FFNNs for Classification and Language Modeling

LING 575K Deep Learning for NLP
Shane Steinert-Threlkeld
April 14 2021

Today's Plan

- Deep Averaging Networks for text classification
- Neural Probabilistic Language Model
- Additional Training Notes
  - Regularization
  - Early stopping
  - Hyper-parameter searching
- HW3 / edugrad / PyTorch

Announcements

- Running time:
  - Many factors influence this, including the load on nodes on patas
  - So don’t worry too much about your raw numbers!
  - Do: run in advance; it will take several hours
- Avoiding node 3 (thanks Levon):
  - Requirements = (Machine != "patas-n3.ling.washington.edu")
- Number of parameters: each real number is a parameter, as opposed to entire vectors/matrices

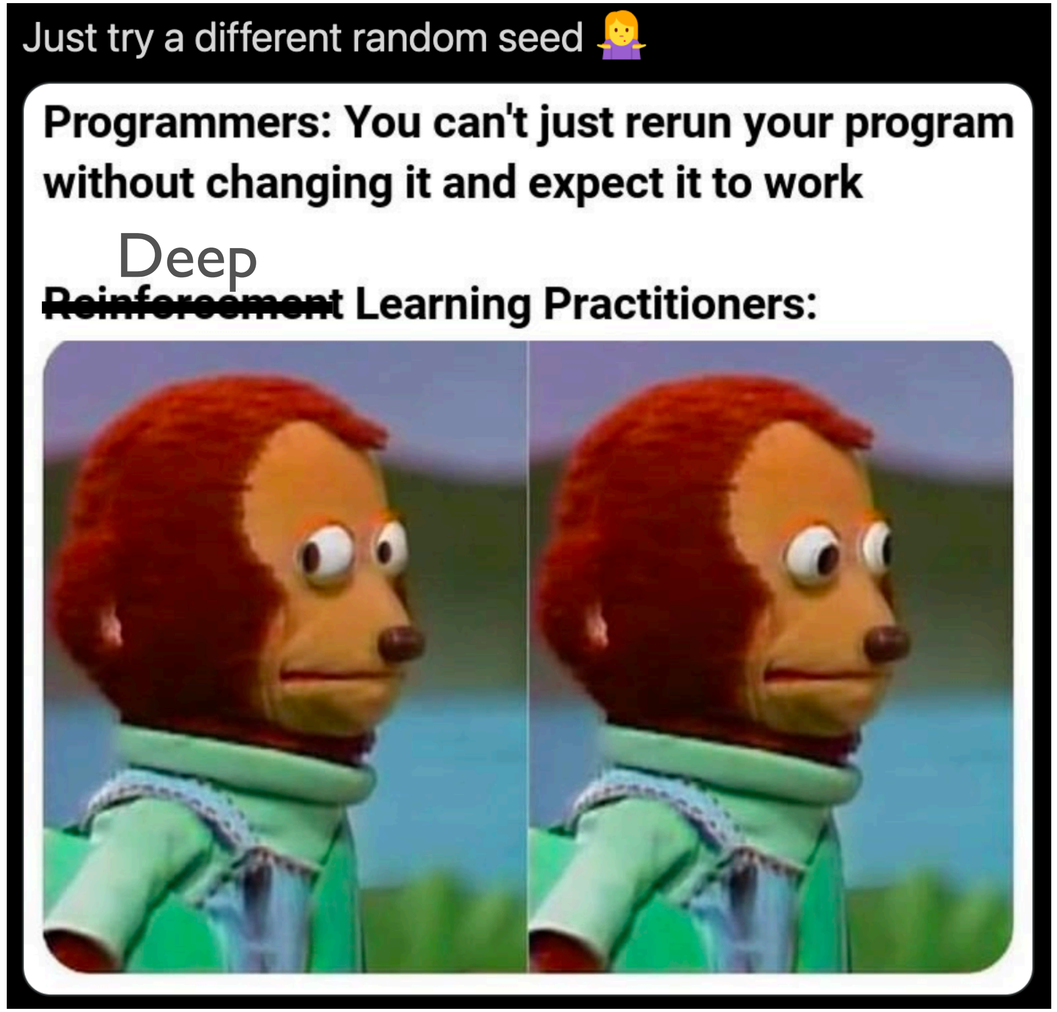
Note on Random Seeds

- In word2vec.py / util.py:
- Random seed:
  - Behavior of pseudo-random number generators is determined by their “seed” value
  - If not specified, determined by e.g. # of seconds since 1970
  - Same seed —> same (non-random behavior)
- Sources of randomness in DL: shuffling the data each epoch, weight initialization, negative *sampling*, …
- Very important for reproducibility!
  - In general, run on several seeds and report means / std’s

```
# set random seed
util.set_seed(args.seed)
```

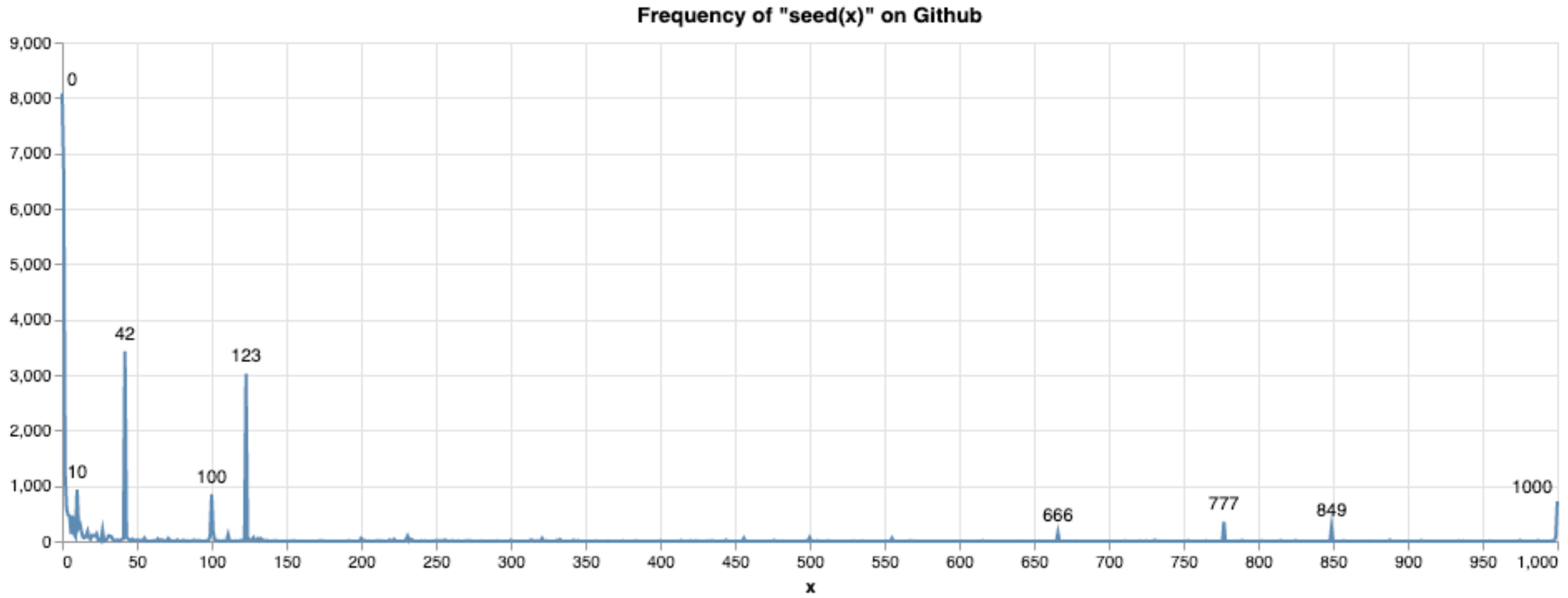
```
def set_seed(seed: int) -> None:
    """Sets various random seeds. """
    random.seed(seed)
    np.random.seed(seed)
```

Random Seeds and Reproducibility



Random Seeds, cont

- Ideally: “randomly generate” seeds, but save/store them!
- Random seed is not a hyper-parameter! (Some discussions in these threads.)



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Deep Averaging Networks

Deep Unordered Composition Rivals Syntactic Methods for Text Classification

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Abstract

Many existing deep learning models for natural language processing tasks focus on learning the *compositionality* of their inputs, which requires many expensive computations. We present a simple deep neural network that competes with and, in some cases, outperforms such models on sen-

results have shown that syntactic functions outperform unordered functions on many tasks (Socher et al., 2013b; Kalchbrenner and Blunsom, 2013).

However, there is a tradeoff: syntactic functions require more training time than unordered composition functions and are prohibitively expensive in the case of huge datasets or limited computing resources. For example, the recursive neural network (Section 2) computes costly matrix/tensor products

Deep, Unordered, Classification

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- Deep:
  - One or more hidden layers in a neural network

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  - One or more hidden layers in a neural network
- Unordered:
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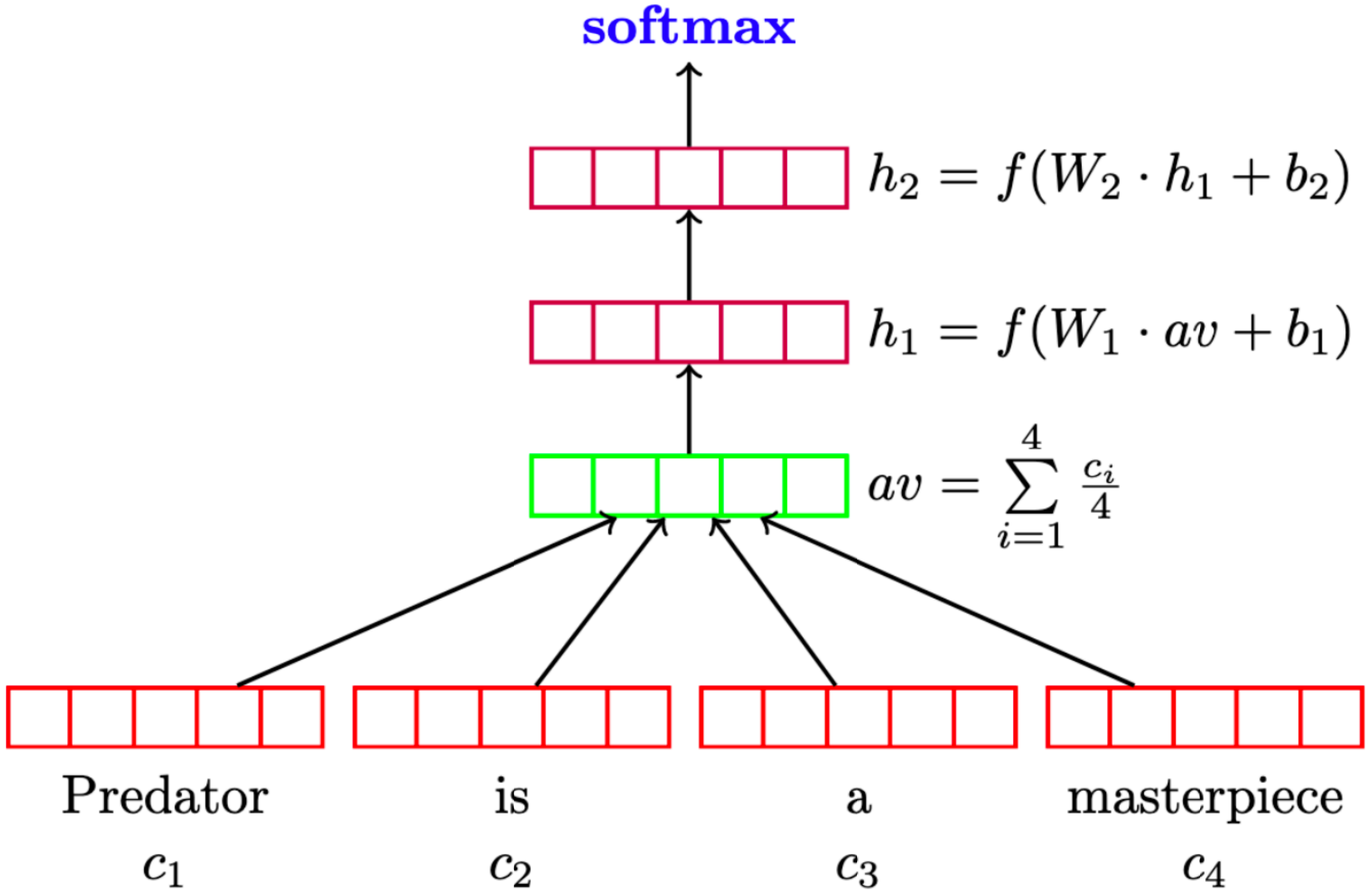
- Classification:
  - Applied to several classification tasks, including SST
  - Via softmax layer

Model Architecture, One Input



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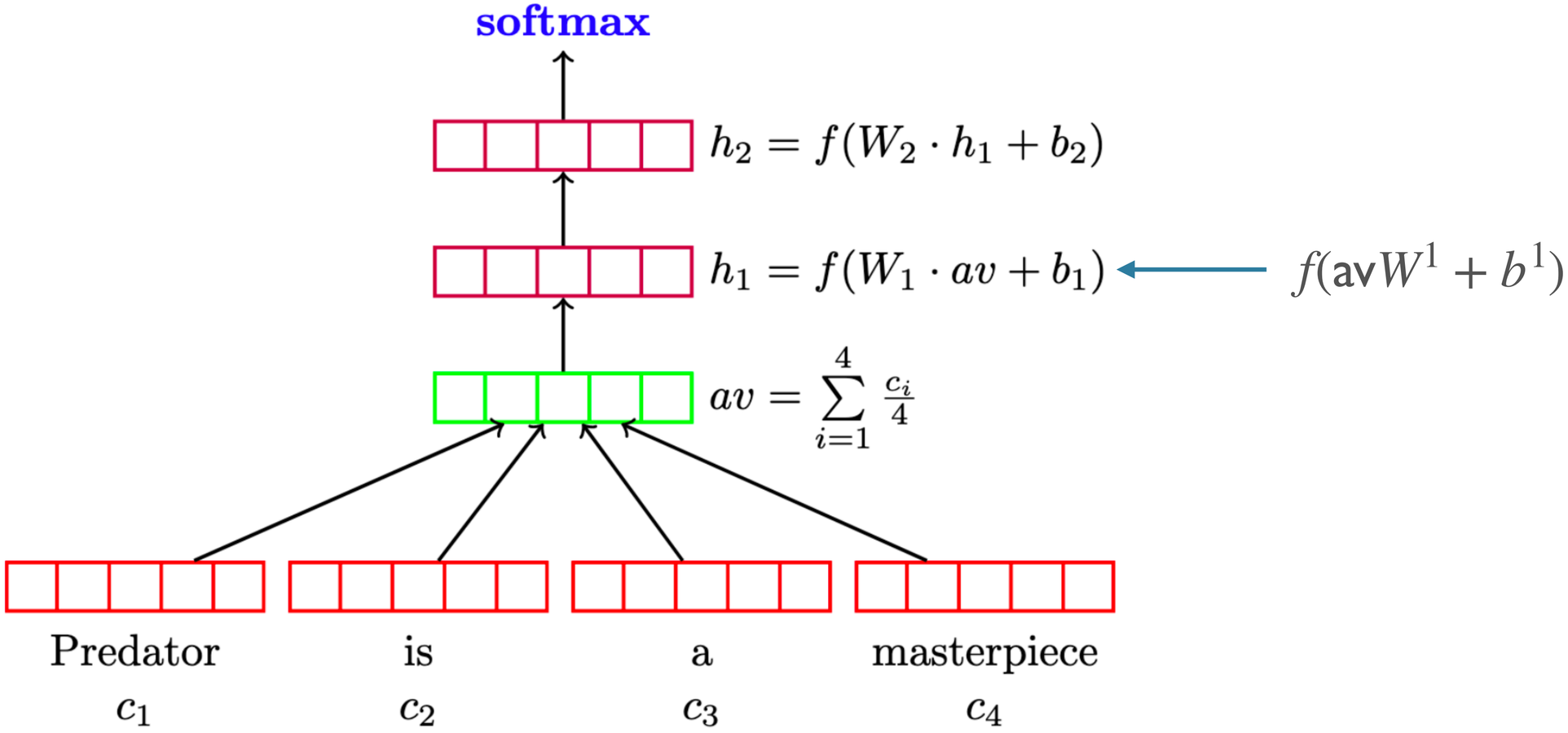

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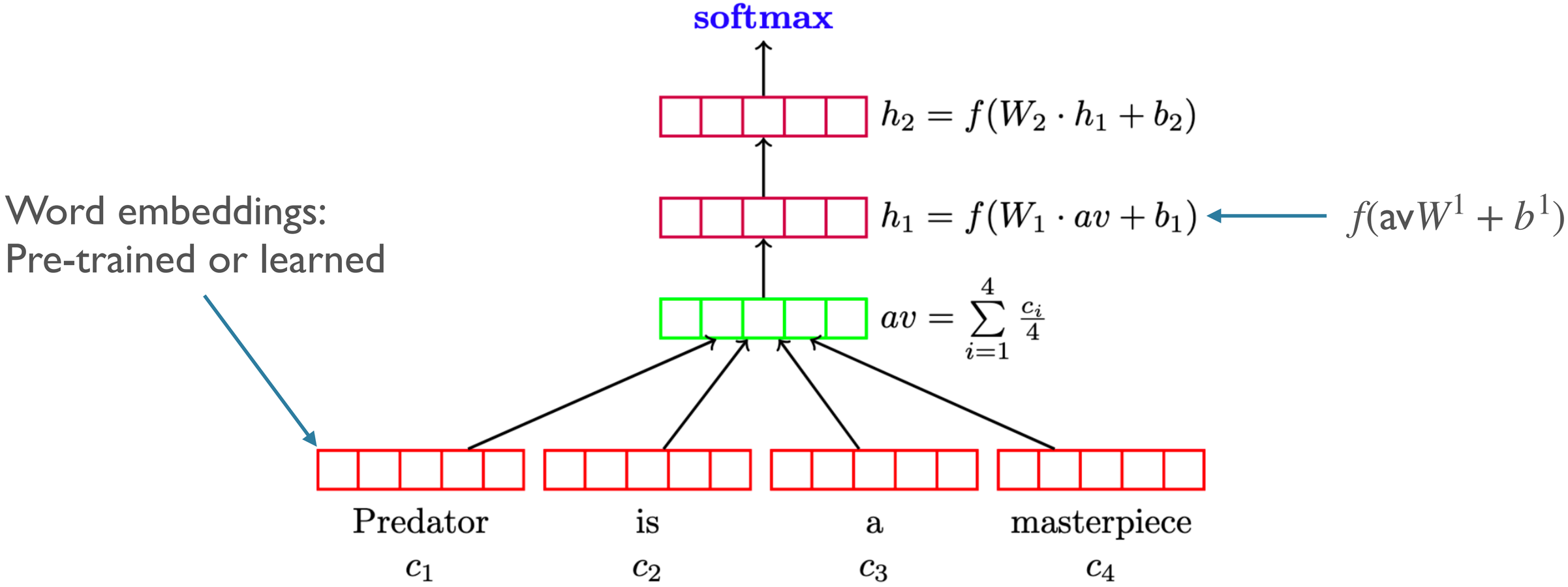

Hyper-parameters

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- For each layer:
  - Activation function
  - Hidden dimension size
- Exercise: find the values for these hyper-parameters in the paper

Note on Embedding Layer

- Let t be the integer index of word w
- One-hot vector (t=4): $w_t = [0 \quad 0 \quad 0 \quad 1 \quad \cdots \quad 0]$
- For E an embedding matrix of shape [vocab_size, embedding_dimension] and E_t the embedding for t:

$$E_t = w_t E$$

- NB: direct look-up is faster than matrix multiplication, but the latter generalizes in useful ways that we will see soon

Batched Computation in DAN

- We saw how to pass one piece of text through the DAN
- How can we leverage larger batch sizes and their advantages?
  - “Predator is a masterpiece”
  - “Parasite won Best Picture for 2019”
- What issues here?
- Different lengths —> different number of embeddings —> different input size (intuitively)
  - But we need a matrix of shape [batch_size, representation_size] for inputs

Batching with Bag of Words

- Bag of words representation:
  - {word1: 3, word36: 1, word651: 1, …}
  - Let s be a sentence words t_i occurring count_i times: $\text{bag}_s := \{t_i : \text{count}_i\}$
- Bag of words vector: $\text{vec}_s := [3 \quad 0 \quad \cdots \quad 1 \quad \cdots \quad 1 \quad \cdots]$

$$\text{vec}_s E = \sum_{i=0}^{\text{len}(s)} E_{t_i}$$

- For every sentence, these vectors have the same size (vocab size)
  - So they can be stacked into a matrix, of shape [batch_size, vocab_size]
  - Divide each row by length of that sentence to get average of embeddings

Output and Loss for Classification

$$\text{logits} = \text{hidden}W + b$$

$$\hat{y} = \text{probs} = \text{softmax}(\text{logits})$$

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One hot for true class label

Results

Model	RT	SST fine
DAN-ROOT	—	46.9
DAN-RAND	77.3	45.4
DAN	80.3	47.7
NBOW-RAND	76.2	42.3
NBOW	79.0	43.6
BiNB	—	41.9
NBSVM-bi	79.4	—
RecNN*	77.7	43.2
RecNTN*	—	45.7
DRecNN	—	49.8
TreeLSTM	—	**50.6**

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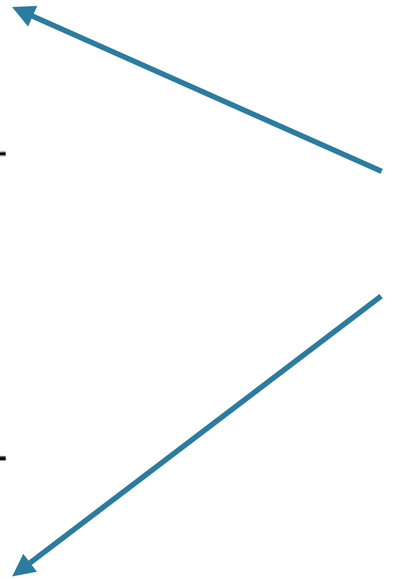

"Rivals syntactic methods"

Error Analysis

Sentence	DAN	DRecNN	Ground Truth
a lousy movie that's not merely unwatchable, but also unlistenable	negative	negative	negative
if you're not a prepubescent girl, you'll be laughing at britney spears' movie-starring debut whenever it does n't have you impatiently squinting at your watch	negative	negative	negative
blessed with immense physical prowess he may well be, but ahola is simply not an actor	positive	neutral	negative
who knows what exactly godard is on about in this film, but his words and images do n't have to add up to mesmerize you.	positive	positive	positive
it's so good that its relentless, polished wit can withstand not only inept school productions, but even oliver parker's movie adaptation	negative	positive	positive
too bad, but thanks to some lovely comedic moments and several fine performances, it's not a total loss	negative	negative	positive
this movie was not good	negative	negative	negative
this movie was good	positive	positive	positive
this movie was bad	negative	negative	negative
the movie was not bad	negative	negative	positive

Two Additional “Tricks”

- Word dropout
  - A type of *regularization* [more later]
- Adagrad optimizer

Word Dropout

- For each input sequence, flip |V| coins with probability *p*
  - If the i'th coin lands tails, set embedding for w_i to all 0s for this example

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Generated randomly for each sentence

Adagrad

- “Adaptive Gradients”
  - Key idea: *adjust the learning rate* per parameter
  - Frequent features —> more updates
  - Adagrad will make the learning rate smaller for those

Adagrad

- Let $g_{t,i} := \nabla_{\theta_{t,i}} \mathscr{L}$
- SGD: $\theta_{t+1,i} = \theta_{t,i} - \alpha g_{t,i}$
- Adagrad: $$\theta_{t+1,i} = \theta_{t,i} - \frac{\alpha}{\sqrt{G_{t,i} + \epsilon}} g_{t,i}$$

$$G_{t,i} = \sum_{k=0}^{t} g_{k,i}^2$$

Adagrad

- Pros:
  - “Balances” parameter importance
  - Less manual tuning of learning rate needed (0.01 default)
- Cons:
  - $G_{t,i}$ increases monotonically, so step-size always gets smaller
- Newer optimizers try to have the pros without the cons
- Resources:
  - Original paper (veeery math-y): https://jmlr.org/papers/volume12/duchi11a/duchi11a.pdf
  - Overview of optimizers: https://ruder.io/optimizing-gradient-descent/index.html#adagrad

Neural Probabilistic Language Model

Language Modeling

- A language model parametrized by θ computes $P_\theta(w_1, \ldots, w_n)$

- Typically (though we'll see variations): $P_\theta(w_1, \ldots, w_n) = \prod_i P_\theta(w_i \mid w_1, \ldots, w_{i-1})$

- E.g. of labeled data: "Today is the third day of 575k." —>
  - (<s>, Today)
  - (<s> Today, is)
  - (<s> Today is, the)
  - (<s> Today is the, third)

N-gram LMs

- Dominant approach for a long time uses n-grams:

$$P_\theta(w_i \mid w_1, \ldots, w_{i-1}) \approx P_\theta(w_i \mid w_{i-1}, w_{i-2}, \ldots, w_{i-n})$$

- Estimate the probabilities by counting in a corpus
  - Fancy variants (back-off, smoothing, etc)
- Some problems:
  - Huge number of parameters: $\approx |V|^n$
  - Doesn't generalize to unseen n-grams

Neural LM

- Core idea behind the Neural Probabilistic LM
  - Make n-gram assumption
  - But: learn word embeddings
  - “N-gram of word vectors”
  - Probabilities: represented by a neural network, not counts

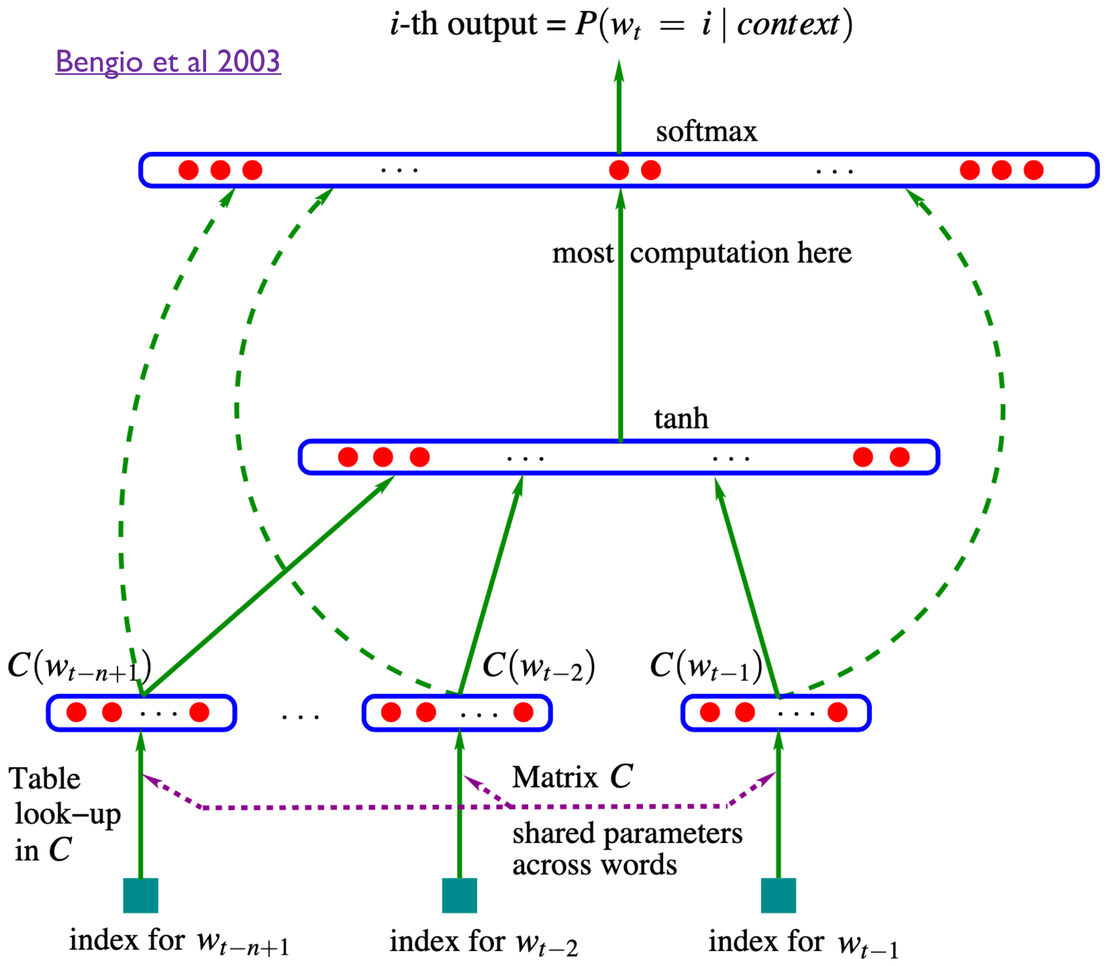
Pros of Neural LM

- Number of parameters:
  - Significantly lower, thanks to “low”-dimensional embeddings
- Generalization: embeddings enable generalizing to similar words

	The cat is walking in the bedroom
to	A dog was running in a room
and likewise to	The cat is running in a room
	A dog is walking in a bedroom
	The dog was walking in the room

Neural LM Architecture

Bengio et al 2003



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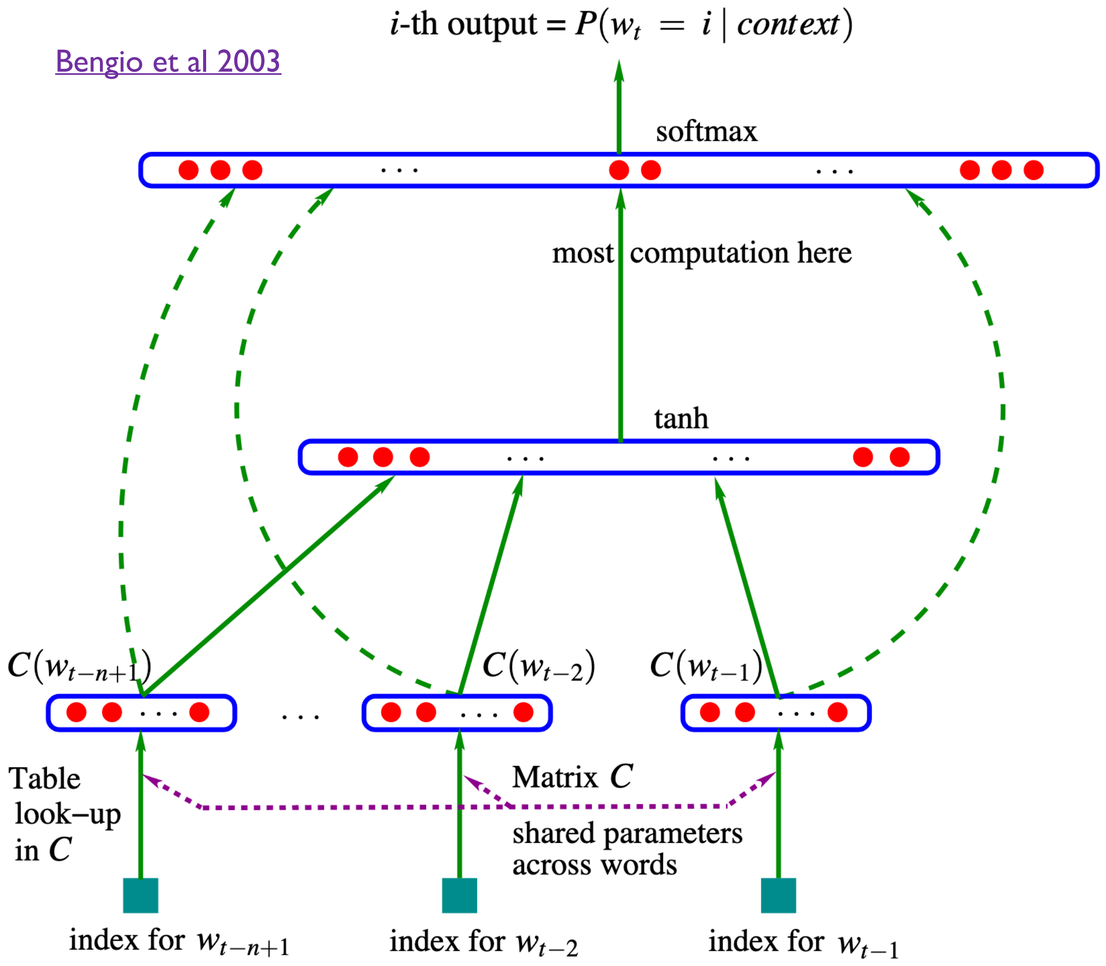

w_t: one-hot vector

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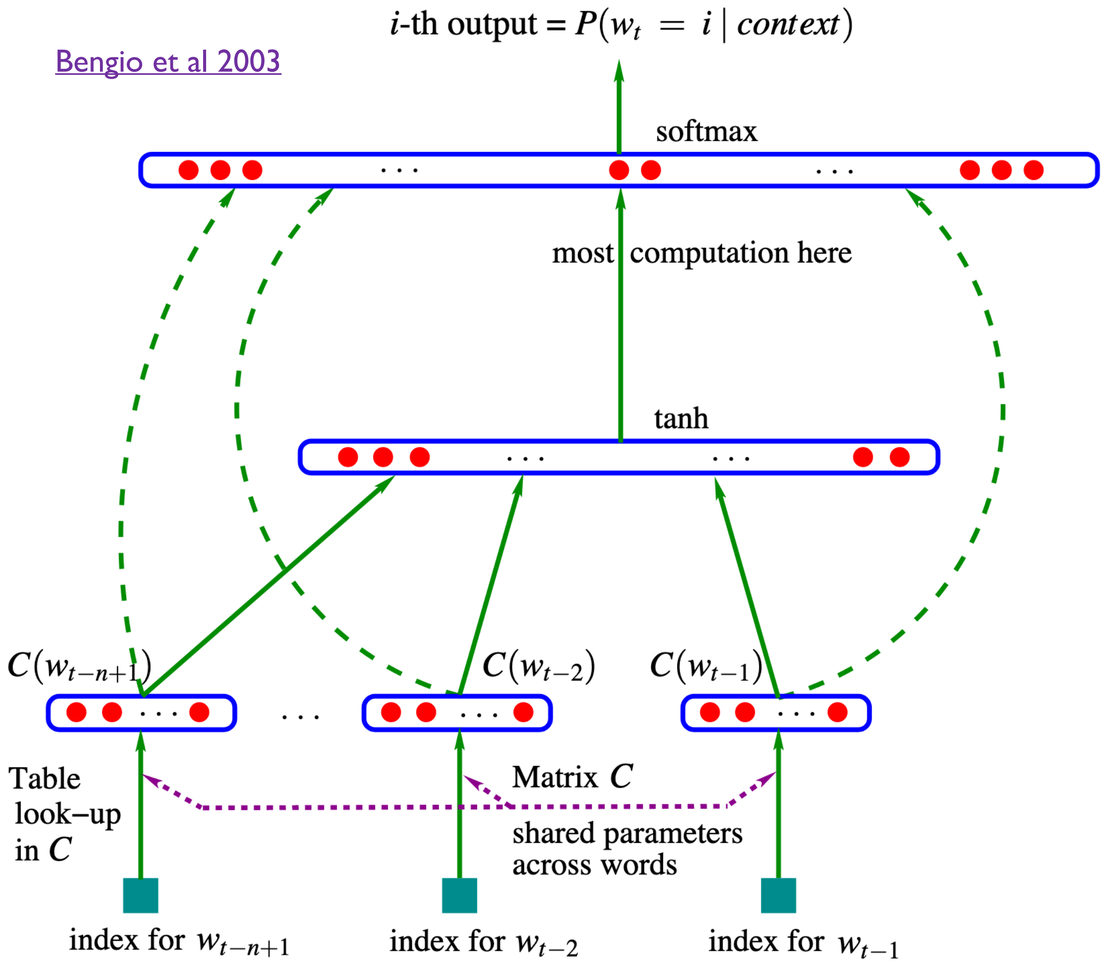

embeddings = concat($w_{t-1}C, w_{t-2}C, \ldots, w_{t-(n+1)}C$)

w_t: one-hot vector

Neural LM Architecture

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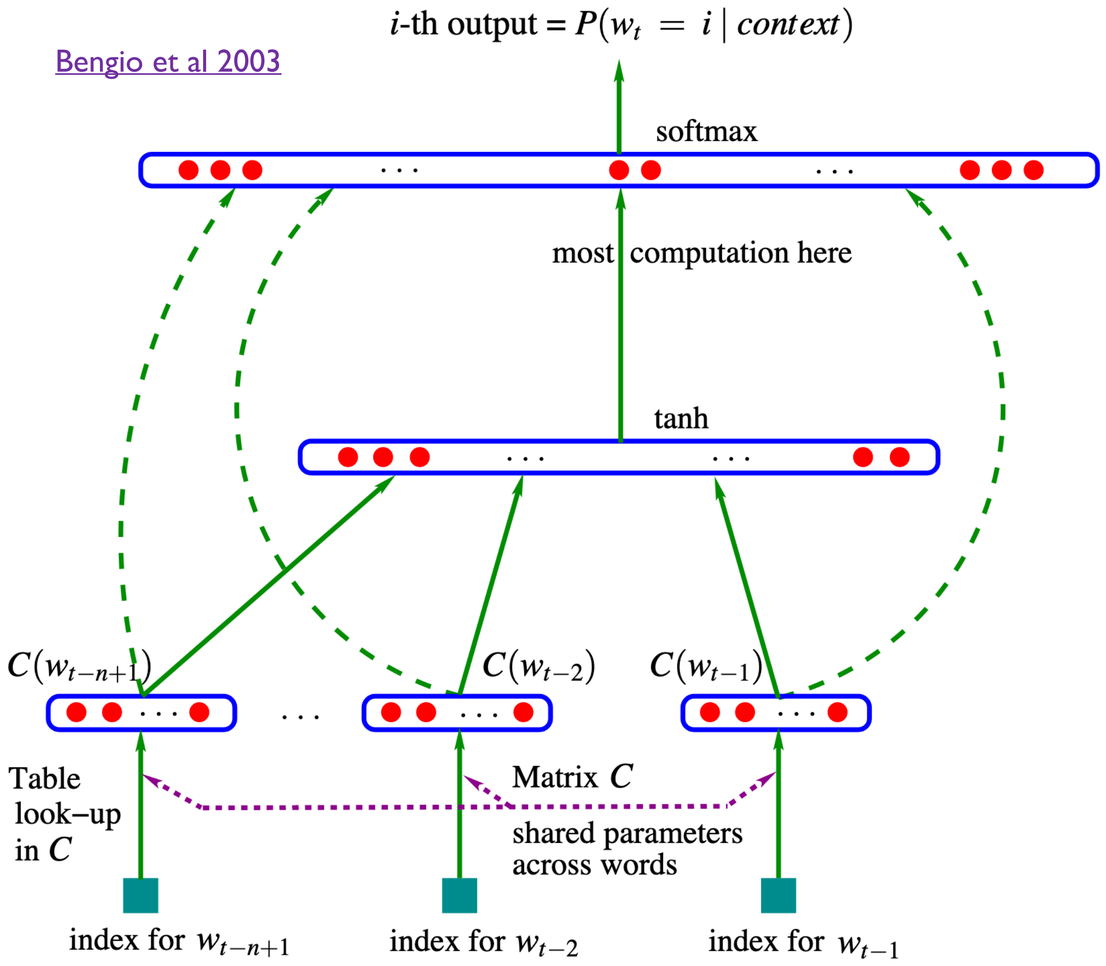

hidden $= \tanh(\text{embeddings} W^1 + b^1)$

embeddings $= \text{concat}(w_{t-1}C, w_{t-2}C, \ldots, w_{t-(n+1)}C)$

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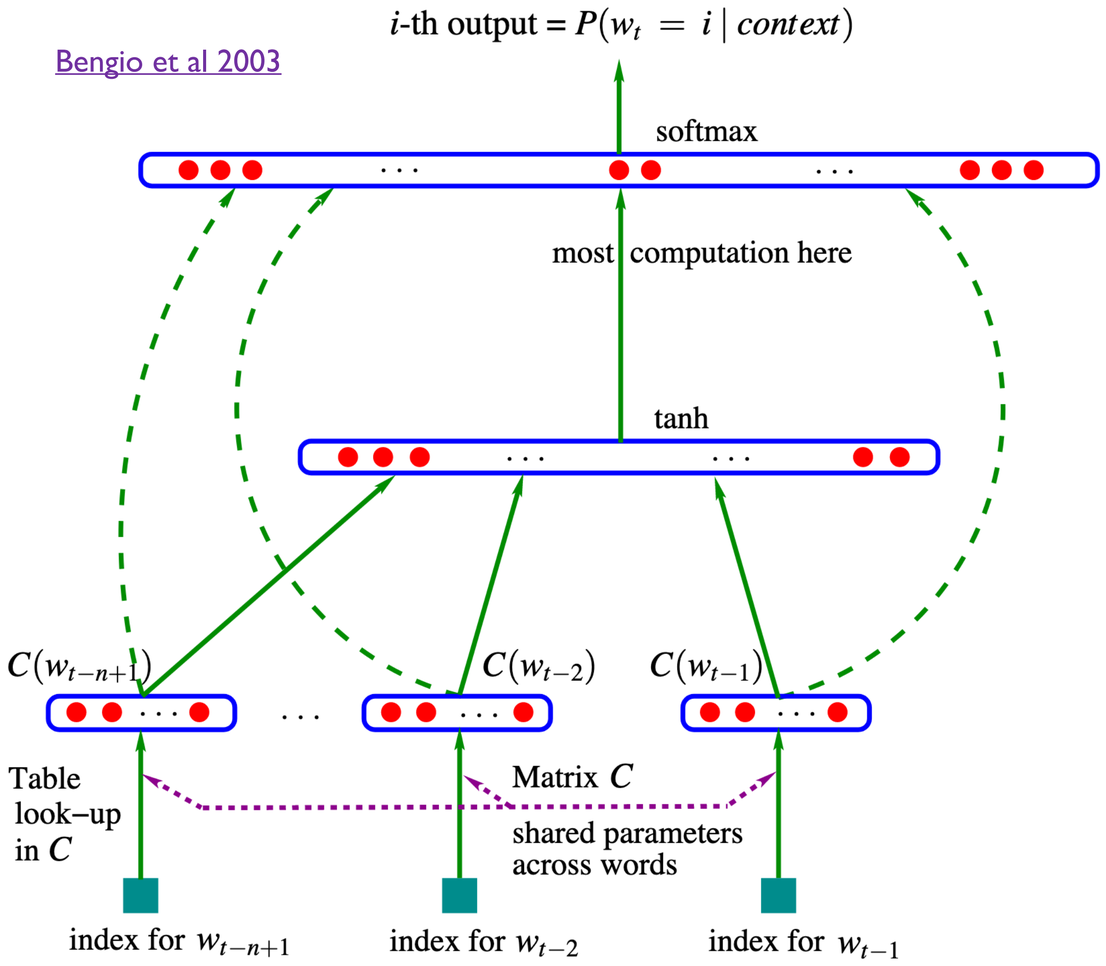

probabilities = softmax(hidden$W^2 + b^2$)

hidden = tanh(embeddings$W^1 + b^1$)

embeddings = concat($w_{t-1}C, w_{t-2}C, \ldots, w_{t-(n+1)}C$)

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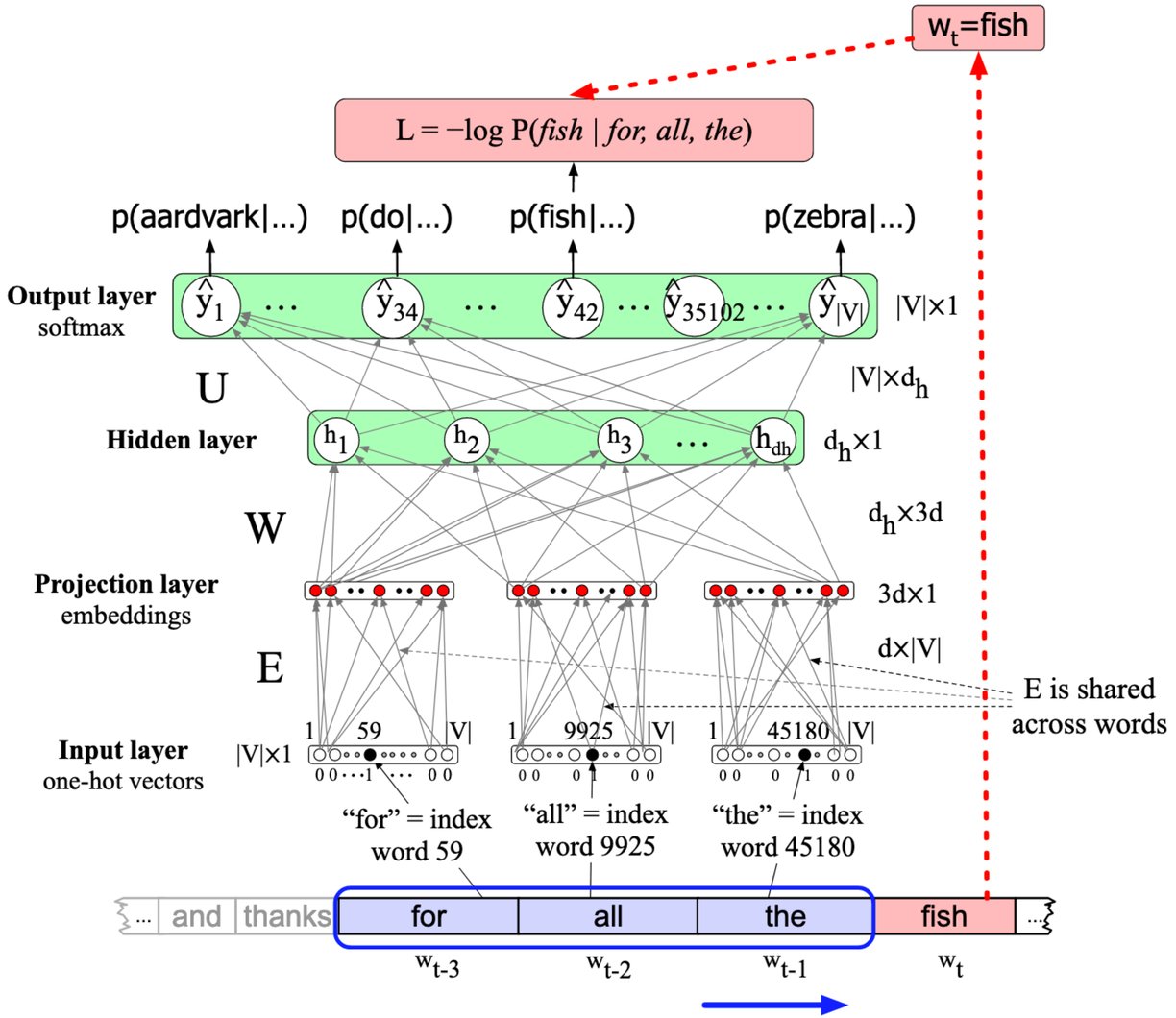
More Detailed Diagram of Architecture



JM sec 7.5

Output and Loss

- Softmax + cross-entropy
  - Essentially, language modeling is |V|-way classification
  - Each word in the vocabulary is a class

Evaluation of LMs

- Extrinsic: use in other NLP systems
- Intrinsic: intuitively, want probability of a test corpus
- Perplexity: inverse probability, weighted by size of corpus
  - NB: lower is better!
  - Only comparable w/ same vocab

$$PP(W) = P(w_1 w_2 \cdots w_n)^{-1/N}$$

$$= \sqrt[N]{\frac{1}{P(w_1 w_2 \cdots w_n)}}$$

$$= \sqrt[N]{\frac{1}{\prod_{i=0}^{|W|} P(w_i \mid w_1, \ldots, w_{i-1})}}$$

$$= 2^{-\frac{1}{N}\sum_{i=0}^{|W|} \log P(w_i | w_1, \ldots, w_{i-1})}$$

Results

	n	c	h	m	direct	mix	train.	valid.	test.
MLP1	5		50	60	yes	no	182	284	268
MLP2	5		50	60	yes	yes		275	257
MLP3	5		0	60	yes	no	201	327	310
MLP4	5		0	60	yes	yes		286	272
MLP5	5		50	30	yes	no	209	296	279
MLP6	5		50	30	yes	yes		273	259
MLP7	3		50	30	yes	no	210	309	293
MLP8	3		50	30	yes	yes		284	270
MLP9	5		100	30	no	no	175	280	276
MLP10	5		100	30	no	yes		265	**252**
Del. Int.	3						31	352	336
Kneser-Ney back-off	3							334	323
Kneser-Ney back-off	4							332	321
Kneser-Ney back-off	5							332	321
class-based back-off	3	150						348	334
class-based back-off	3	200						354	340
class-based back-off	3	500						326	**312**
class-based back-off	3	1000						335	319
class-based back-off	3	2000						343	326
class-based back-off	4	500						327	312
class-based back-off	5	500						327	312

More Complete Picture of This Model

Revisiting Simple Neural Probabilistic Language Models

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University of Massachusetts Amherst
{simengsun, miyyer}@cs.umass.edu

Abstract

Recent progress in language modeling has been driven not only by advances in neural architectures, but also through hardware and optimization improvements. In this paper, we revisit the neural probabilistic language model (NPLM) of Bengio et al. (2003), which simply concatenates word embeddings within a fixed window and passes the result through a feed-forward network to predict the next word. When scaled up to modern hardware, this model (despite its many limitations) performs

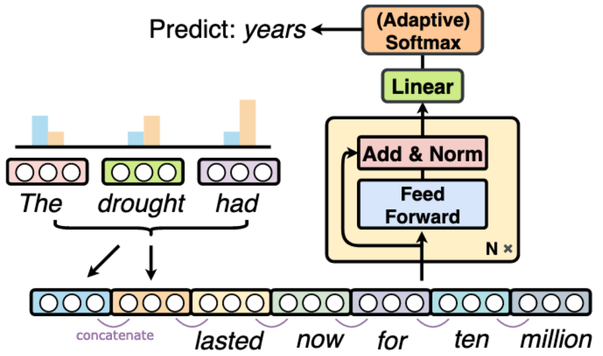


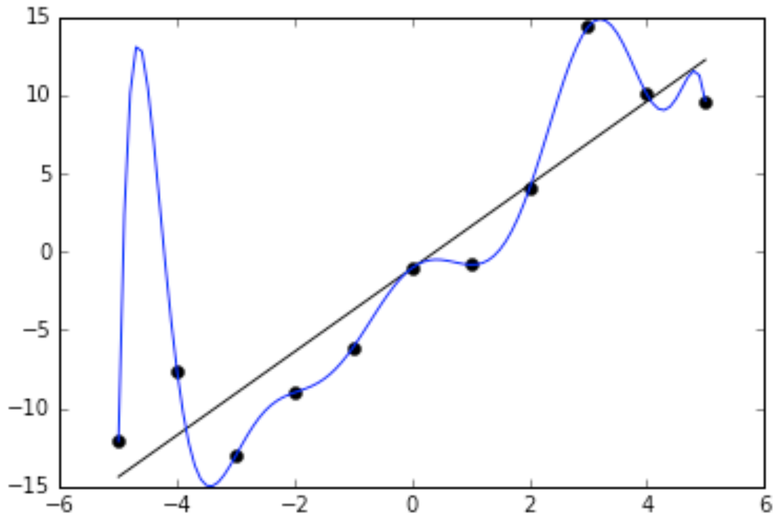
Figure 1: A modernized version of the neural probabilistic language model of Bengio et al. (2003), which

source (NAACL '21)

Additional Training Notes: Regularization and Hyper-Parameters

Overfitting

- Over-fitting: model too closely mimics the training data
  - Therefore, cannot *generalize* well
- Common when models are “over-parameterized”
  - E.g. fitting a high-degree polynomial
- Key questions:
  - How to detect overfitting?
  - How to prevent it?



Train, Dev, Test Set Splits

- Split total data into three chunks: train, dev (aka valid), test
  - Common: 70/15/15, 80/10/10%
- Train: used for individual model training, as we've seen so far
- Dev/valid:
  - Evaluation during training
  - Hyper-parameter tuning
  - Model selection
- Test:
  - Final evaluation; DO NOT TOUCH otherwise

Early stopping

source

Early stopping

- One: Pick # of epochs, hope for no overfitting

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- Better: pick max # of epochs, and “patience”
  - Halt when validation error does not improve over patience-many epochs

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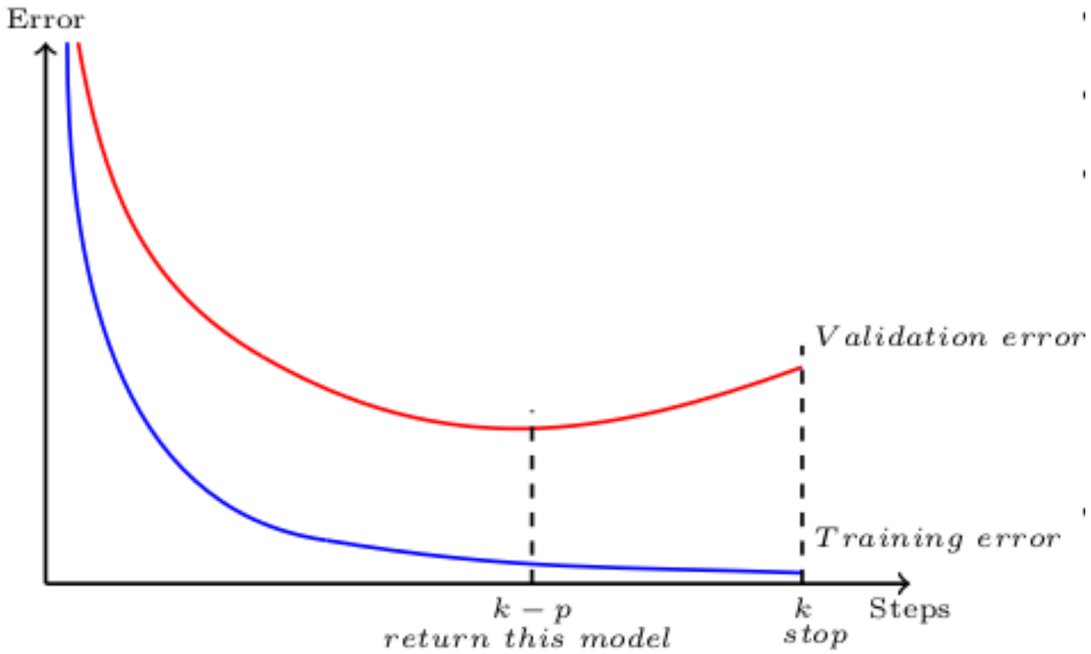

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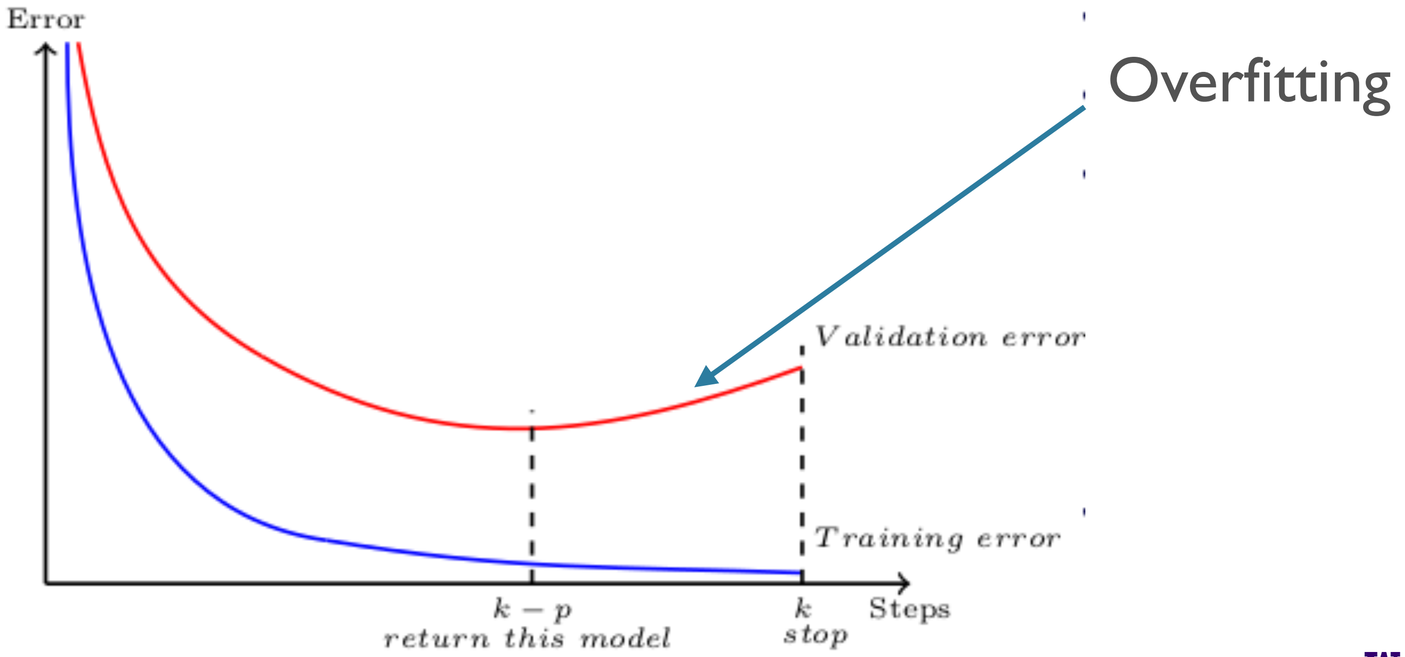

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Regularization

- NNs are often *overparameterized*, so regularization helps
- L1/L2: $\mathscr{L}'(\theta, y) = \mathscr{L}(\theta, y) + \lambda \|\theta\|^2$
- Dropout:
  - *During training*, randomly turn off X% of neurons in each layer
  - (Don't do this during testing/predicting)
- Batch Normalization / Layer Norm
- NB: batch size 🤯

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1\ldots m}\}$;
Parameters to be learned: γ, β
Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma^2_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma^2_{\mathcal{B}} + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Hyper-parameters

- In addition to the model architecture ones mentioned earlier
- Optimizer: SGD, Adam, Adagrad, RMSProp, ….
  - Optimizer-specific hyper-parameters: learning rate, alpha, beta, …
  - NB: backprop computes gradients; optimizer uses them to update parameters
- Regularization: L1/L2, Dropout, BN, …
  - regularizer-specific ones: e.g. dropout rate
- Batch size
- Number of epochs to train for
  - Early stopping criterion (e.g. number of epochs, “patience”)

A note on hyper-parameter tuning

- Grid search: specify range of values for each hyper-parameter, try all possible combinations thereof
- Random search: specify possible values for all parameters, randomly sample values for each, stop when some criterion is met

Bergstra and Bengio 2012

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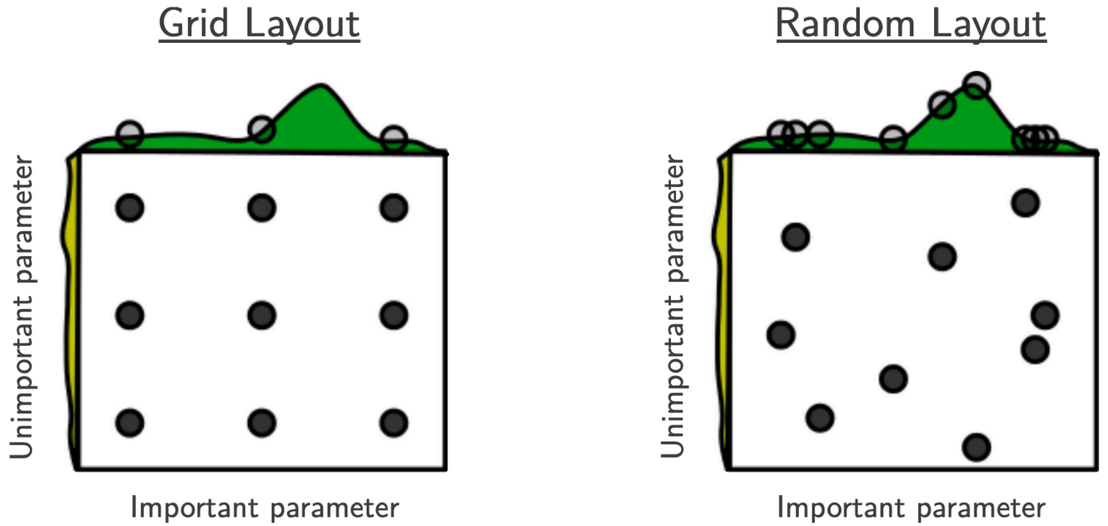
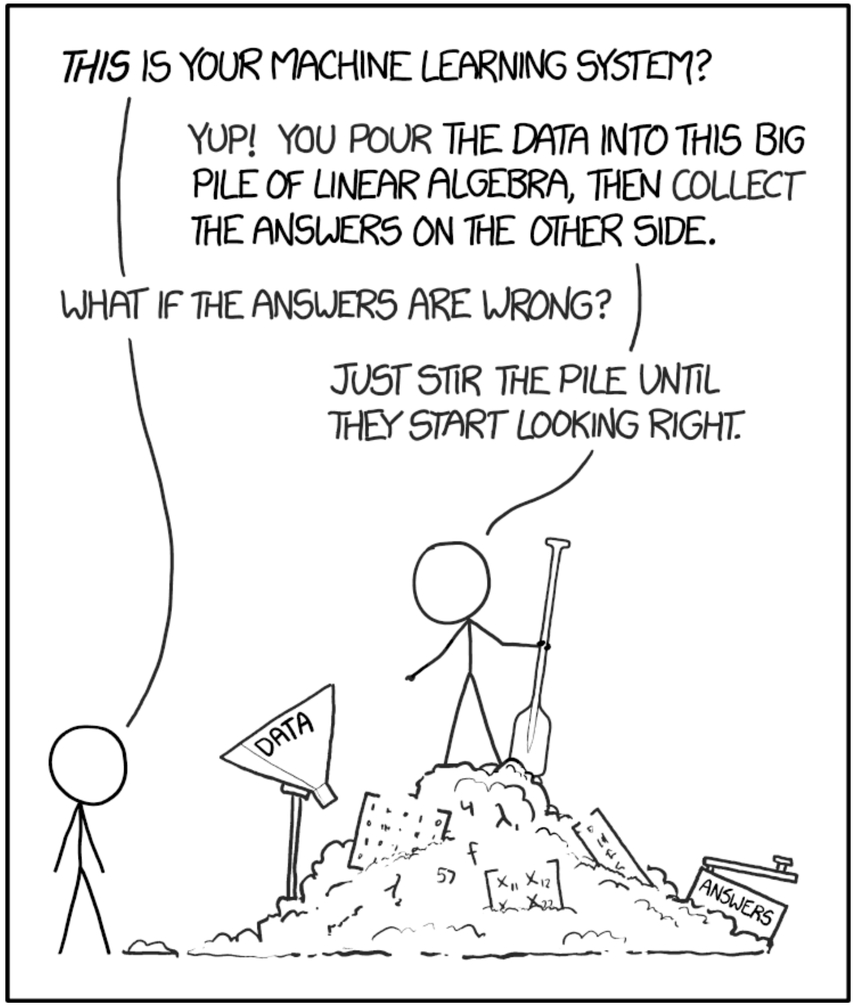


Bergstra and Bengio 2012

Craft/Art of Deep Learning



https://xkcd.com/1838/

Some Practical Pointers

- Hyper-parameter tuning and the like are not the focus of this course
- For some helpful hand-on advice about training NNs from scratch, debugging under “silent failures”, etc:
  - http://karpathy.github.io/2019/04/25/recipe/

Hyper-parameter Tuning

h/t CM Downey

Homework 3

SGNS in Computation Graphs

- Learning goals:
  - Deepen understanding / familiarity with computation graphs
  - Develop understanding of back propagation
  - Implement several operations in forward/backward API
- Main objective:
  - Implementing Skip-gram with Negative Sampling in edugrad, a minimal / bare-bones implementation of the PyTorch API
  - Components: sigmoid, log, element-wise multiplication, dot products

Edugrad

Edugrad, intro

- https://github.com/shanest/edugrad
- Minimal re-implementation of PyTorch API, for educational purposes
  - Forward/backward API for operations
    - Automatic differentiation via backprop
  - Dynamic computation graph
- Why? Modern DL libraries have so much additional cruft that you cannot chase back lots of method calls to their implementations.
  - E.g. what *really* happens when you call `loss.backward()`?
- NB: no performance optimizations, no GPU usage, etc. in edugrad

Edugrad: Tensor

- Tensor: wrapper around a numpy array (stored in .value attribute)
  - value: np array
  - grad: current gradient! (Set to 0 initially, populated during back propagation)
- Primary operators overloaded: +, -, ** (raise to a power)
  - More on implementation of those in a second

```
>>> import numpy as np
>>> from edugrad.tensor import Tensor
>>> t1 = Tensor(np.array([[1, 2], [3, 4]]))
>>> t2 = Tensor(np.array([[1, 2], [3, 4]]))
>>> t1 + t2
<edugrad.tensor.Tensor object at 0x7f97a81d5940>
>>> (t1 + t2).value
array([[2, 4],
       [6, 8]])
```

Edugrad: Operation

- Operation: defines forward/backward
  - Operates on np arrays, *not* Tensors
- @tensor_op:
  - Takes an Operation, turns it into a method that takes Tensor arguments and returns Tensor outputs
    - And which *builds the computation graph*
  - @: decorator; add = tensor_op(add)
- Basic ops provided:
  - https://github.com/shanest/edugrad/blob/master/edugrad/ops.py

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```
@tensor_op
class add(Operation):
    @staticmethod
    def forward(ctx, a, b):
        return a + b

    @staticmethod
    def backward(ctx, grad_output):
        return grad_output, grad_output
```

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```
>>> from edugrad.ops import add
>>> add(t1, t2).value
array([[2, 4],
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```
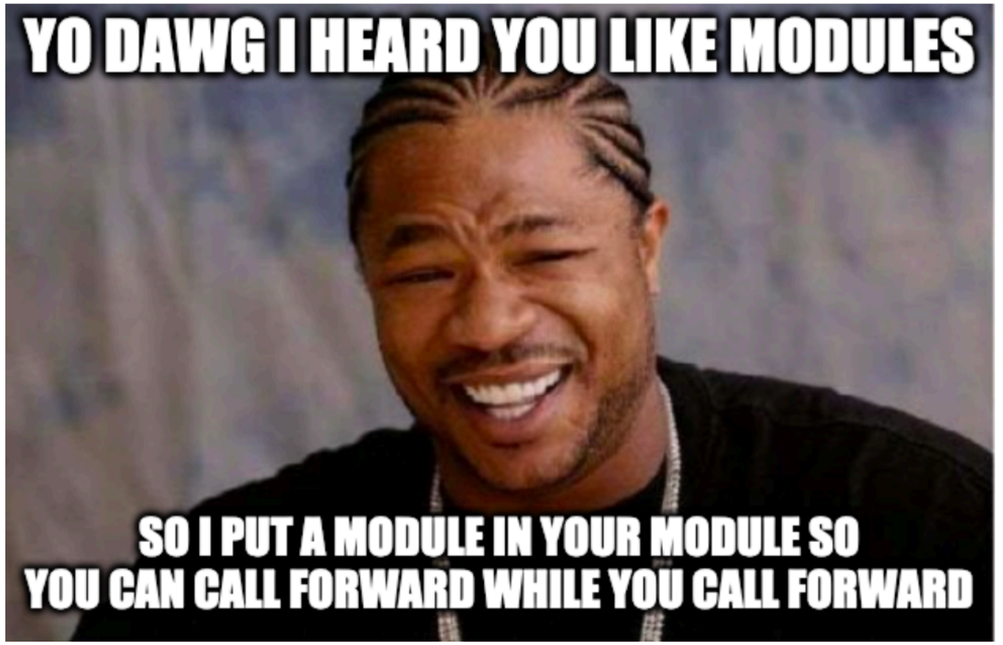

Edugrad: nn.Module

- edugrad.nn.Module:
  - As in PyTorch, basic model class
  - Stores parameters [accessed via .parameters()]
  - Can be nested (modules within modules)
  - Implements `forward`
- Defining a custom module:
  - Sub-class nn.Module
  - Initialize params in __init__
  - Implement custom forward method



Edugrad: Linear Module example

```python
class Linear(Module):
    def __init__(
        self,
        input_size: int,
        output_size: int,
        bias: bool = True,
    ):
        """A Linear module computes defines weights W, optionally biases b, and
        computers wX + b.

        Weight vector will have shape (input size, output size)

        Args:
            input_size: dimension of input vectors
            output_size: dimension of output vectors
            initializer: how to initialize weights and biases
            bias: whether or not to include the bias term; not needed for, e.g. embeddings
        """
        super(Linear, self).__init__()
        scale = 1 / np.sqrt(input_size)
        self.weight = Tensor(uniform_initializer((input_size, output_size), scale=scale), name="W")
        self.has_bias = bias
        if self.has_bias:
            # biases initialize to 0
            self.bias = Tensor(uniform_initializer((output_size,), scale=scale), name="b")
```

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Always do this first!!

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Define parameters

Edugrad: Linear Module

```
def forward(self, inputs: Tensor):
    mul_node = ops.matmul(inputs, self.weight)
    if self.has_bias:
        # NOTE: this is a hack-ish way of handling shape issues with biases
        expanded_biases = ops.copy_rows(self.bias, num=inputs.value.shape[0])
        return ops.add(mul_node, expanded_biases)
    return mul_node
```

Edugrad: Basic Training Demo

- https://github.com/shanest/edugrad/blob/master/examples/toy_half_sum/main.py
  - Trains an MLP on f(x) = sum(x)/2 for bit vectors x
- MLP as a nn.Module:
- NB: don't hard-code hyper-parameters like this :)

```
class MLP(nn.Module):
    def __init__(self, input_size, output_size):
        super(MLP, self).__init__()
        self.fc1 = nn.Linear(input_size, 32)
        self.fc2 = nn.Linear(32, 32)
        self.output = nn.Linear(32, output_size)

    def forward(self, inputs):
        hidden = edugrad.ops.relu(self.fc1(inputs))
        hidden = edugrad.ops.relu(self.fc2(hidden))
        return self.output(hidden)
```

Training Loop

```
model = MLP(input_size, 1)
optimizer = edugrad.optim.SGD(model.parameters(), lr=1e-3)
train_iterator = edugrad.data.BatchIterator(batch_size=batch_size)

for epoch in range(num_epochs):
    total_loss = 0.0
    for batch in train_iterator(inputs, targets):
        predicted = model(batch.inputs)
        loss = edugrad.ops.mse_loss(predicted, batch.targets)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        total_loss += loss.value
    print(f"Epoch {epoch} loss: {total_loss / train_iterator.num_batches}")
```