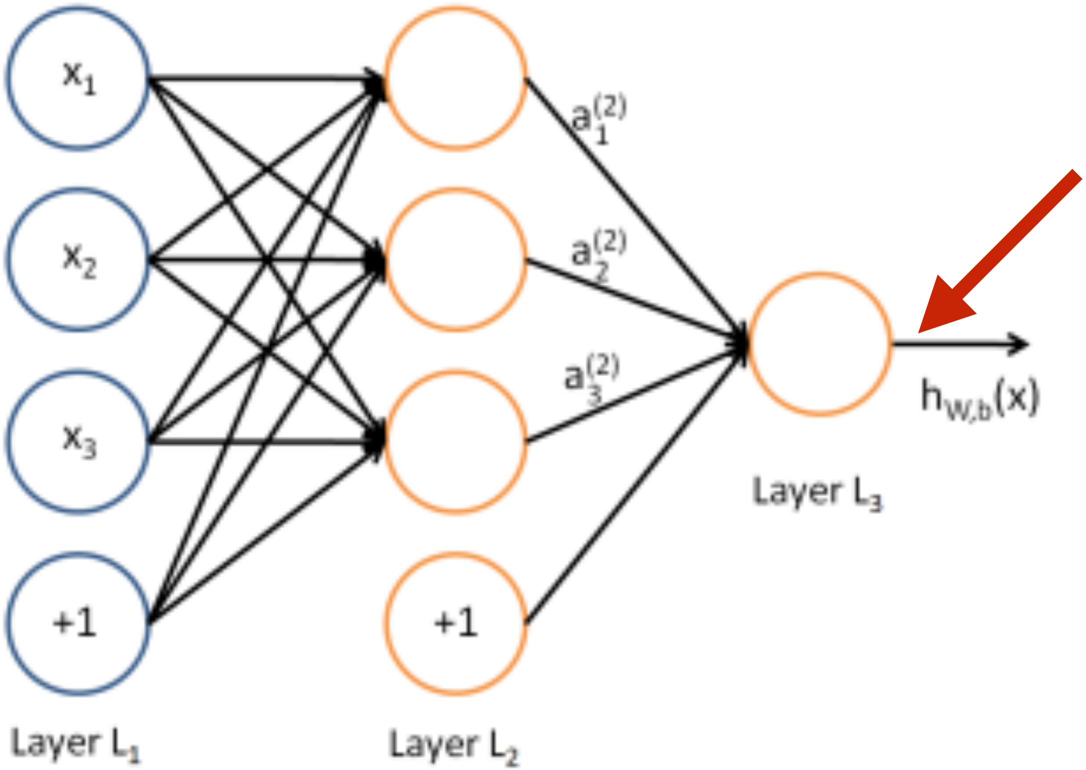
$$a_1^{(2)} = f\left(W_{11}^{(1)} x_1 + W_{12}^{(1)} x_2 + W_{13}^{(1)} x_3 + b_1^{(1)}\right)$$



$$a_2^{(2)} = f\left(W_{21}^{(1)} x_1 + W_{22}^{(1)} x_2 + W_{23}^{(1)} x_3 + b_2^{(1)}\right)$$

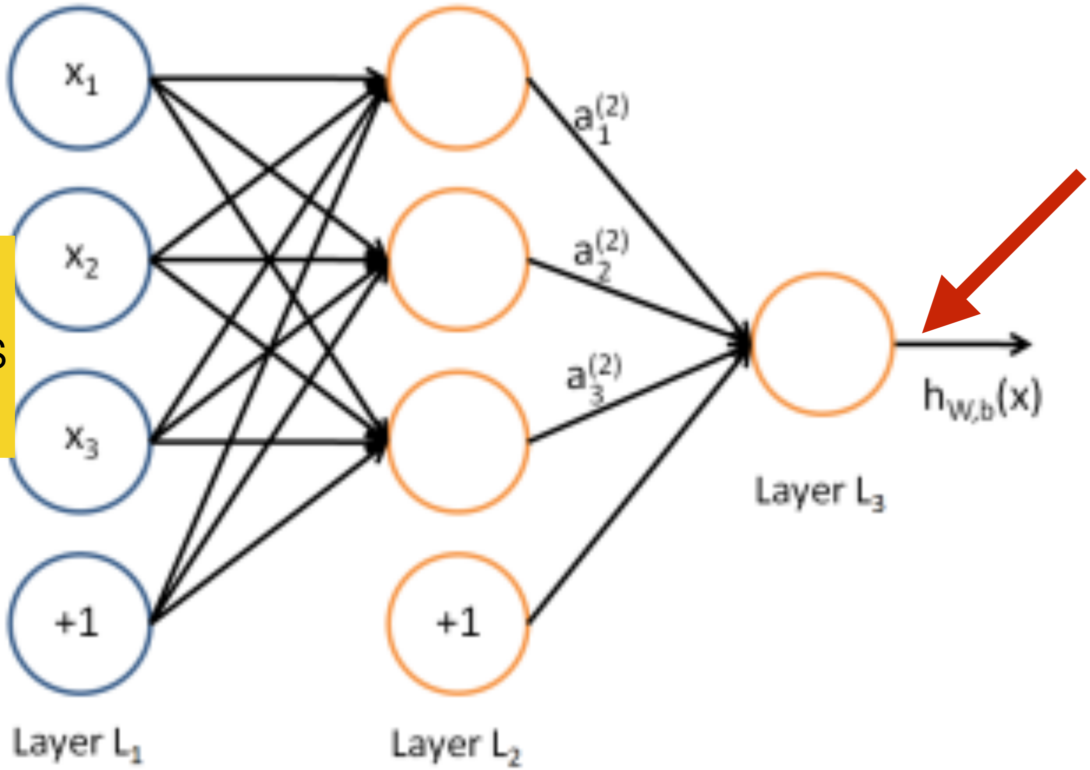


$$a_3^{(2)} = f\left(W_{31}^{(1)} x_1 + W_{32}^{(1)} x_2 + W_{33}^{(1)} x_3 + b_3^{(1)}\right)$$



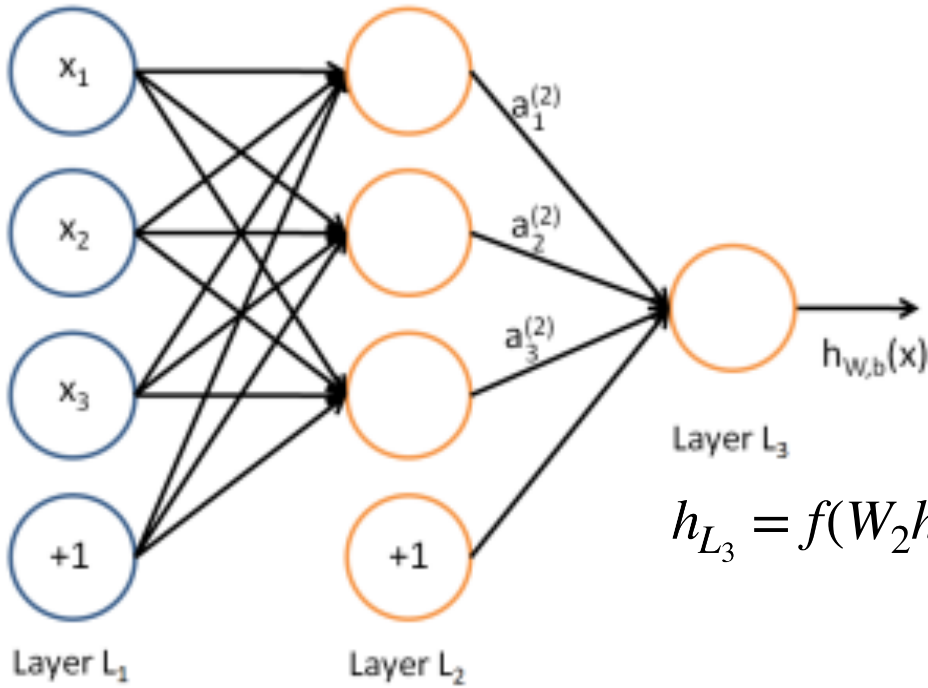
$$h_{W,b}(x) = a_1^{(3)} = f\left(W_{11}^{(2)} a_1^{(2)} + W_{12}^{(2)} a_2^{(2)} + W_{13}^{(2)} a_3^{(2)} + b_1^{(2)}\right)$$

we will be learning the x's and the W's!



$$h_{W,b}(x) = a_1^{(3)} = f\left(W_{11}^{(2)} a_1^{(2)} + W_{12}^{(2)} a_2^{(2)} + W_{13}^{(2)} a_3^{(2)} + b_1^{(2)}\right)$$

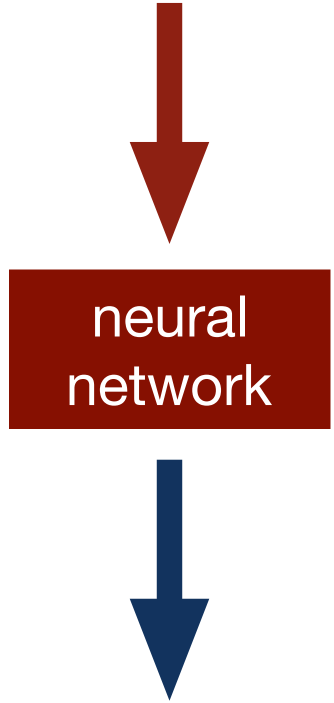
in matrix-vector notation…



$$h_{L_3} = f(W_2 h_{L_2} + b)$$

$$h_{L_2} = f(W_1 x + b)$$

Dracula is a really good book!



Positive

softmax function

- let's say I have 3 classes (e.g., positive, neutral, negative)
- use multiclass logreg with "cross product" features between input vector **x** and 3 output classes. for every class *c*, i have an associated weight vector β_c , then

$$P(y = c \mid \mathbf{x}) = \frac{e^{\beta_c \mathbf{x}}}{\sum_{k=1}^{3} e^{\beta_k \mathbf{x}}}$$

softmax function

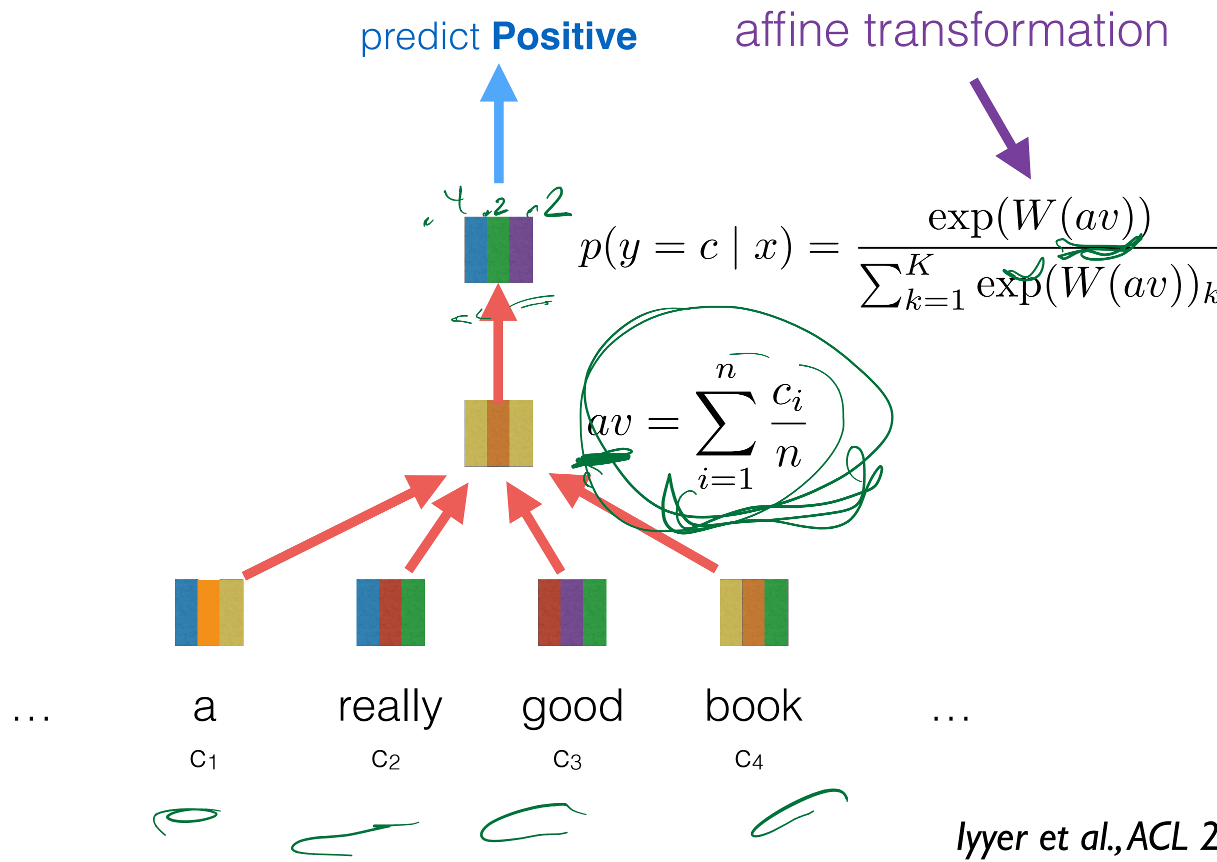
$$\text{softmax}(x) = \frac{e^{x}}{\sum_j e^{x_j}}$$

x is a vector

x_j is dimension *j* of x

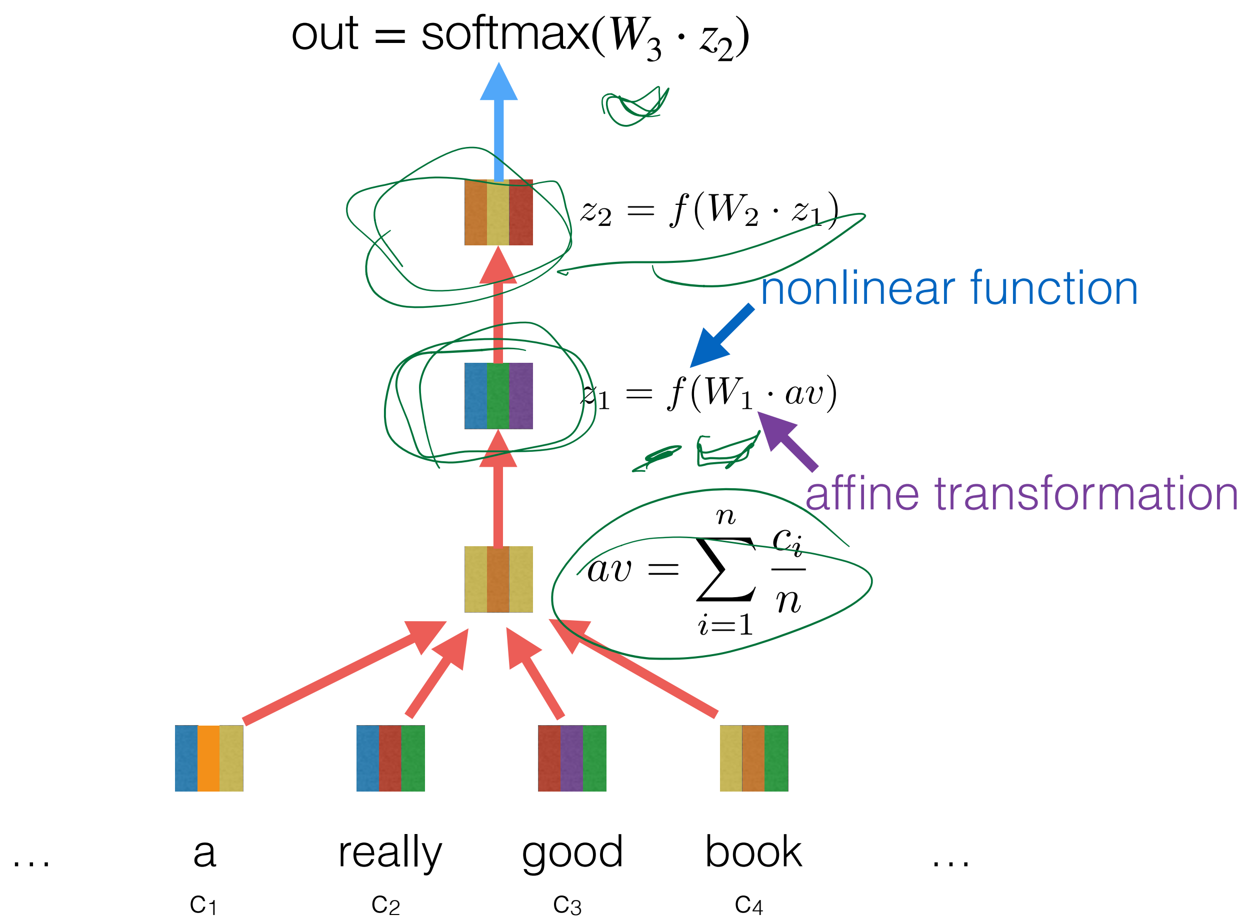
each dimension *j* of the softmaxed output represents the probability of class *j*

“bag of embeddings”



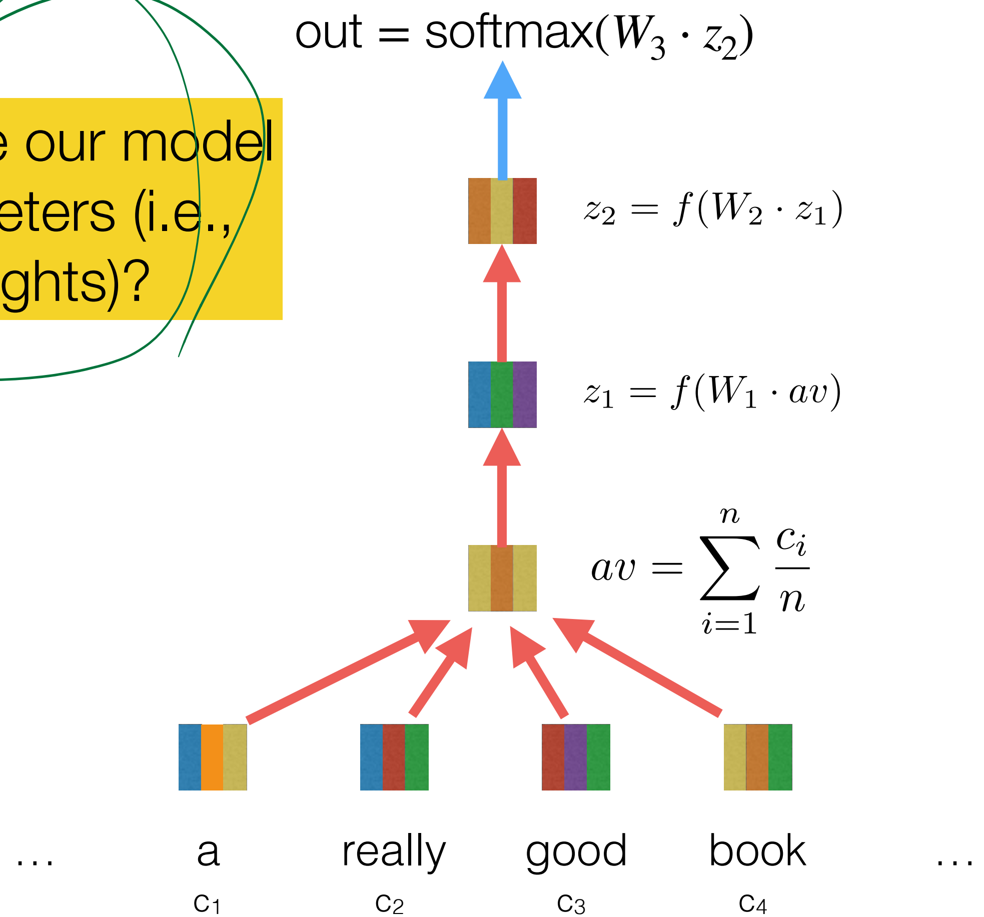
Iyyer et al., ACL 2015

deep averaging networks



deep averaging networks

what are our model parameters (i.e., weights)?

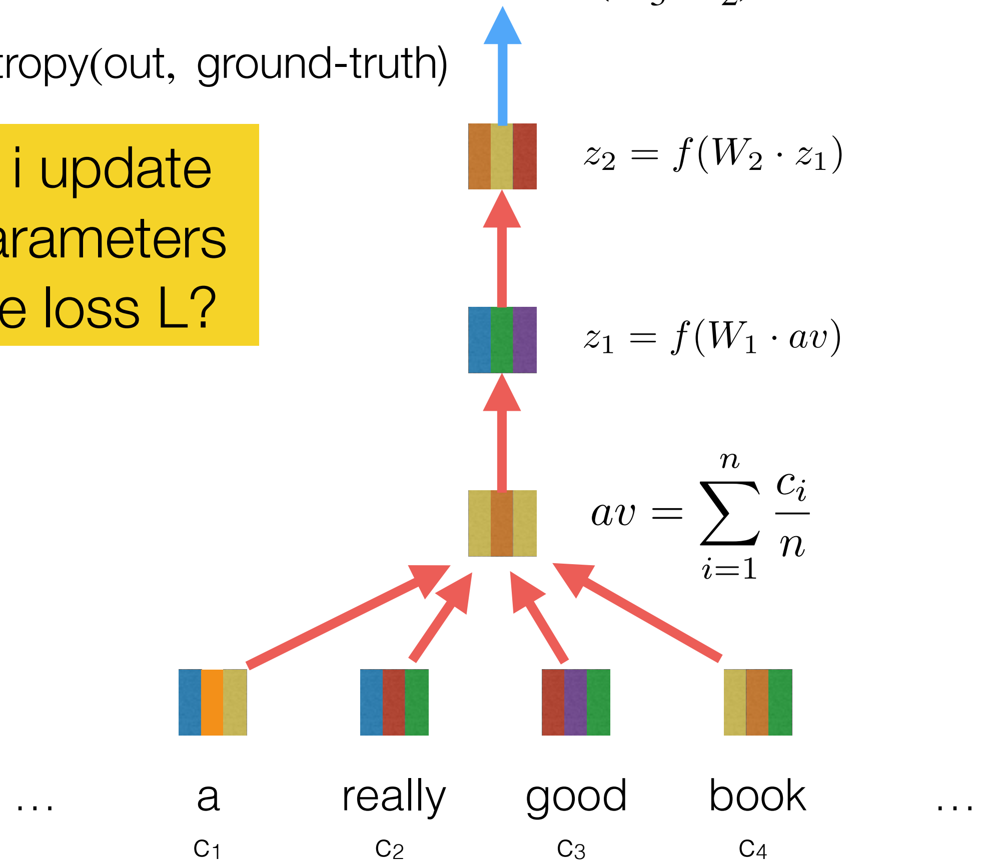


deep averaging networks

$\text{out} = \text{softmax}(W_3 \cdot z_2)$

$L = \text{cross-entropy}(\text{out, ground-truth})$

how do i update these parameters given the loss L?



deep averaging networks

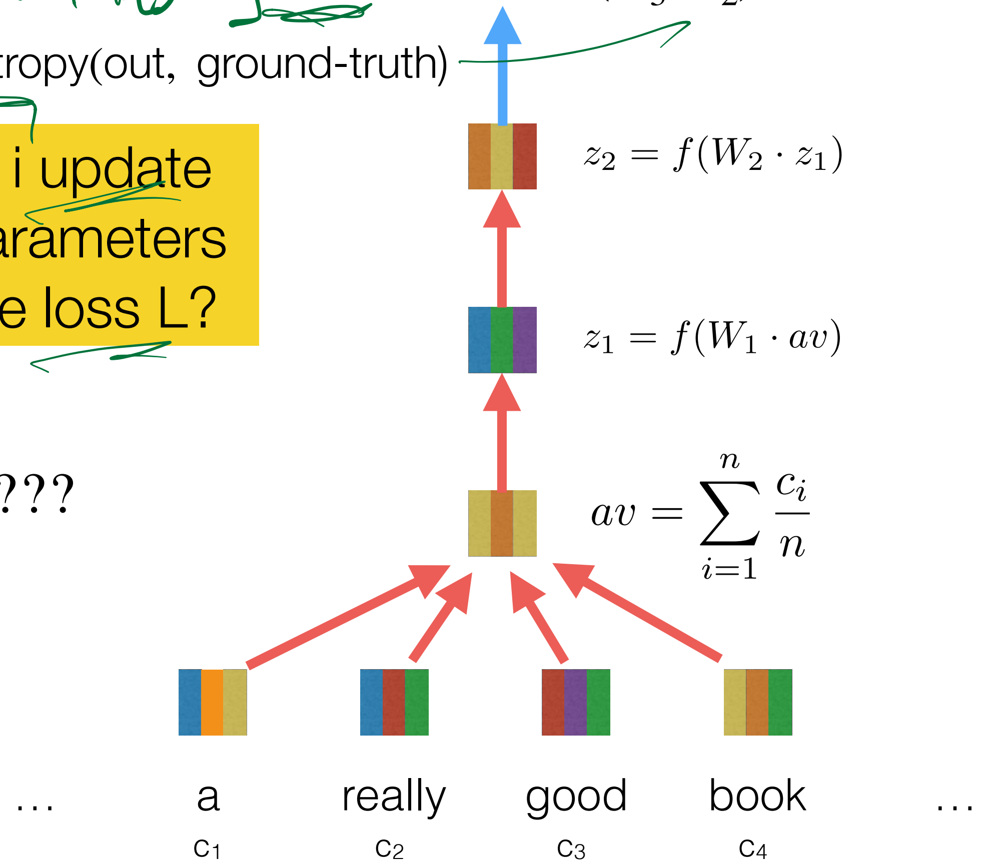
$-\log \text{outprob}[y_{gold}]$

out = $\text{softmax}(W_3 \cdot z_2)$

L = cross-entropy(out, ground-truth)

how do i update these parameters given the loss L?

$$\frac{\partial L}{\partial c_i} = ???$$



$$z_2 = f(W_2 \cdot z_1)$$

$$z_1 = f(W_1 \cdot av)$$

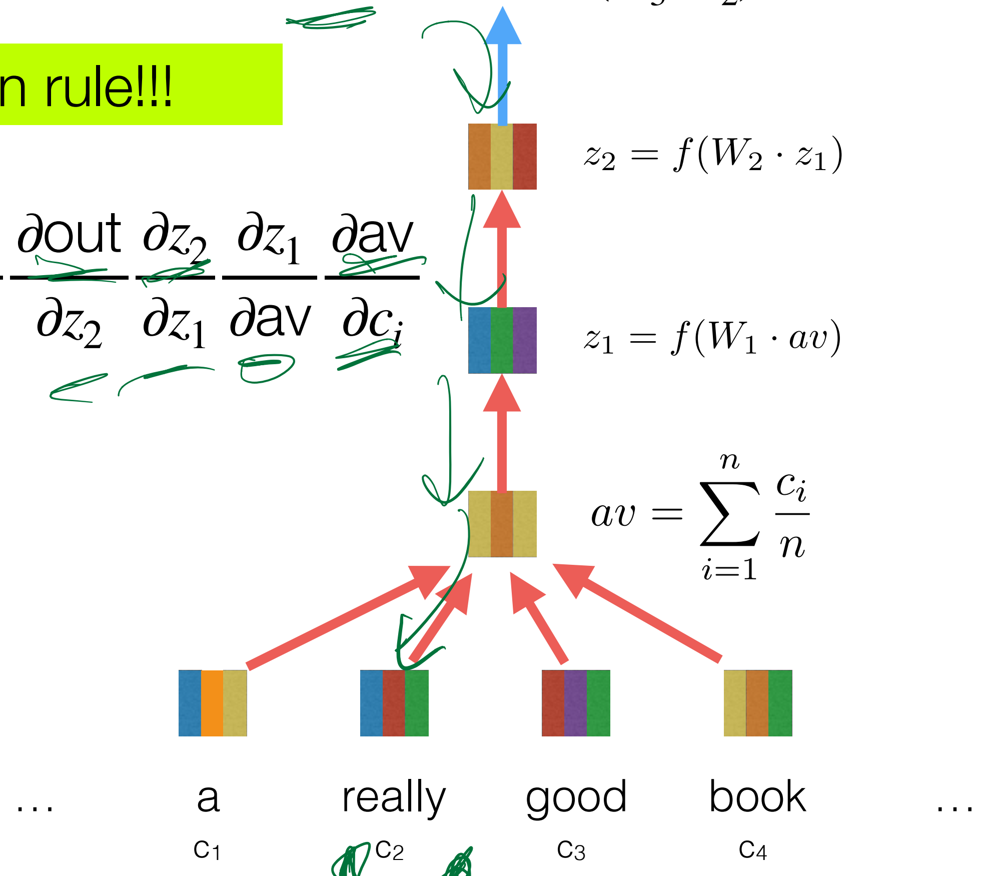
$$av = \sum_{i=1}^{n} \frac{c_i}{n}$$

deep averaging networks

$$\text{out} = \text{softmax}(W_3 \cdot z_2)$$

chain rule!!!

$$\frac{\partial L}{\partial c_i} = \frac{\partial L}{\partial \text{out}} \frac{\partial \text{out}}{\partial z_2} \frac{\partial z_2}{\partial z_1} \frac{\partial z_1}{\partial \text{av}} \frac{\partial \text{av}}{\partial c_i}$$



$$z_2 = f(W_2 \cdot z_1)$$

$$z_1 = f(W_1 \cdot av)$$

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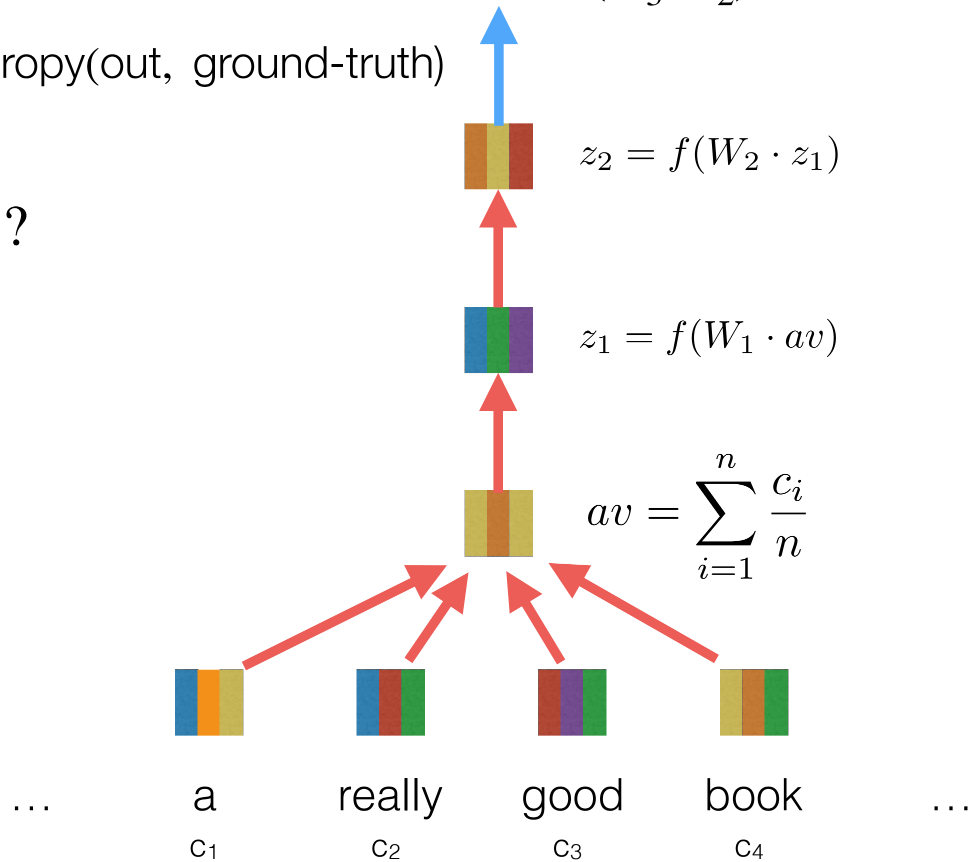
deep averaging networks

$$\text{out} = \text{softmax}(W_3 \cdot z_2)$$

$$L = \text{cross-entropy}(\text{out},\ \text{ground-truth})$$

$$\frac{\partial L}{\partial W_2} = ???$$



deep averaging networks

$$\text{out} = \text{softmax}(W_3 \cdot z_2)$$

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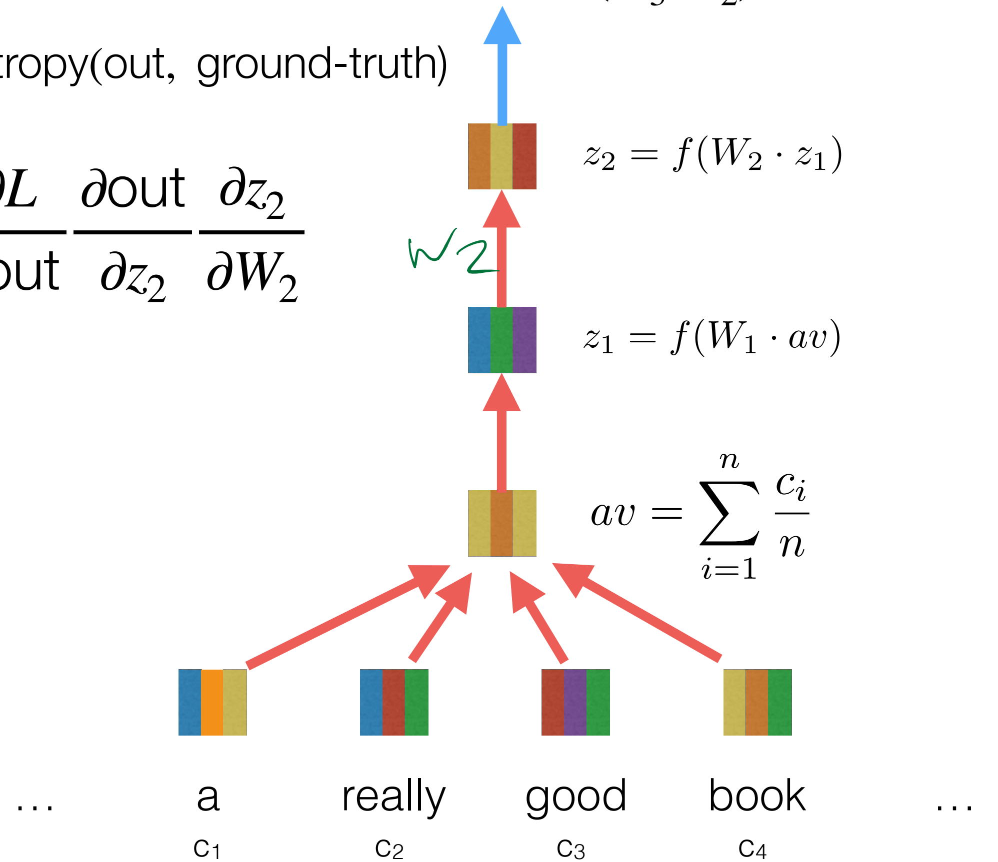
$$\frac{\partial L}{\partial W_2} = \frac{\partial L}{\partial \text{out}} \frac{\partial \text{out}}{\partial z_2} \frac{\partial z_2}{\partial W_2}$$



backpropagation

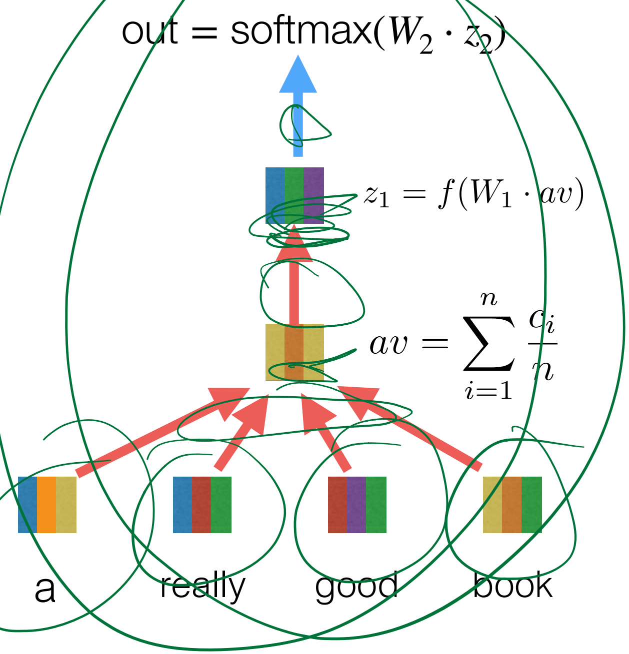
- use the chain rule to compute partial derivatives w/ respect to each parameter
- trick: re-use derivatives computed for higher layers to compute derivatives for lower layers!

$$\frac{\partial L}{\partial c_i} = \frac{\partial L}{\partial \text{out}} \frac{\partial \text{out}}{\partial z_2} \frac{\partial z_2}{\partial z_1} \frac{\partial z_1}{\partial \text{av}} \frac{\partial \text{av}}{\partial c_i}$$

$$\frac{\partial L}{\partial W_2} = \frac{\partial L}{\partial \text{out}} \frac{\partial \text{out}}{\partial z_2} \frac{\partial z_2}{\partial W_2}$$

Rumelhart et al., 1986

deep learning frameworks make building NNs super easy!

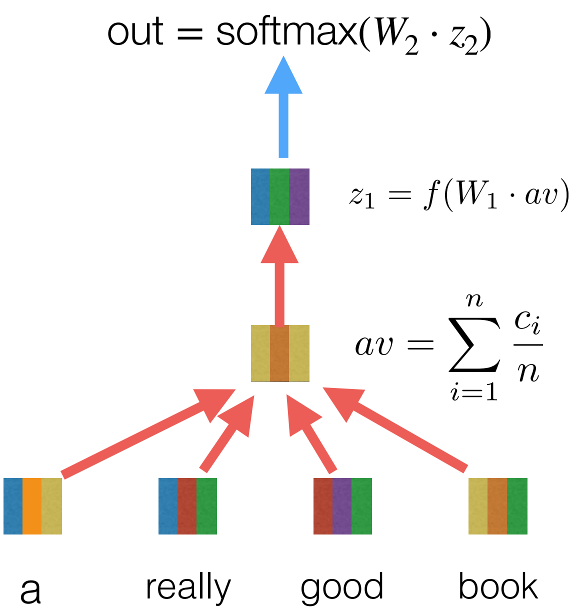


PyTorch

set up the network

```
def __init__(self, n_classes, vocab_size, emb_dim=300,
             n_hidden_units=300):
    super(DanModel, self).__init__()
    self.n_classes = n_classes
    self.vocab_size = vocab_size
    self.emb_dim = emb_dim
    self.n_hidden_units = n_hidden_units
    self.embeddings = nn.Embedding(self.vocab_size,
                                   self.emb_dim)
    self.classifier = nn.Sequential(
           nn.Linear(self.n_hidden_units,
                     self.n_hidden_units),
           nn.ReLU(),
           nn.Linear(self.n_hidden_units,
                     self.n_classes))
    self._softmax = nn.Softmax()
```

deep learning frameworks make building NNs super easy!

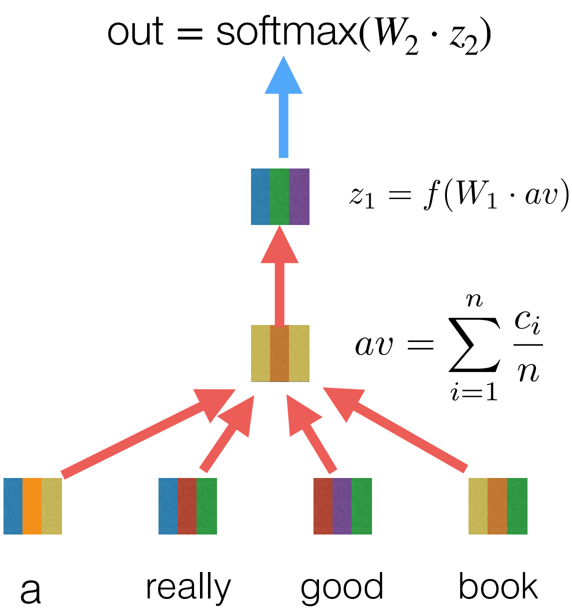


<u>do a forward pass to compute prediction</u>

```
def forward(self, batch, probs=False):
    text = batch['text']['tokens']
    length = batch['length']
    text_embed = self._word_embeddings(text)
    # Take the mean embedding. Since padding results
    # in zeros its safe to sum and divide by length
    encoded = text_embed.sum(1)
    encoded /= lengths.view(text_embed.size(0), -1)

    # Compute the network score predictions
    logits = self.classifier(encoded)
    if probs:
        return self._softmax(logits)
    else:
        return logits
```

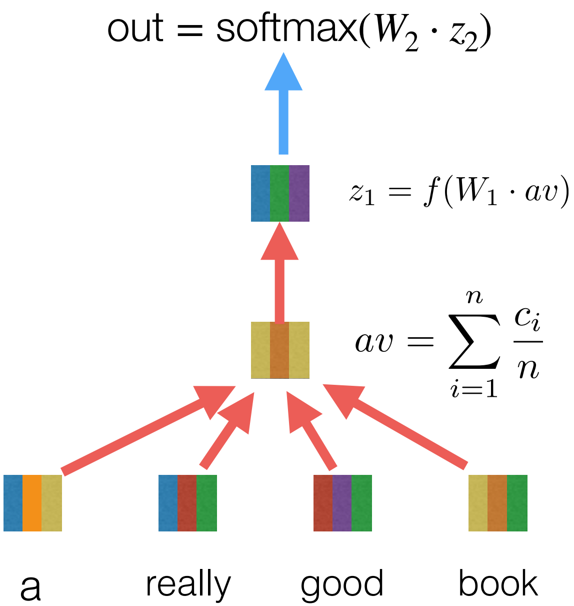
deep learning frameworks make building NNs super easy!



<u>do a backward pass to update weights</u>

```
def _run_epoch(self, batch_iter, train=True):
    self._model.train()
    for batch in batch_iter:
        model.zero_grad()
        out = model(batches)
        batch_loss = criterion(out,
                               batch['label'])
        batch_loss.backward()
        self.optimizer.step()
```

deep learning frameworks make building NNs super easy!



do a backward pass to update weights

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        batch_loss = criterion(out,
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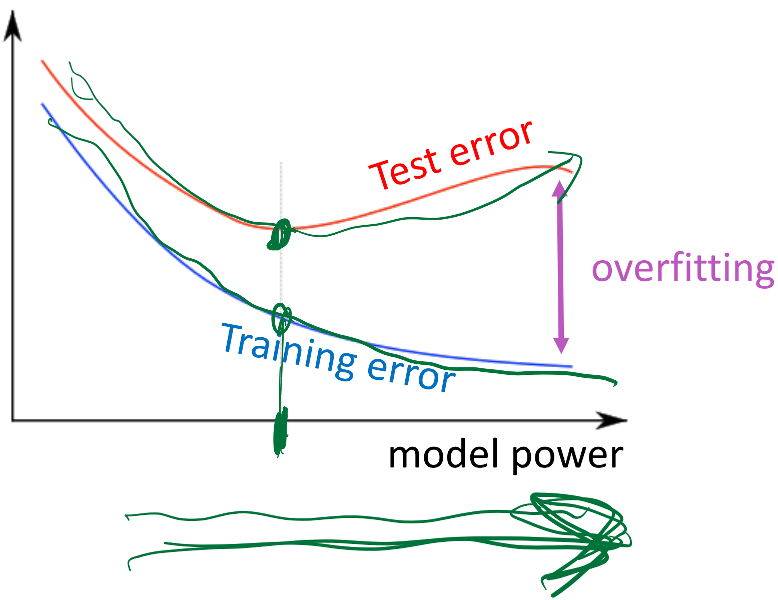
        batch_loss.backward()
        self.optimizer.step()
```

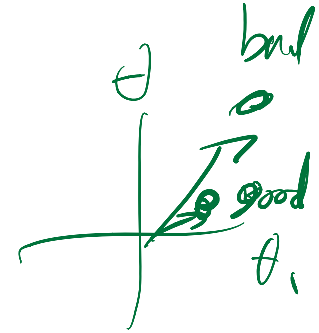
that’s it! no need to compute gradients by hand!

Regularization

- Regularization prevents overfitting when we have a lot of features (or later a very powerful/deep model,++)



L2 regularization



$$J(\theta) = \frac{1}{N}\sum_{i=1}^{N} -\log\left(\frac{e^{f_{y_i}}}{\sum_{c=1}^{C} e^{f_c}}\right) + \lambda \sum_{k} \theta_k^2$$

θ represents all of the model's parameters!

strength of regul.

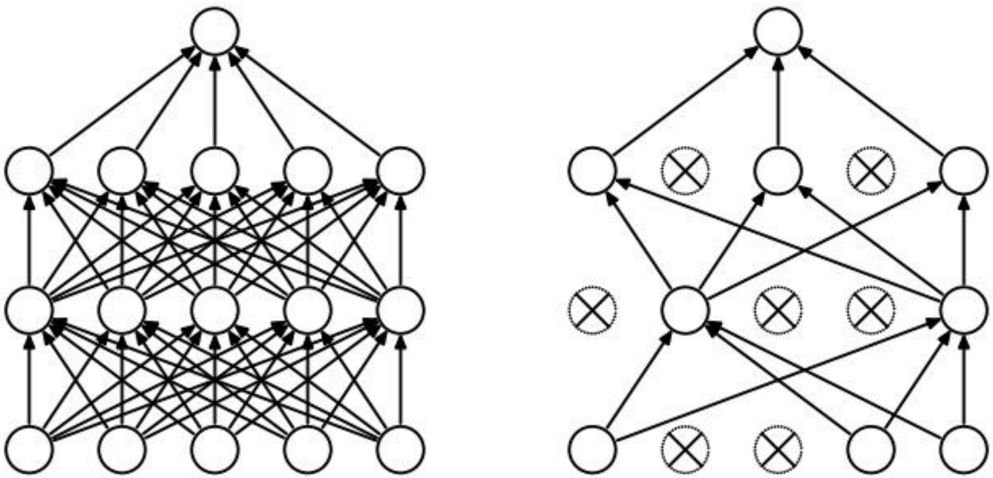
penalizing their norm leads to smaller weights
we are constraining the parameter space
we are putting a prior on our model

$\lambda = 1e6$

Tune regul. λ on devset data

Dropout for NNs

randomly set *p*% of neurons to 0 in the forward pass

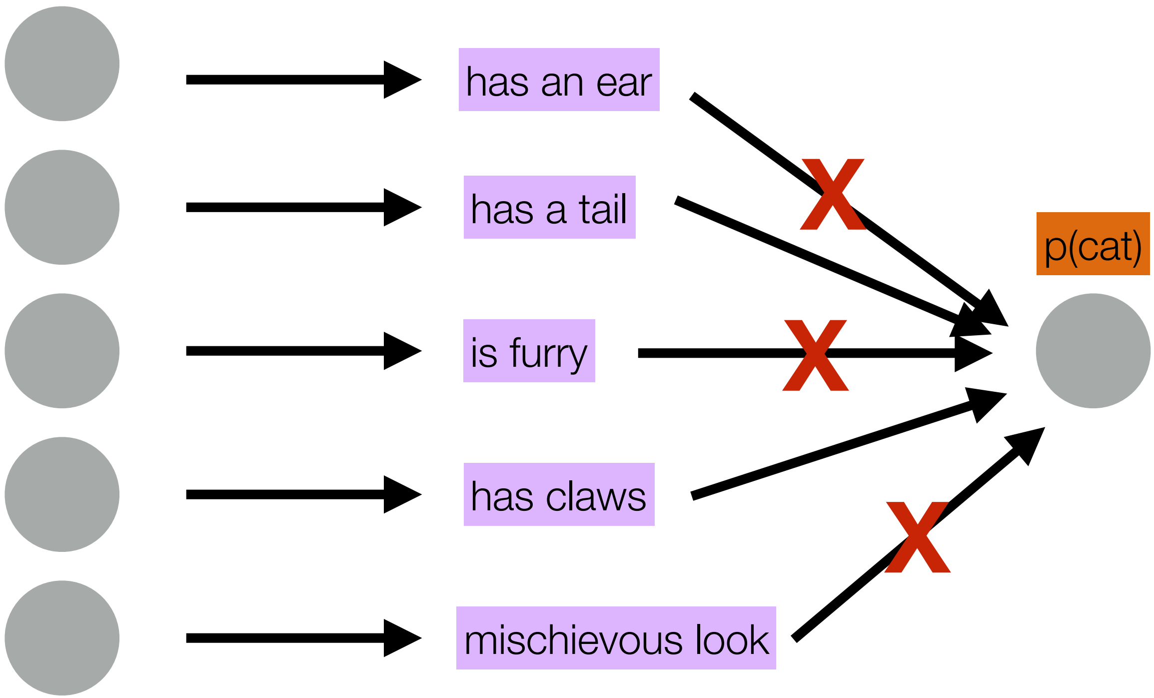


(a) Standard Neural Net (b) After applying dropout.

[Srivastava et al., 2014]

Why?

randomly set *p*% of neurons to 0 in the forward pass



A few other tricks

- Training can be unstable! Therefore some tricks.
    - Initialization — random small but reasonable values can help.
    - Layer normalization (very important for some recent architectures)
- Big, robust open-source libraries to let you computation graphs, then run backprop for you
    - PyTorch, Tensorflow (+ many higher-level libraries on top; e.g. HuggingFace, AllenNLP…)