10-418/10-618 Machine Learning for Structured Data

Machine Learning Department
School of Computer Science
Carnegie Mellon University

1D CNNs

+

Sequence-to-sequence (seq2seq) Models

Matt Gormley
Lecture 3
Sep. 7, 2022

Reminders

- **Homework 1: Neural Networks for Sequence Tagging**
  - **Out: Wed, Sep 7** (later today!)
  - **Due: Fri, Sep 16 at 11:59pm**
  - Two parts:
    1. written part to Gradescope (Written slot)
    2. programming part to Gradescope (Programming slot)

Q&A

Q&A

Q: Can you show us a module-based AD example in PyTorch?

A: Sure thing! (next slide)

PyTorch

The same simple neural network we defined in pseudocode can also be defined in PyTorch.

```python
# Define model
class NeuralNetwork(nn.Module):
    def __init__(self):
        super(NeuralNetwork, self).__init__()
        self.flatten = nn.Flatten()
        self.linear1 = nn.Linear(28*28, 512)
        self.sigmoid = nn.Sigmoid()
        self.linear2 = nn.Linear(512,512)

    def forward(self, x):
        x = self.flatten(x)
        a = self.linear1(x)
        z = self.sigmoid(a)
        b = self.linear2(z)
        return b

# Take one step of SGD
def one_step_of_sgd(X, y):
    loss_fn = nn.CrossEntropyLoss()
    optimizer = torch.optim.SGD(model.parameters(), lr=1e-3)

    # Compute prediction error
    pred = model(X)
    loss = loss_fn(pred, y)

    # Backpropagation
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

Example adapted from https://pytorch.org/tutorials/beginner/basics/quickstart_tutorial.html

Q&A

Q: Can you show us a module-based AD example in PyTorch?

A: Sure thing! (next slide)

Q: That's pretty clean. Can you show us some more examples of PyTorch?

A: Sure thing! Come to recitation on Friday.

1D CONVOLUTION

1D Convolutional Neural Network

- Popularized for NLP by Collobert & Weston (2008)
- Two modules
  - **Embedding module:** each word type is mapped to a vector of parameters
  - **Convolution module:** each window of k embedding vectors is concatenated and then multiplied by a parameter matrix, to produce one vector per word token

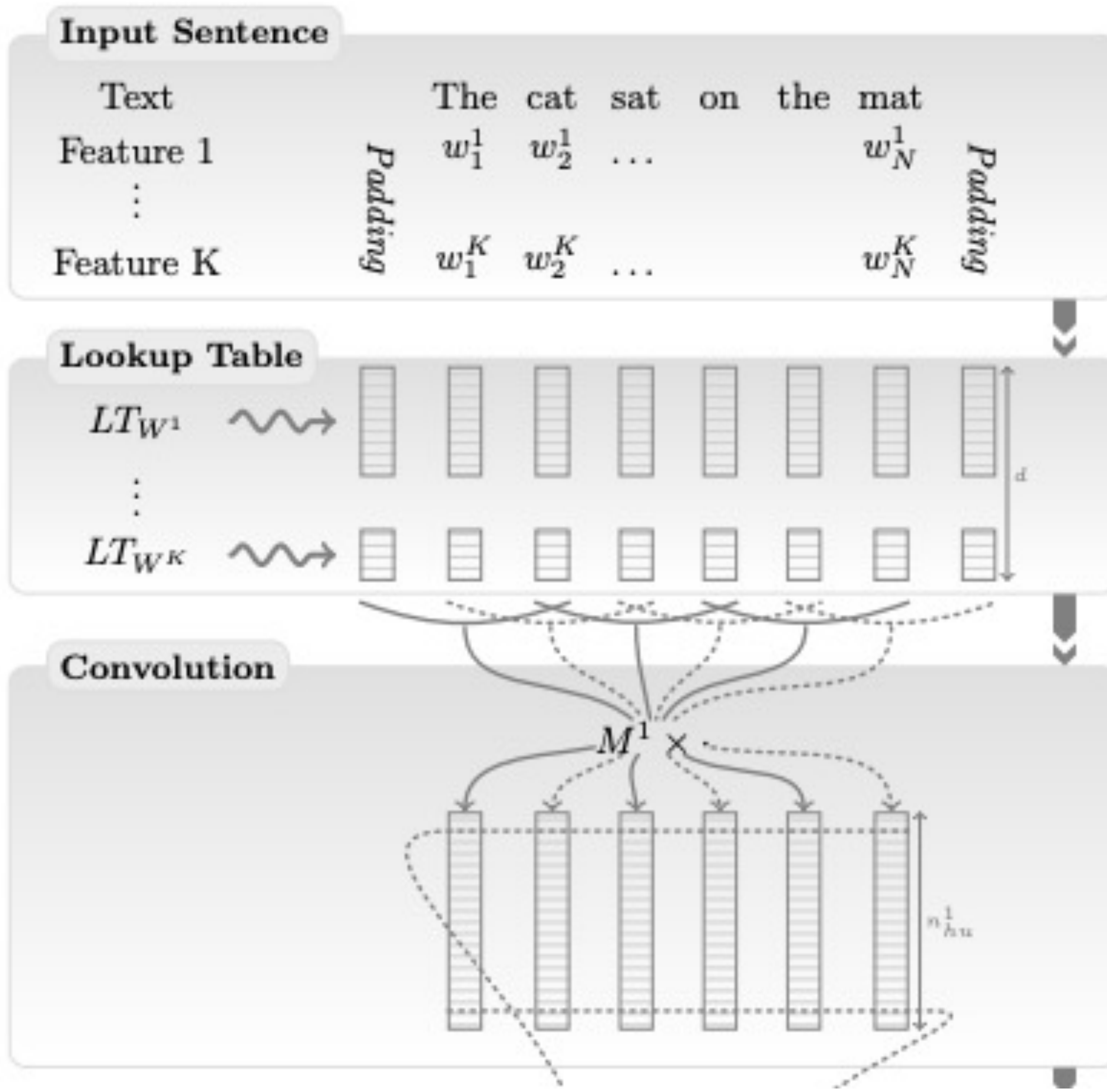
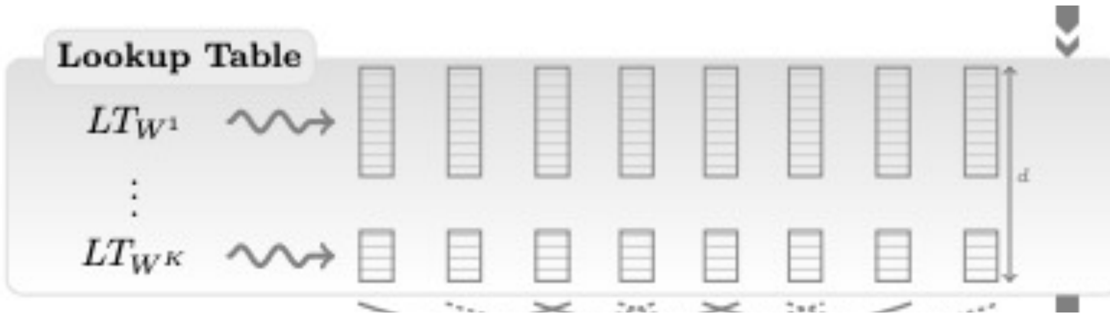


Figure from https://jmlr.org/papers/volume12/collobert11a/collobert11a.pdf

1D Convolutional Neural Network



Embedding Module

More formally, for each word $w \in \mathcal{D}$, an internal d_{wrd}-dimensional feature vector representation is given by the *lookup table* layer $LT_W(\cdot)$:

$$LT_W(w) = \langle W \rangle_w^1 \,,$$

where $W \in \mathbb{R}^{d_{wrd} \times |\mathcal{D}|}$ is a matrix of parameters to be learned, $\langle W \rangle_w^1 \in \mathbb{R}^{d_{wrd}}$ is the w^{th} column of W and d_{wrd} is the word vector size (a hyper-parameter to be chosen by the user). Given a sentence or any sequence of T words $[w]_1^T$ in $\mathcal{D}$, the lookup table layer applies the same operation for each word in the sequence, producing the following output matrix:

$$LT_W([w]_1^T) = \begin{pmatrix} \langle W \rangle_{[w]_1}^1 & \langle W \rangle_{[w]_2}^1 & \ldots & \langle W \rangle_{[w]_T}^1 \end{pmatrix} . \qquad (1)$$

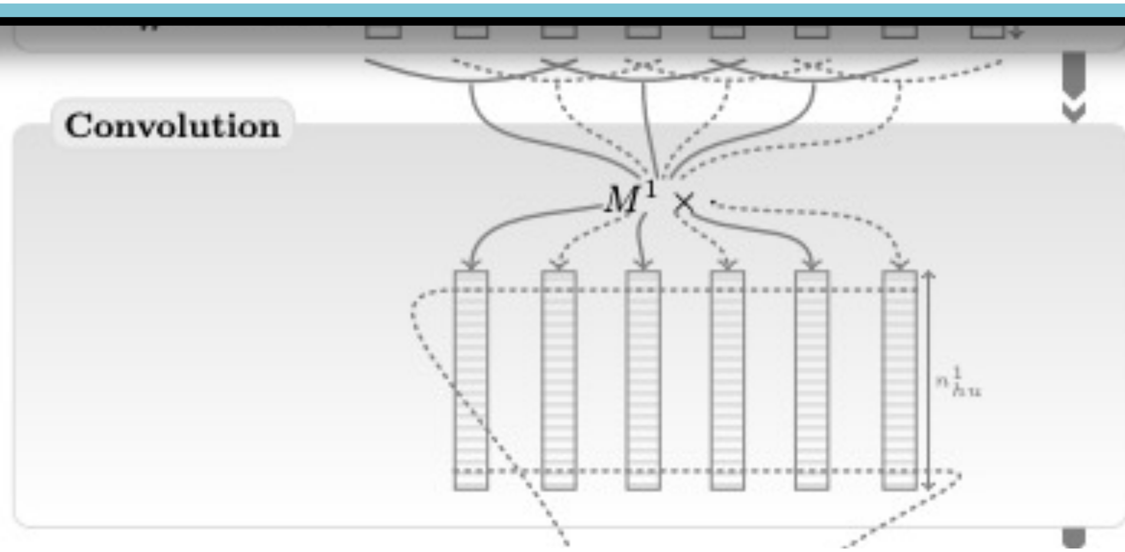
This matrix can then be fed to further neural network layers, as we will see below.

1D Convolutional Neural Network

1D Convolution Module

A window approach assumes the tag of a word depends mainly on its neighboring words. Given a word to tag, we consider a fixed size k_{sz} (a hyper-parameter) window of words around this word. Each word in the window is first passed through the lookup table layer (1) or (2), producing a matrix of word features of fixed size $d_{wrd} \times k_{sz}$. This matrix can be viewed as a $d_{wrd}\, k_{sz}$-dimensional vector by concatenating each column vector, which can be fed to further neural network layers. More formally, the word feature window given by the first network layer can be written as:

$$f_\theta^1 = \langle LT_W([w]_1^T) \rangle_t^{d_{win}} = \begin{pmatrix} \langle W \rangle^1_{[w]_{t-d_{win}/2}} \\ \vdots \\ \langle W \rangle^1_{[w]_t} \\ \vdots \\ \langle W \rangle^1_{[w]_{t+d_{win}/2}} \end{pmatrix} . \quad (3)$$



1D Convolutional Neural Network

1D Convolution Module

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Linear Layer. The fixed size vector f_θ^1 can be fed to one or several standard neural network layers which perform affine transformations over their inputs:

$$f_\theta^l = W^l\, f_\theta^{l-1} + b^l\,, \tag{4}$$

where $W^l \in \mathbb{R}^{n_{hu}^l \times n_{hu}^{l-1}}$ and $b^l \in \mathbb{R}^{n_{hu}^l}$ are the parameters to be *trained*. The hyper-parameter n_{hu}^l is usually called the *number of hidden units* of the l^{th} layer.

1D Convolutional Neural Network

1D Convolution Module

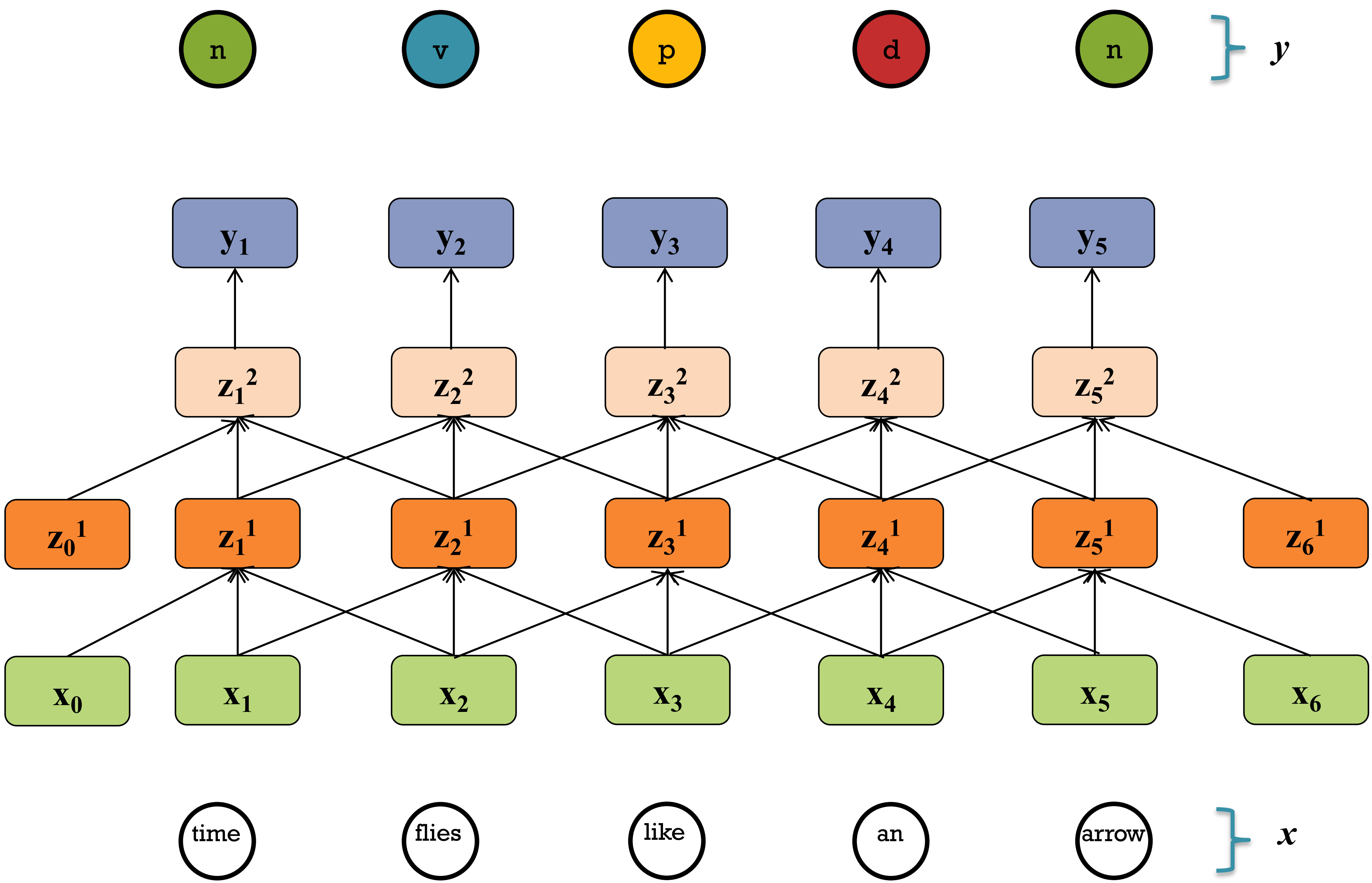
Convolutional Layer. A convolutional layer can be seen as a generalization of a window approach: given a sequence represented by columns in a matrix f_θ^{l-1} (in our lookup table matrix (1)), a matrix-vector operation as in (4) is applied to each window of successive windows in the sequence.

Using previous notations, the t^{th} output column of the l^{th} layer can be computed as:

$$\langle f_\theta^l \rangle_t^1 = W^l \, \langle f_\theta^{l-1} \rangle_t^{d_{win}} + b^l \quad \forall t\,, \tag{6}$$

where the weight matrix W^l is the same across all windows t in the sequence. Convolutional layers extract local features around each window of the given sequence. As for standard affine layers (4), convolutional layers are often stacked to extract higher level features. In this case, each layer must be followed by a non-linearity (5) or the network would be equivalent to one convolutional layer.

1D Convolutional Neural Network



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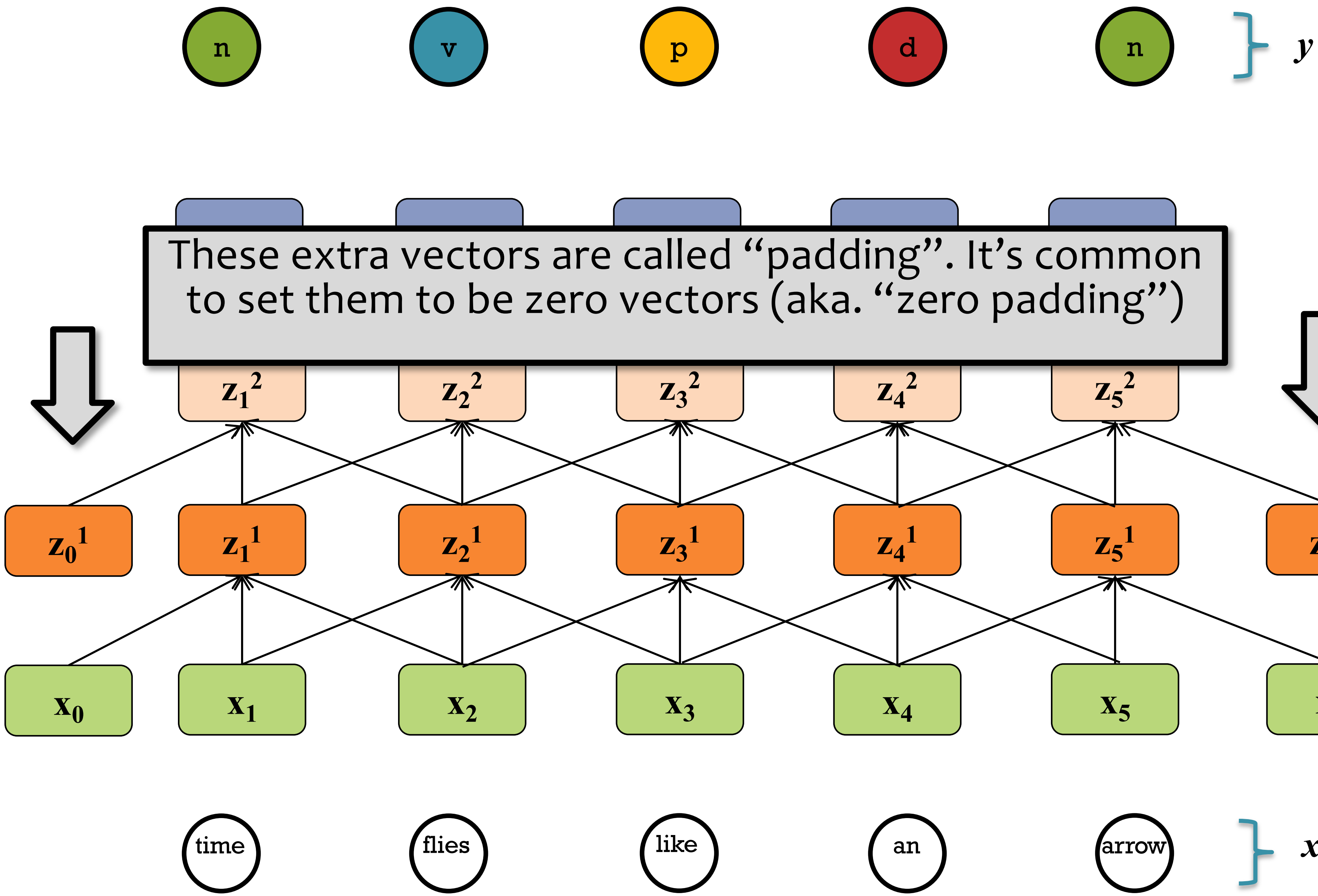

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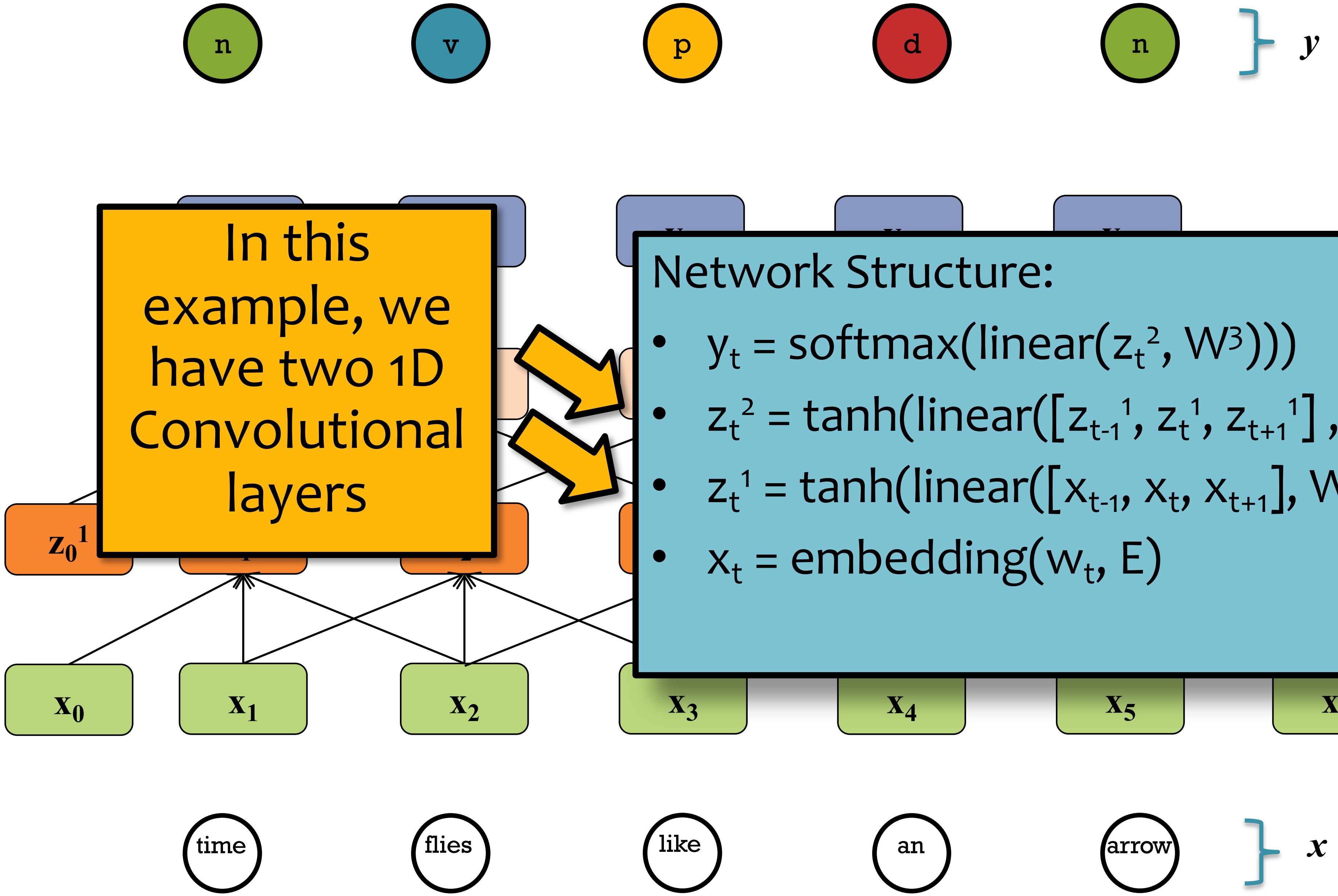


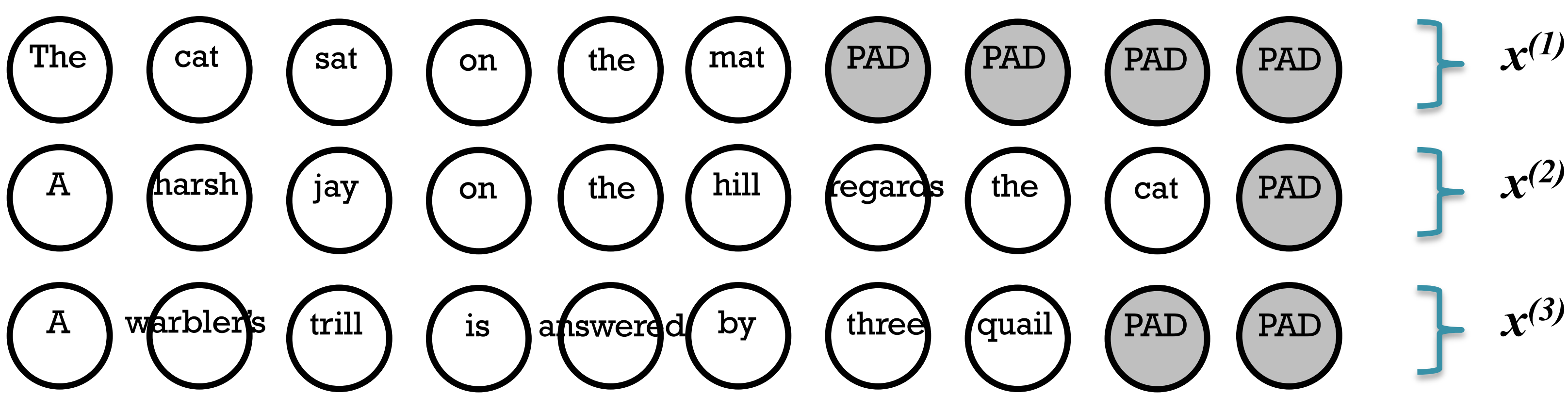
In this example, we have two 1D Convolutional layers

Network Structure:

- y_t = softmax(linear(z_t^2, W^3)))
- z_t^2 = tanh(linear([z_{t-1}^1, z_t^1, z_{t+1}^1] , W^2))
- z_t^1 = tanh(linear([x_{t-1}, x_t, x_{t+1}], W^1))
- x_t = embedding(w_t, E)

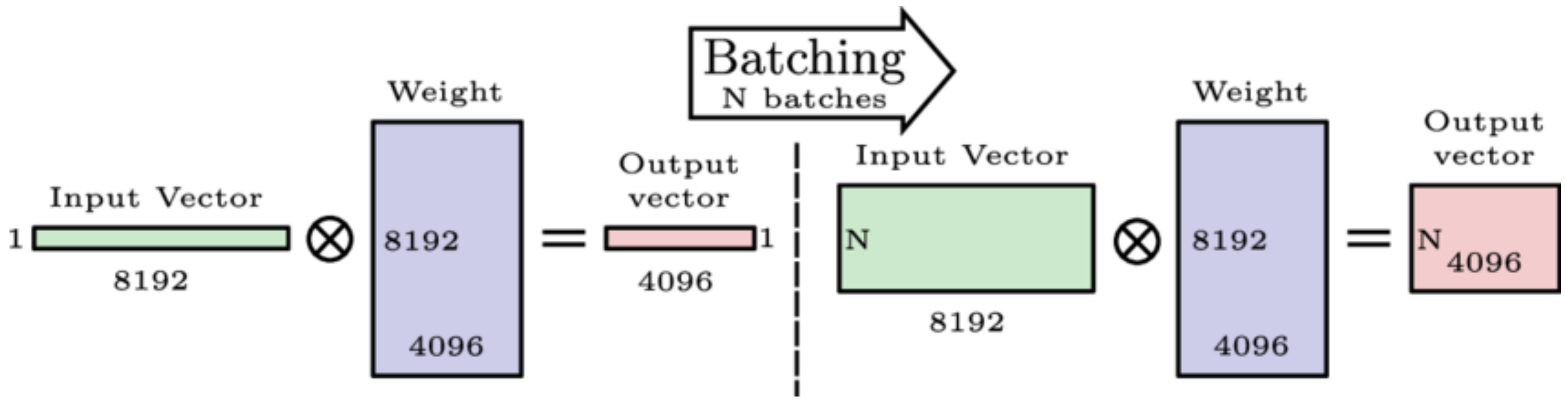
Efficiency Tricks

- Padding:
  - When working with sentences of different lengths, it's common to work with a fixed maximum length L
  - For a sentence of length T < L, we append (L – T) zero vectors after the sentence (i.e. pad the sentence)



Efficiency Tricks

- Batching:
  - The most computationally intensive modules involve matrix-vector arithmetic
  - These computations can be made more efficient by squashing a collection of input vectors together into an input matrix



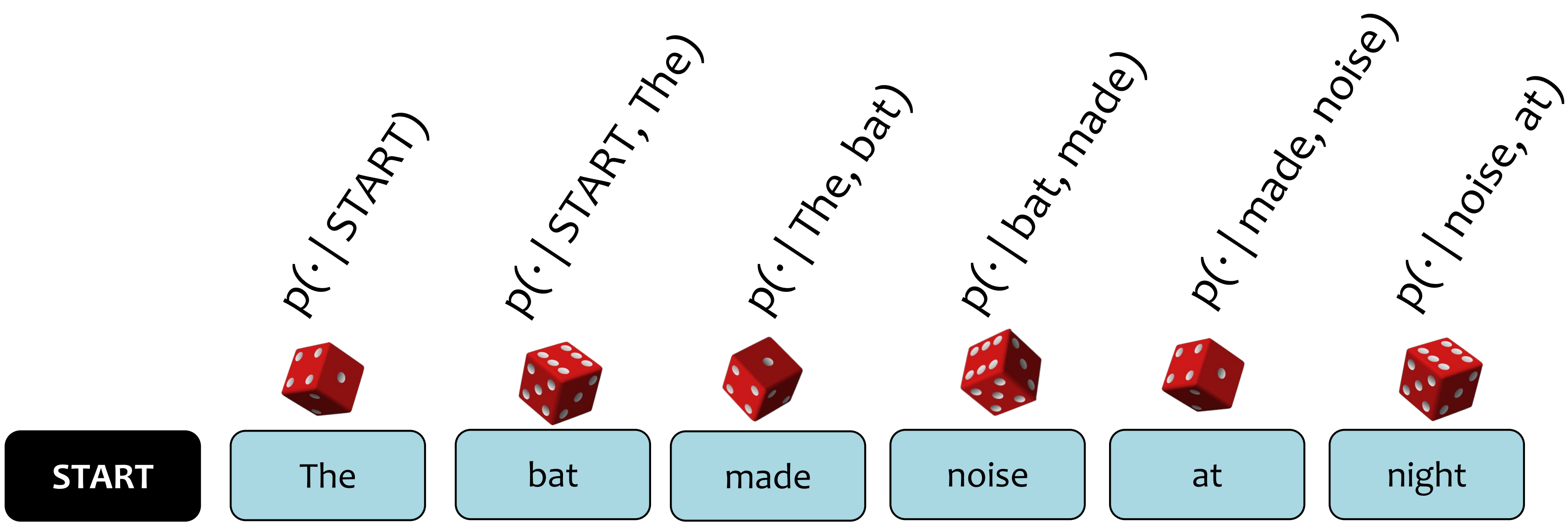
- Batching Sentences:
  - If our input are sentences, then we can group together a collection of sentences (all of length L, thanks to padding)
  - That group is called a "batch" and passed through each layer as a unit
  - Each layer in module-based AD can then be implemented to support this batched input efficiently

Figure from https://www.researchgate.net/publication/350991979_Learning_on_Hardware_A_Tutorial_on_Neural_Netw

BACKGROUND:
N-GRAM LANGUAGE MODELS

n-Gram Language Model

- *Goal*: Generate realistic looking sentences in a human language
- *Key Idea*: condition on the last n-1 words to sample the n^{th} word



n-Gram Language Model

<u>*Question*</u>: How can we **define** a probability distribution over a sequence of length T?

The	bat	made	noise	at	night
w_1	w_2	w_3	w_4	w_5	w_6

n-Gram Model (n=2)

$$p(w_1, w_2, \dots, w_T) = \prod_{t=1}^{T} p(w_t \mid w_{t-1})$$

$$p(w_1, w_2, w_3, \dots, w_6) =$$

The	$p(w_1)$
The bat	$p(w_2 \mid w_1)$
bat made	$p(w_3 \mid w_2)$
made noise	$p(w_4 \mid w_3)$
noise at	$p(w_5 \mid w_4)$
at night	$p(w_6 \mid w_5)$

n-Gram Language Model

<u>*Question*</u>: How can we **define** a probability distribution over a sequence of length T?

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n-Gram Model (n=3)

$$p(w_1, w_2, \ldots, w_T) = \prod_{t=1}^{T} p(w_t \mid w_{t-1}, w_{t-2})$$

$p(w_1, w_2, w_3, \ldots, w_6) =$

The	$p(w_1)$
The bat	$p(w_2 \mid w_1)$
The bat made	$p(w_3 \mid w_2, w_1)$
bat made noise	$p(w_4 \mid w_3, w_2)$
made noise at	$p(w_5 \mid w_4, w_3)$
noise at night	$p(w_6 \mid w_5, w_4)$

n-Gram Language Model

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$p(w_1, w_2, w_3, \ldots, w_6) =$

The $\quad p(w_1)$

The

The

Note: This is called a **model** because we made some **assumptions** about how many previous words to condition on (i.e. only n-1 words)

Learning an n-Gram Model

<u>*Question*</u>: How do we **learn** the probabilities for the n-Gram Model?

$p(w_t \mid w_{t-2} = \text{The}, w_{t-1} = \text{bat})$

w_t	$p(\cdot \mid \cdot, \cdot)$
ate	0.015
…	
flies	0.046
…	
zebra	0.000

$p(w_t \mid w_{t-2} = \text{made}, w_{t-1} = \text{noise})$

w_t	$p(\cdot \mid \cdot, \cdot)$
at	0.020
…	
pollution	0.030
…	
zebra	0.000

$p(w_t \mid w_{t-2} = \text{cows}, w_{t-1} = \text{eat})$

w_t	$p(\cdot \mid \cdot, \cdot)$
corn	0.420
…	
grass	0.510
…	
zebra	0.000

Learning an n-Gram Model

Question: How do we **learn** the probabilities for the n-Gram Model?

Answer: From data! Just **count** n-gram frequencies

… the **cows eat** **grass**…
… our **cows eat hay** daily…
… factory-farm **cows eat** **corn**…
… on an organic farm, **cows eat hay** and…
… do your **cows eat** **grass** or corn?...
… what do **cows eat if** they have…
… **cows eat** **corn** when there is no…
… which **cows eat which** foods depends…
… if **cows eat** **grass**…
… when **cows eat** **corn** their stomachs…
… should we let **cows eat** **corn**?...

$p(w_t \mid w_{t-2} = \text{cows}, w_{t-1} = \text{eat})$

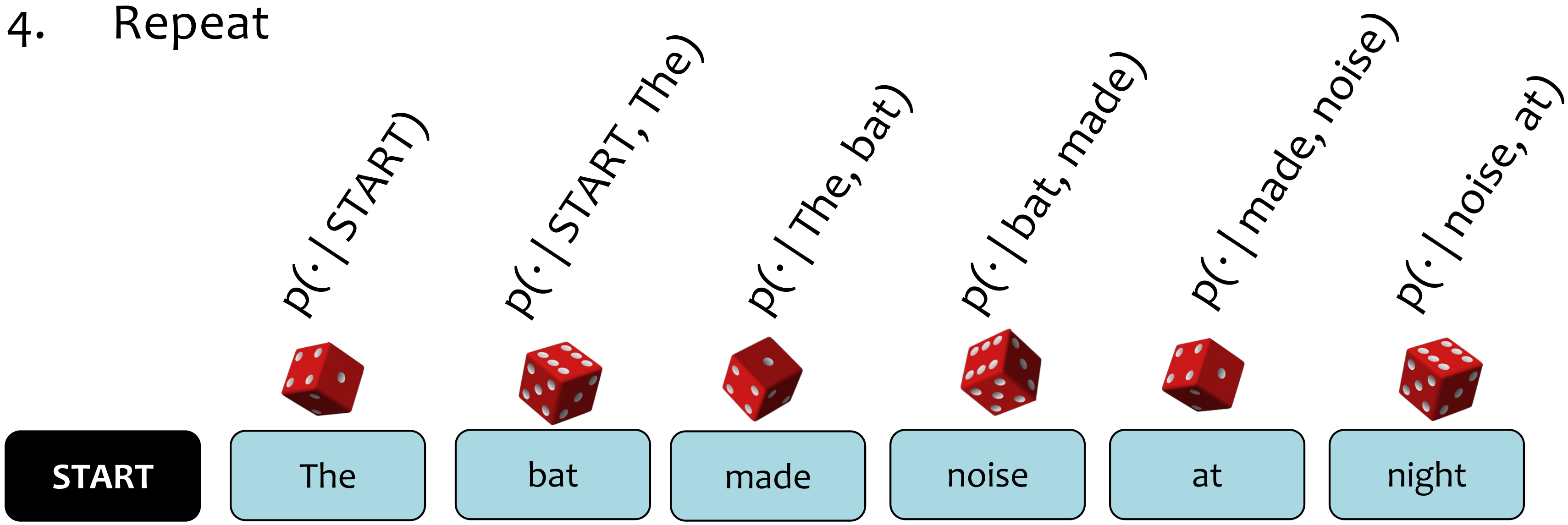
w_t	$p(\cdot \mid \cdot, \cdot)$
corn	4/11
grass	3/11
hay	2/11
if	1/11
which	1/11

Sampling from a Language Model

Question: How do we sample from a Language Model?

Answer:

1. Treat each probability distribution like a (50k-sided) weighted die
2. Pick the die corresponding to $p(w_t \mid w_{t-2}, w_{t-1})$
3. Roll that die and generate whichever word w_t lands face up
4. Repeat



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Training Data (Shakespeaere)	**5-Gram Model**
I tell you, friends, most charitable care ave the patricians of you. For your wants, Your suffering in this dearth, you may as well Strike at the heaven with your staves as lift them Against the Roman state, whose course will on The way it takes, cracking ten thousand curbs Of more strong link asunder than can ever Appear in your impediment. For the dearth, The gods, not the patricians, make it, and Your knees to them, not arms, must help.	`Approacheth, denay. dungy Thither! Julius think: grant,--O Yead linens, sheep's Ancient, Agreed: Petrarch plaguy Resolved pear! observingly honourest adulteries wherever scabbard guess; affirmation--his monsieur; died. jealousy, chequins me. Daphne building. weakness: sun-rise, cannot stays carry't, unpurposed. prophet-like drink; back-return 'gainst surmise Bridget ships? wane; interim? She's striving wet;`

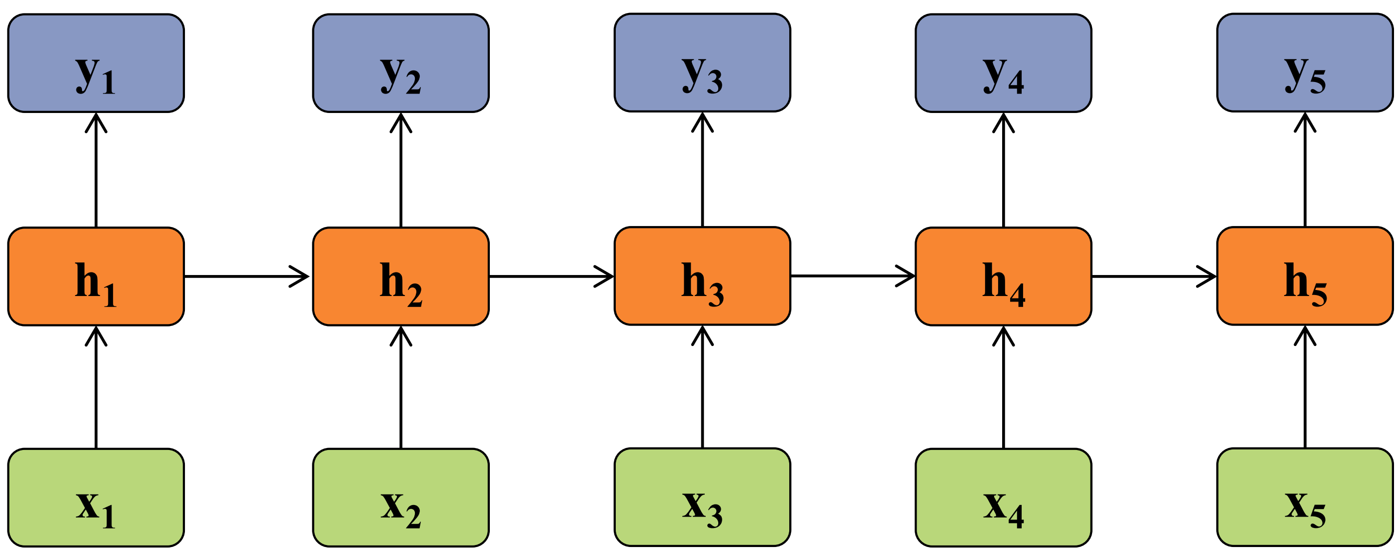
RECURRENT NEURAL NETWORK (RNN) LANGUAGE MODELS

Recurrent Neural Networks (RNNs)

$$\text{inputs: } \mathbf{x} = (x_1, x_2, \dots, x_T), x_i \in \mathcal{R}^I$$
$$\text{hidden units: } \mathbf{h} = (h_1, h_2, \dots, h_T), h_i \in \mathcal{R}^J$$
$$\text{outputs: } \mathbf{y} = (y_1, y_2, \dots, y_T), y_i \in \mathcal{R}^K$$
$$\text{nonlinearity: } \mathcal{H}$$

Definition of the RNN:

$$h_t = \mathcal{H}\left(W_{xh}x_t + W_{hh}h_{t-1} + b_h\right)$$
$$y_t = W_{hy}h_t + b_y$$



The Chain Rule of Probability

Recall...

Question: How can we **define** a probability distribution over a sequence of length T?

The	bat	made	noise	at	night
w_1	w_2	w_3	w_4	w_5	w_6

Chain rule of probability: $p(w_1, w_2, \ldots, w_T) = \prod_{t=1}^{T} p(w_t \mid w_{t-1}, \ldots, w_1)$

$p(w_1, w_2, w_3, \ldots, w_6) =$

The

$p(w_1)$

The

$p(w_2 \mid w_1)$

The

The

The

$\ldots w_1)$

The

$p(w_6 \mid w_5, w_4, w_3, w_2, w_1)$

Note: This is called the chain rule because it is **always** true for every probability distribution

RNN Language Model

RNN Language Model: $p(w_1, w_2, \ldots, w_T) = \prod_{t=1}^{T} p(w_t \mid f_{\boldsymbol{\theta}}(w_{t-1}, \ldots, w_1))$

$$p(w_1, w_2, w_3, \ldots, w_6) =$$

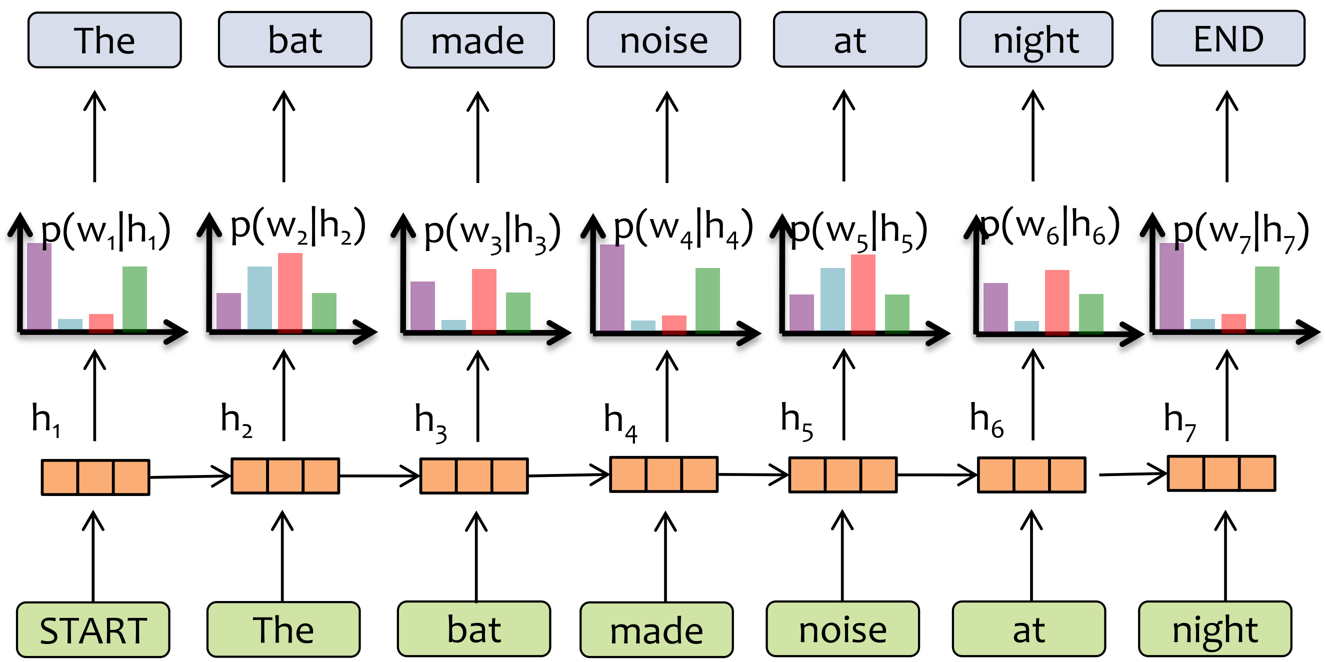
The						$p(w_1)$
The	bat					$p(w_2 \mid f_\theta(w_1))$
The	bat	made				$p(w_3 \mid f_\theta(w_2, w_1))$
The	bat	made	noise			$p(w_4 \mid f_\theta(w_3, w_2, w_1))$
The	bat	made	noise	at		$p(w_5 \mid f_\theta(w_4, w_3, w_2, w_1))$
The	bat	made	noise	at	night	$p(w_6 \mid f_\theta(w_5, w_4, w_3, w_2, w_1))$

Key Idea:

(1) convert all previous words to a **fixed length vector**

(2) define distribution $p(w_t \mid f_\theta(w_{t-1}, \ldots, w_1))$ that conditions on the vector

RNN Language Model



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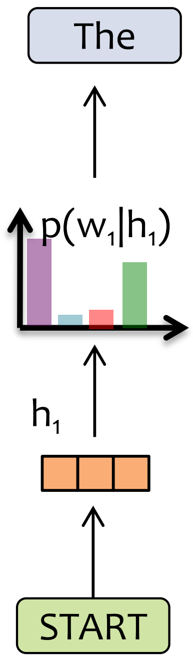

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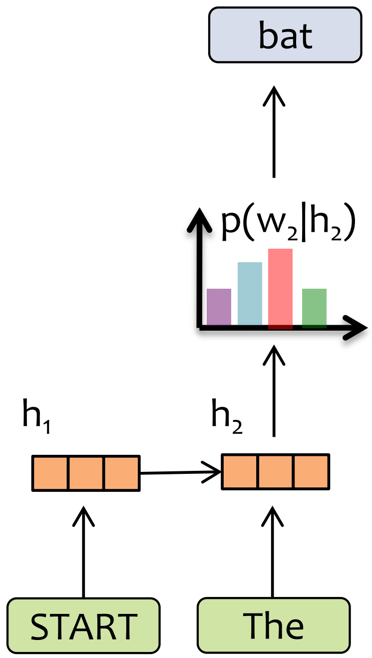

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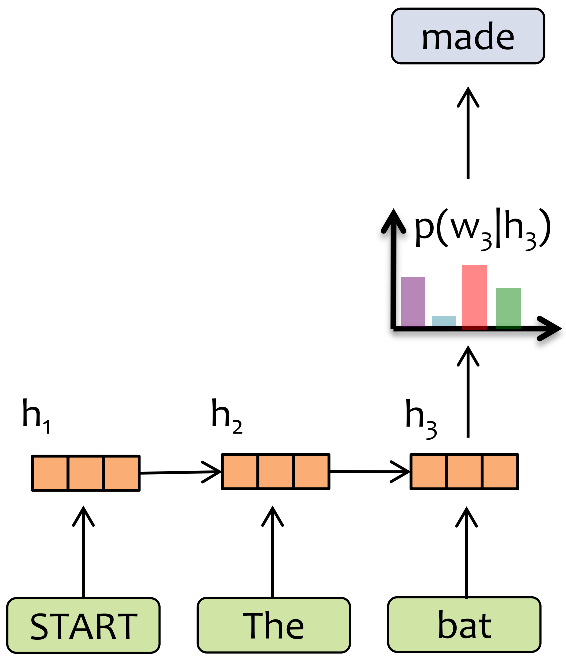

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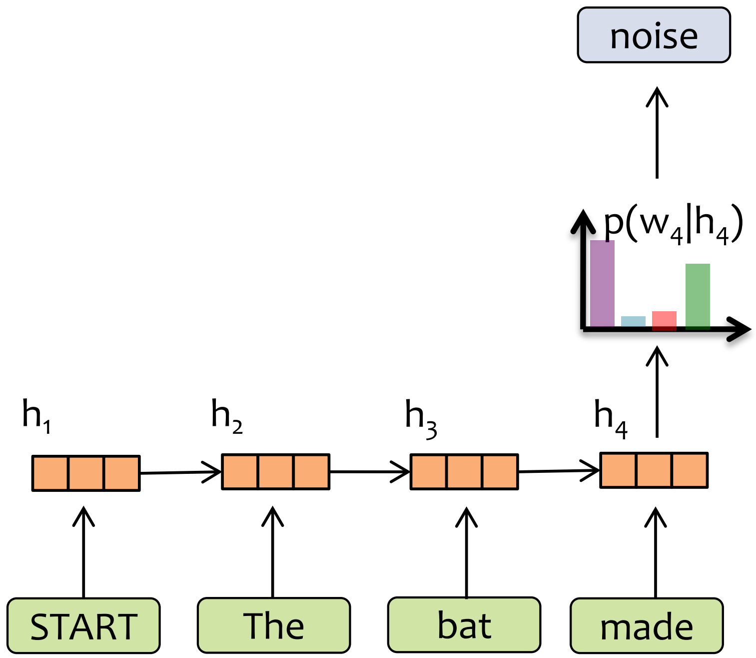

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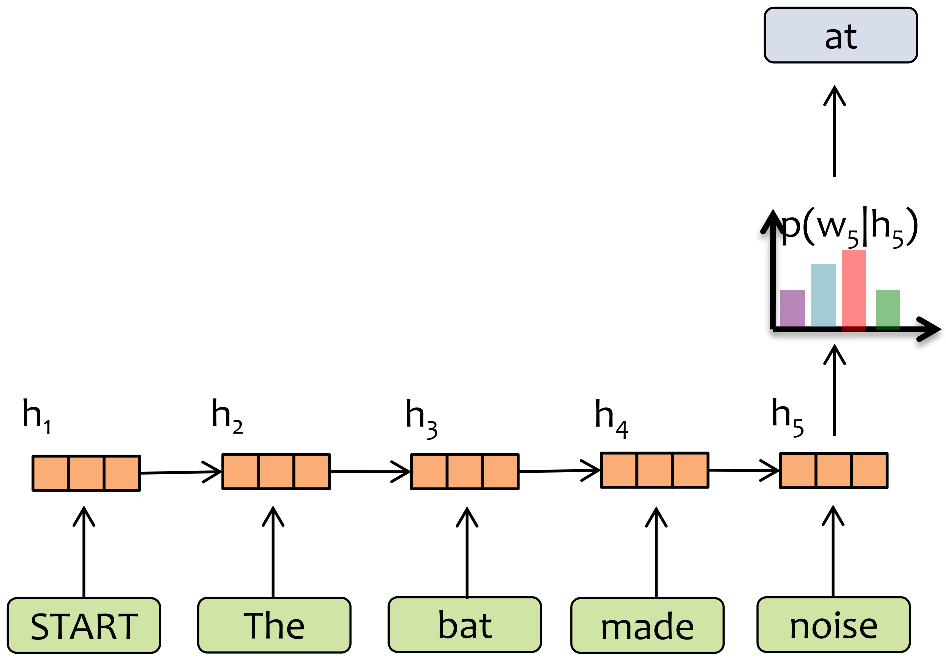

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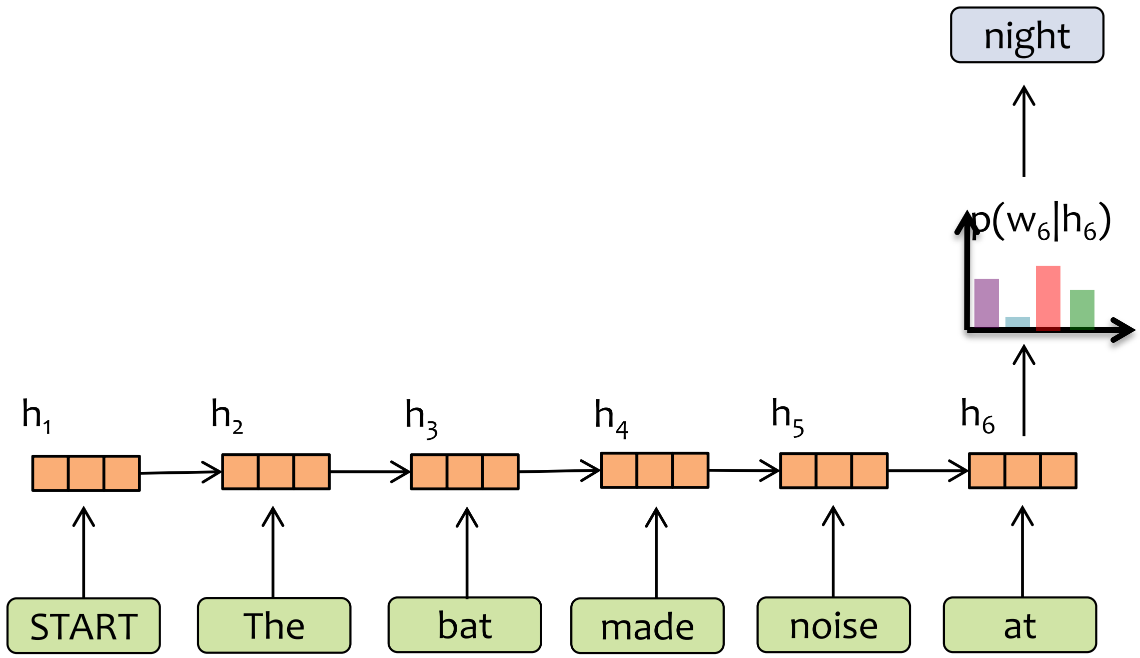

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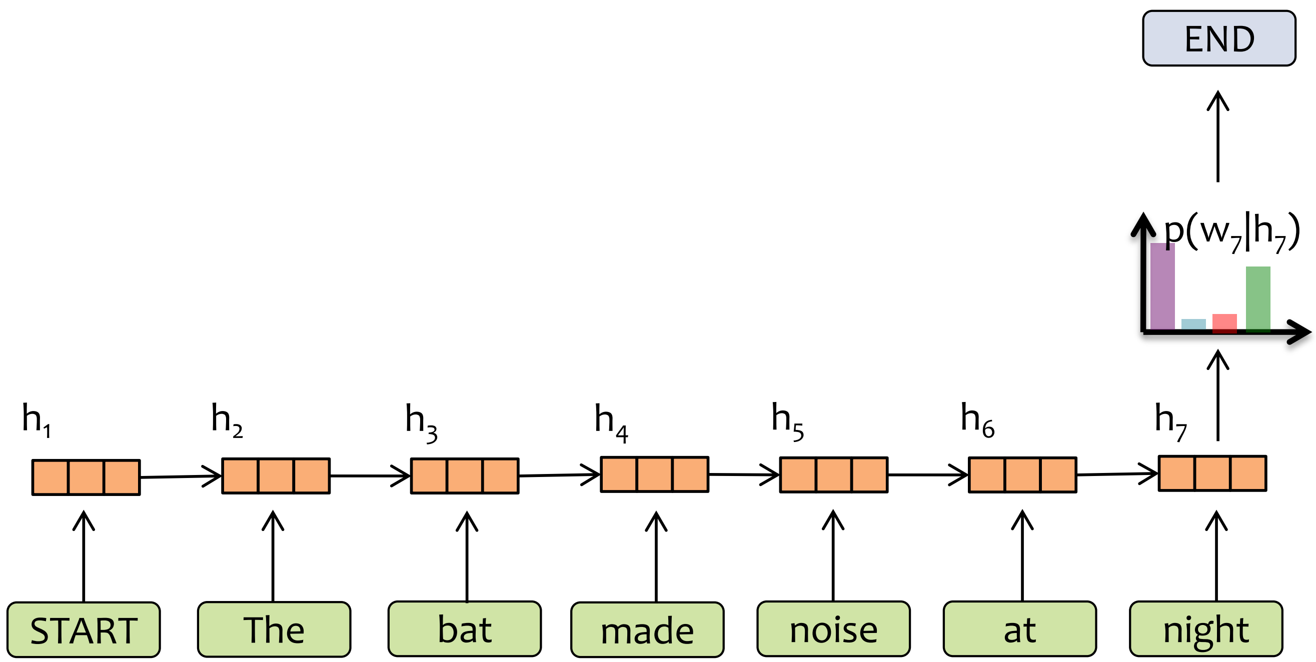

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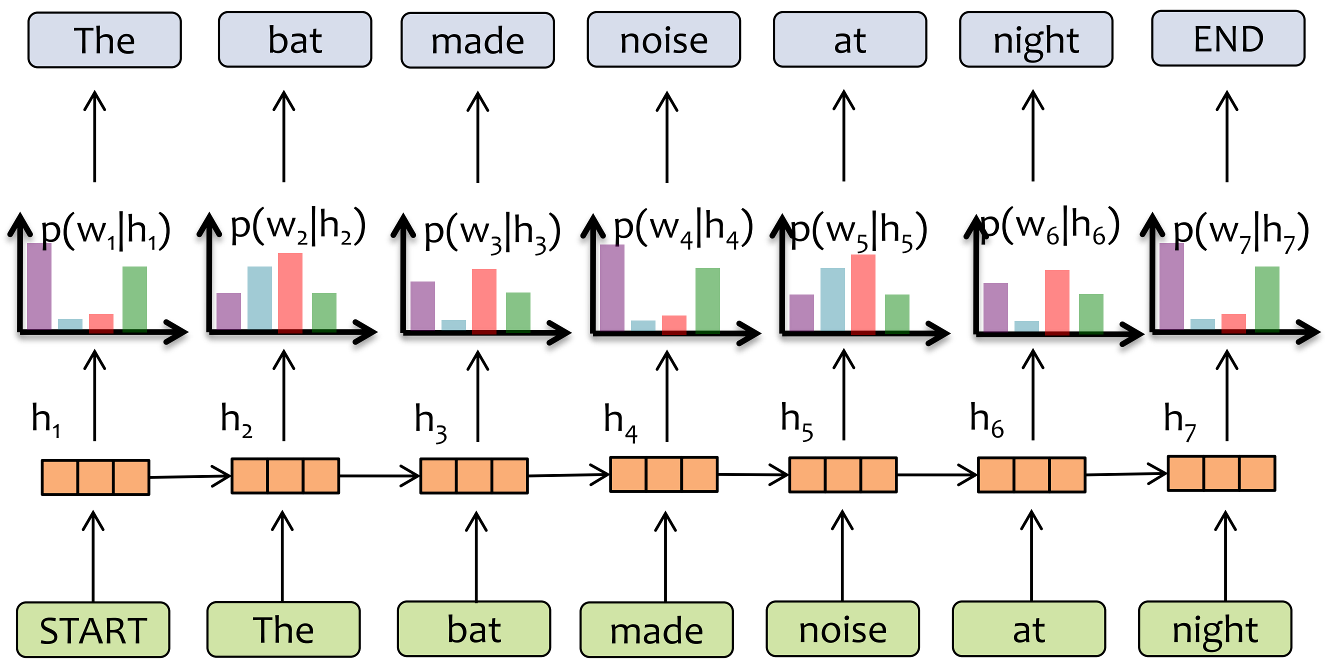
RNN Language Model



$$p(w_1, w_2, w_3, \ldots, w_T) = p(w_1 \mid h_1)\, p(w_2 \mid h_2) \ldots\, p(w_2 \mid h_T)$$

Sampling from a Language Model

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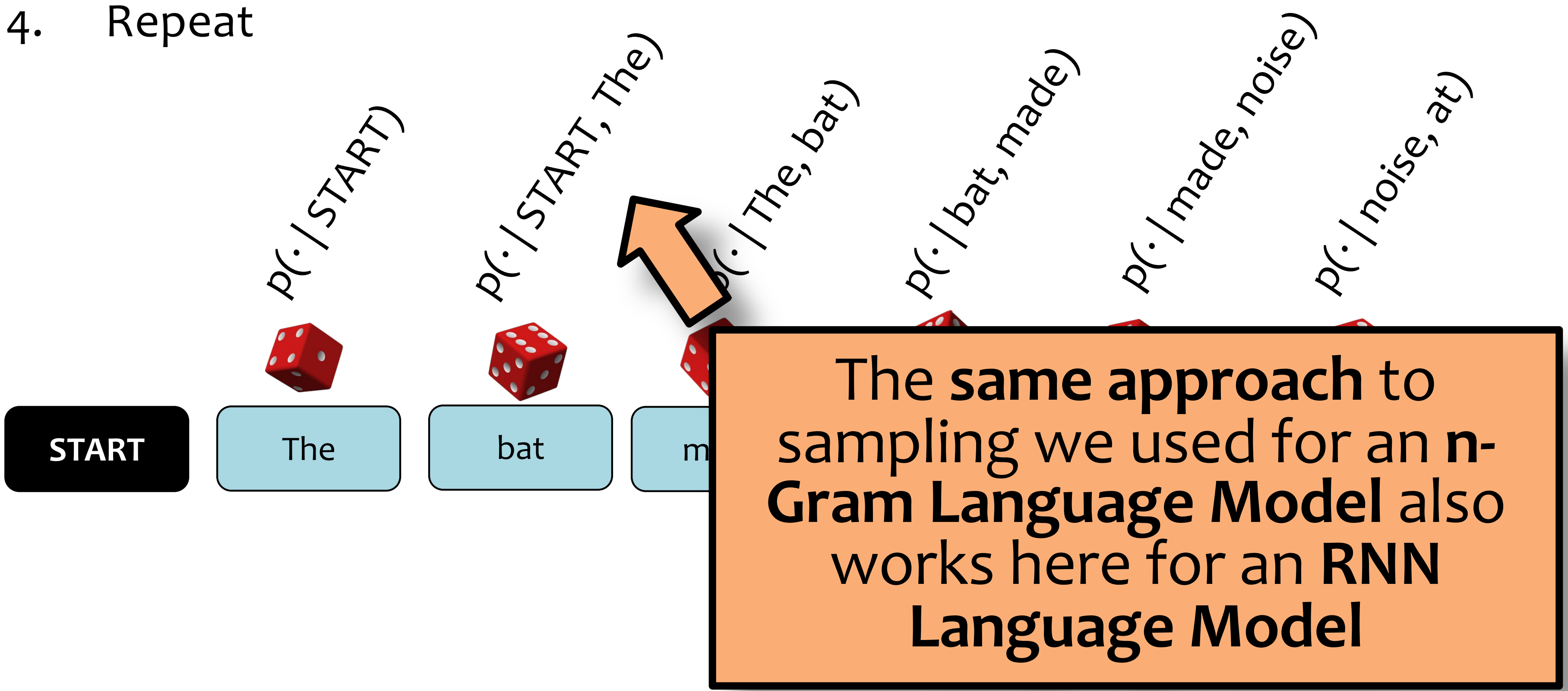

Sampling from an RNN-LM

??

VIOLA: Why, Salisbury must find his flesh and thought That which I am not aps, not a man and in fire, To show the reining of the raven and the wars To grace my hand reproach within, and not a fair are hand, That Caesar and my goodly father's world; When I was heaven of presence and our fleets, We spare with hours, but cut thy council I am great, Murdered a [illegible] master's ready there My powe [illegible] so much as hell: Some service i [illegible] bondman here, Would show hi [illegible]

KING LEAR: O, if you we [illegible] feeble sight, the courtesy of your law, Your sight and several breath, will wear the gods With his heads, and my hands are wonder'd at the deeds, So drop upon your lordship's head, and your opinion Shall be against your honour.

??

CHARLES: Marry, do I, sir; and I came to acquaint you with a matter. I am given, sir, secretly to understand that your younger brother Orlando hath a disposition to come in disguised against me to try a fall. To-morrow, sir, I wrestle for my credit; and he that escapes me without some broken limb shall acquit him [illegible] is but young and tender; and, [illegible] uld be loath to foil him, as I [illegible] honour, if he come in: [illegible] ny love to you, I came hither to acquaint you wi [illegible] that either you might stay him from his int [illegible] ent or brook such disgrace well as he sh [illegible] n into, in that it is a thing of his own search and altogether against my will.

TOUCHSTONE: For my part, I had rather bear with you than bear you; yet I should bear no cross if I did bear you, for I think you have no money in your purse.

Which is the real Shakespeare?!

Example from http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Sampling from an RNN-LM

Shakespeare's As You Like It

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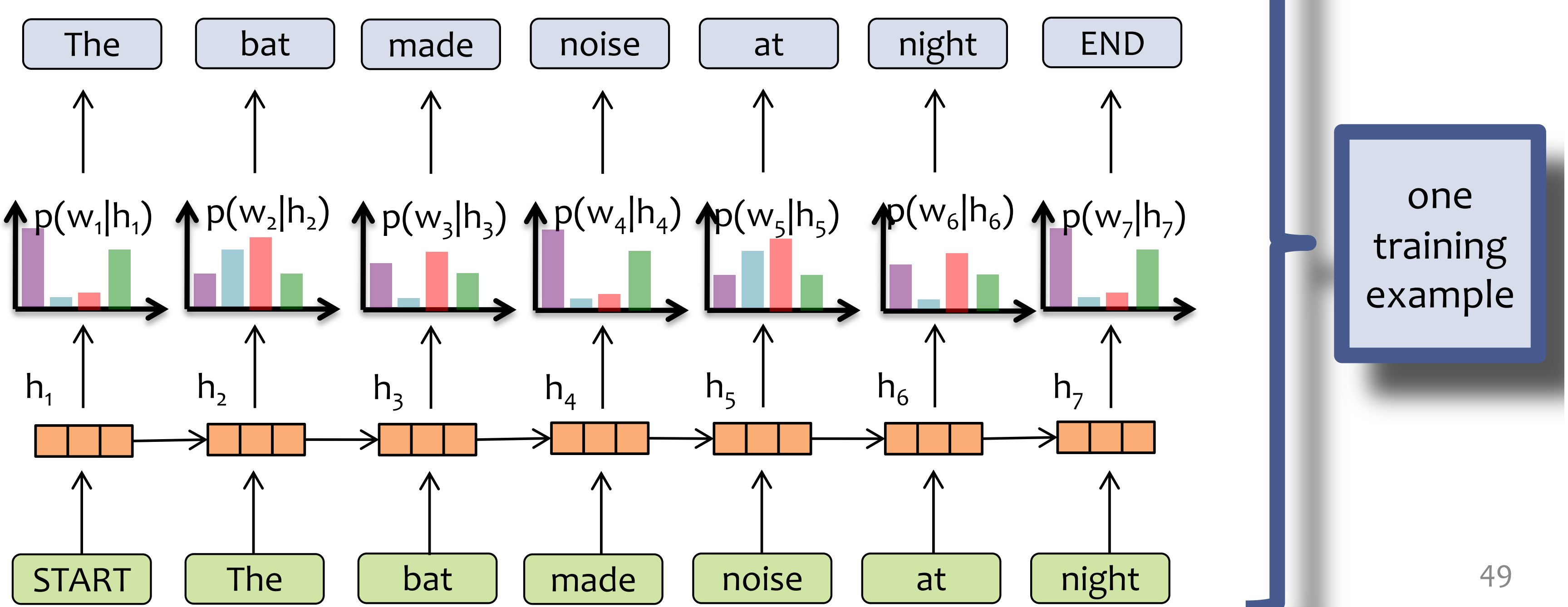
Learning an RNN-LM

- Each training example is a sequence (e.g. sentence), so we have training data $D = \{\mathbf{w}^{(1)}, \mathbf{w}^{(2)}, \ldots, \mathbf{w}^{(N)}\}$
- The objective function for an RNN-LM is (typically) the log-likelihood of the training examples: $J(\boldsymbol{\theta}) = \Sigma_i \log p_{\boldsymbol{\theta}}(\mathbf{w}^{(i)})$
- We train by mini-batch SGD (or your favorite flavor of mini-batch SGD)

$$\log p(\mathbf{w}) = \log p(w_1, w_2, w_3, \ldots, w_T)$$
$$= \log p(w_1 \mid h_1) + \log p(w_2 \mid h_2) + \ldots + \log p(w_2 \mid h_T)$$



Language Modeling

An aside:

- State-of-the-art language models currently tend to rely on **transformer networks** (e.g. GPT-2)
- RNN-LMs comprised most of the early neural LMs that **led to** current SOTA architectures

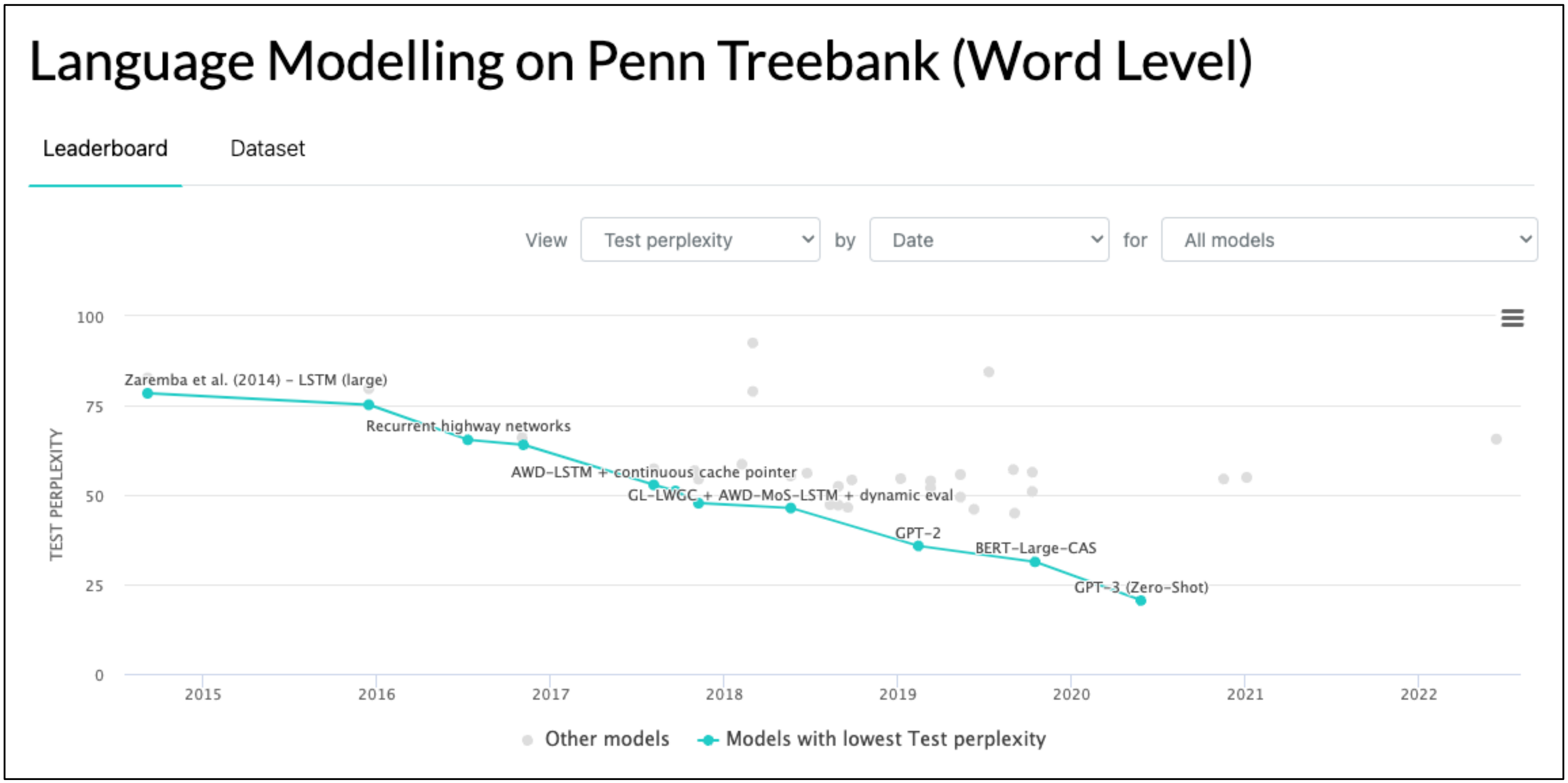


Figure from https://paperswithcode.com/sota/language-modelling-on-penn-treebank-word

Why does efficiency matter?

Case Study: GPT-3

- # of training tokens = 500 billion
- # of parameters = 175 billion
- # of cycles = 50 petaflop/s-days (each of which are 8.64e+19 flops)

Dataset	Quantity (tokens)	Weight in training mix	Epochs elapsed when training for 300B tokens
Common Crawl (filtered)	410 billion	60%	0.44
WebText2	19 billion	22%	2.9
Books1	12 billion	8%	1.9
Books2	55 billion	8%	0.43
Wikipedia	3 billion	3%	3.4

Table 2.2: Datasets used to train GPT-3. "Weight in training mix" refers to the fraction of examples during training that are drawn from a given dataset, which we intentionally do not make proportional to the size of the dataset. As a result, when we train for 300 billion tokens, some datasets are seen up to 3.4 times during training while other datasets are seen less than once.

Model Name	n_{params}	n_{layers}	d_{model}	n_{heads}	d_{head}	Batch Size	Learning Rate
GPT-3 Small	125M	12	768	12	64	0.5M	6.0×10^{-4}
GPT-3 Medium	350M	24	1024	16	64	0.5M	3.0×10^{-4}
GPT-3 Large	760M	24	1536	16	96	0.5M	2.5×10^{-4}
GPT-3 XL	1.3B	24	2048	24	128	1M	2.0×10^{-4}
GPT-3 2.7B	2.7B	32	2560	32	80	1M	1.6×10^{-4}
GPT-3 6.7B	6.7B	32	4096	32	128	2M	1.2×10^{-4}
GPT-3 13B	13.0B	40	5140	40	128	2M	1.0×10^{-4}
GPT-3 175B or "GPT-3"	175.0B	96	12288	96	128	3.2M	0.6×10^{-4}

Table 2.1: Sizes, architectures, and learning hyper-parameters (batch size in tokens and learning rate) of the models which we trained. All models were trained for a total of 300 billion tokens.

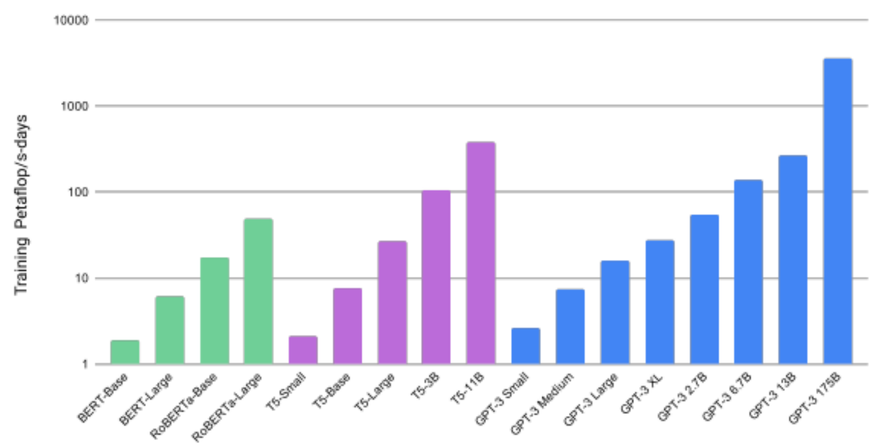


Figure 2.2: Total compute used during training. Based on the analysis in Scaling Laws For Neural Language Models [KMH+20] we train much larger models on many fewer tokens than is typical. As a consequence, although GPT-3 3B is almost 10x larger than RoBERTa-Large (355M params), both models took roughly 50 petaflop/s-days of compute during pre-training. Methodology for these calculations can be found in Appendix D.

Figure from https://arxiv.org/pdf/2005.14165

GPT-3 Example Output

Context

```
The City
BY C. P. CAVAFY
TRANSLATED BY EDMUND KEELEY
[Poem text omitted]


SOME TREES
John Ashbery
[Poem text omitted]


Shadows on the Way
Wallace Stevens
```

Generated Poem

```
I must have shadows on the way
If I am to walk I must have
Each step taken slowly and alone
To have it ready made

And I must think in lines of grey
To have dim thoughts to be my guide
Must look on blue and green
And never let my eye forget
That color is my friend
And purple must surround me too

The yellow of the sun is no more
Intrusive than the bluish snow
That falls on all of us.  I must have
Grey thoughts and blue thoughts walk with me
If I am to go away at all.
```

Conditional Sampling:

To draw a sample, feed in a prompt (i.e. context) and then sample from the model conditioned on that prompt

Examples from GPT-3

What else can a large LM (attempt to) do?

Using the idea of **prompts**, we can apply LMs to a **variety of different problems** in natural language processing.

In the **zero-shot setting**, we simply feed the context to the model and observe how it completes the sequence. (i.e. there is no additional training)

Answer fact-based questions:

Context →	Organisms require energy in order to do what?
Correct Answer →	mature and develop.
Incorrect Answer →	rest soundly.
Incorrect Answer →	absorb light.
Incorrect Answer →	take in nutrients.

Complete sentences logically:

Context →	My body cast a shadow over the grass because
Correct Answer →	the sun was rising.
Incorrect Answer →	the grass was cut.

Complete sentences logically:

Context →	lull is to trust as
Correct Answer →	cajole is to compliance
Incorrect Answer →	balk is to fortitude
Incorrect Answer →	betray is to loyalty
Incorrect Answer →	hinder is to destination
Incorrect Answer →	soothe is to passion

Reading comprehension:

Context →	anli 1: anli 1: Fulton James MacGregor MSP is a Scottish politician who is a Scottish National Party (SNP) Member of Scottish Parliament for the constituency of Coatbridge and Chryston. MacGregor is currently Parliamentary Liaison Officer to Shona Robison, Cabinet Secretary for Health & Sport. He also serves on the Justice and Education & Skills committees in the Scottish Parliament. Question: Fulton James MacGregor is a Scottish politican who is a Liaison officer to Shona Robison who he swears is his best friend. True, False, or Neither?
Correct Answer →	Neither
Incorrect Answer →	True
Incorrect Answer →	False

Examples from GPT-3

RNN Language Models

Whiteboard:

– RNNLM for scoring of a path in a search space

– What's missing? Dependence on the input.

SEQUENCE TO SEQUENCE MODELS

Why seq2seq?

Motivating Question:
How can we model input/output pairs when the length of the input might be **different** from the length of the output?

Why seq2seq?

- **10+ years ago:** state-of-the-art machine translation or speech recognition systems were complex pipelines
  - MT
    - unsupervised word-level alignment of sentence-parallel corpora (e.g. via GIZA++)
    - build phrase tables based on (noisily) aligned data (use prefix trees and on demand loading to reduce memory demands)
    - use factored representation of each token (word, POS tag, lemma, morphology)
    - learn a separate language model (e.g. SRILM) for target
    - combine language model with phrase-based decoder
    - tuning via minimum error rate training (MERT)
  - ASR
    - MFCC and PLP feature extraction
    - acoustic model based on Gaussian Mixture Models (GMMs)
    - model phones via Hidden Markov Models (HMMs)
    - learn a separate n-gram language model
    - learn a phonetic model (i.e. mapping words to phones)
    - combine language model, acoustic model, and phonetic model in a weighted finite-state transducer (WFST) framework (e.g. OpenFST)
    - decode from a confusion network (lattice)
- **Today:** just use a seq2seq model
  - *encoder*: reads the input one token at a time to build up its vector representation
  - *decoder*: starts with encoder vector as context, then decodes one token at a time – feeding its own outputs back in to maintain a vector representation of what was produced so far

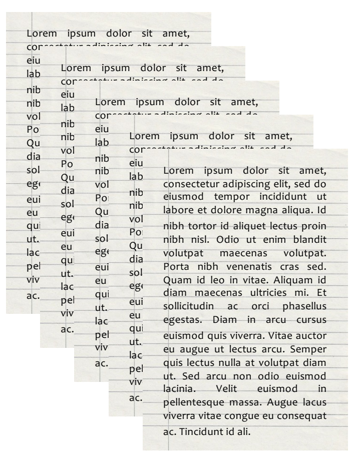
Sequence to Sequence Model

Speech Recognition

Machine Translation

기계 번역은 특히 영어와 한국어와 같은 언어 쌍의 경우 매우 어렵습니다.

Summarization



Sequence to Sequence Model

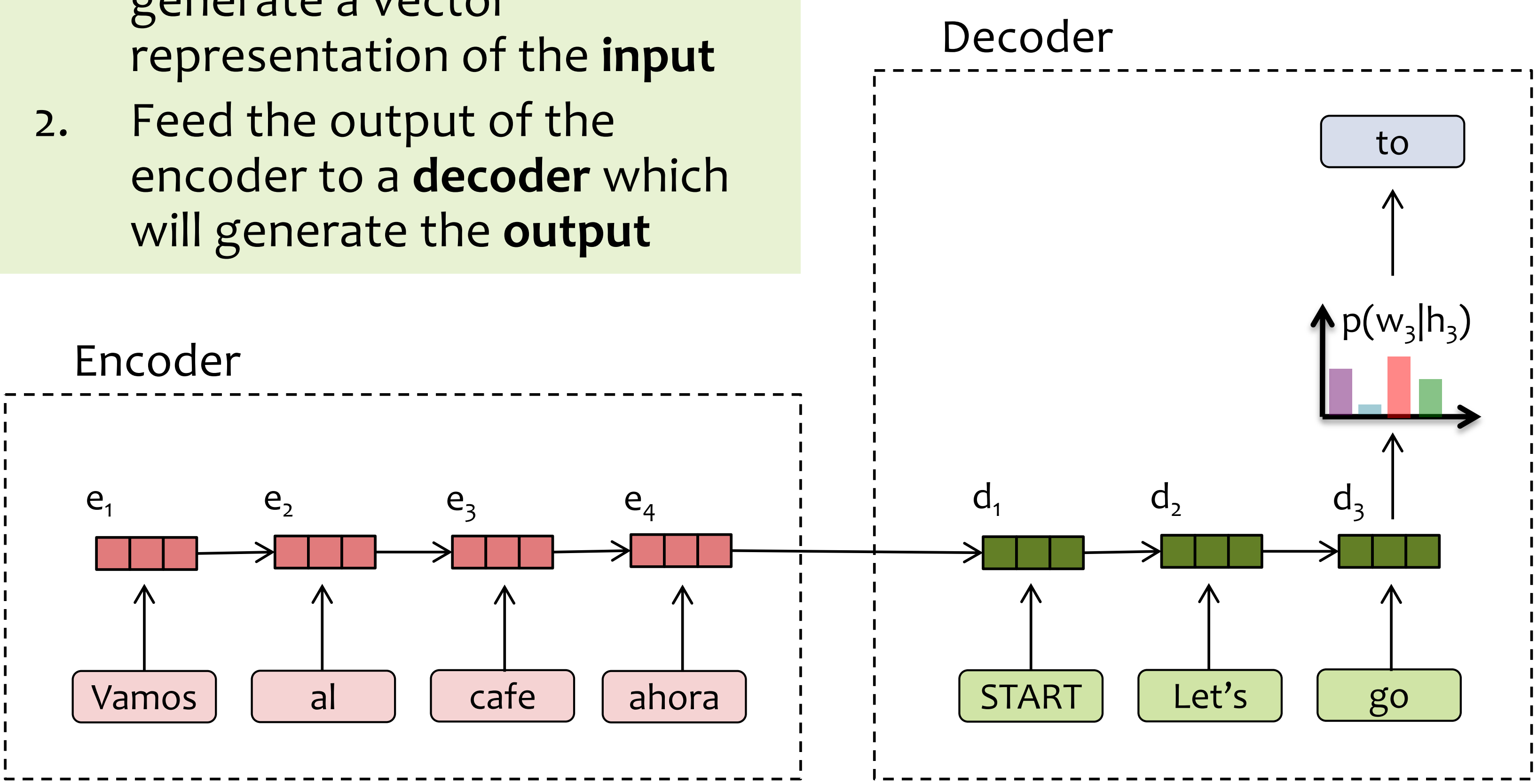
Now suppose you want generate a sequence conditioned on another input

Key Idea:

1. Use an **encoder** model to generate a vector representation of the **input**
2. Feed the output of the encoder to a **decoder** which will generate the **output**

Applications:

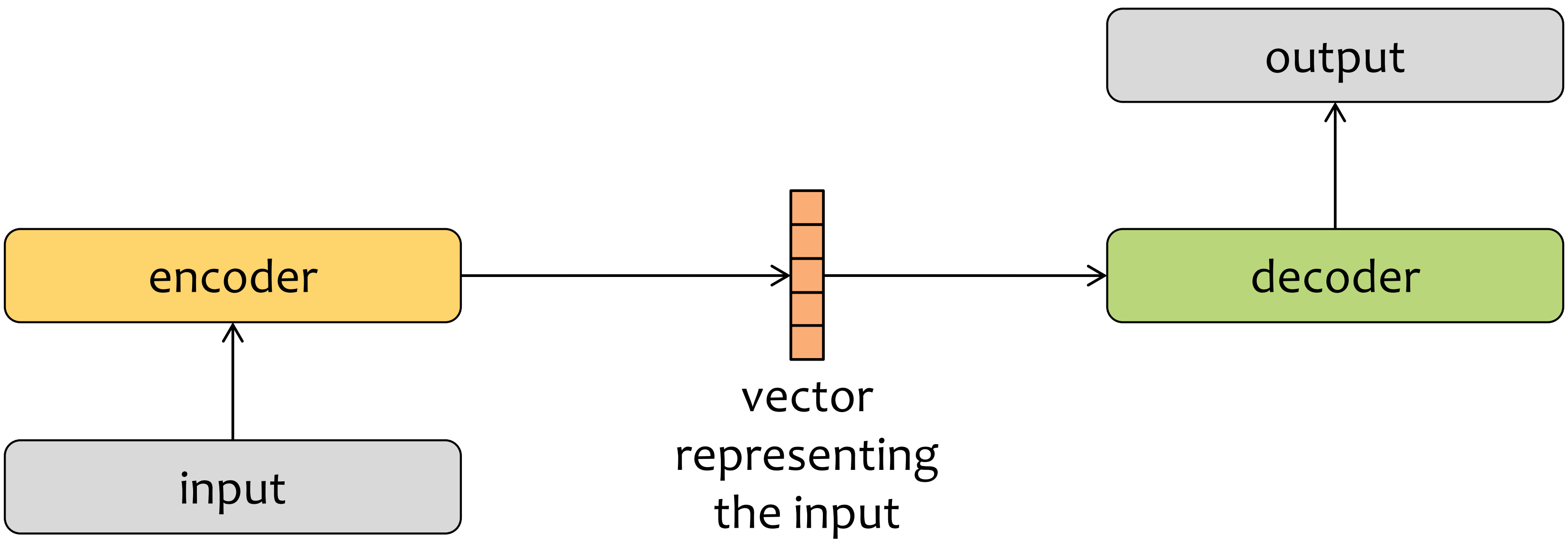
- translation:
  Spanish → English
- summarization:
  article → summary
- speech recognition:
  speech signal → transcription



Encoder-Decoder Architectures

For (1) ASR (2) MT (3) Image captioning…

(1) transcript
(2) target language
(3) caption



(1) speech
(2) source language
(3) image

Encoder-Decoder Architectures

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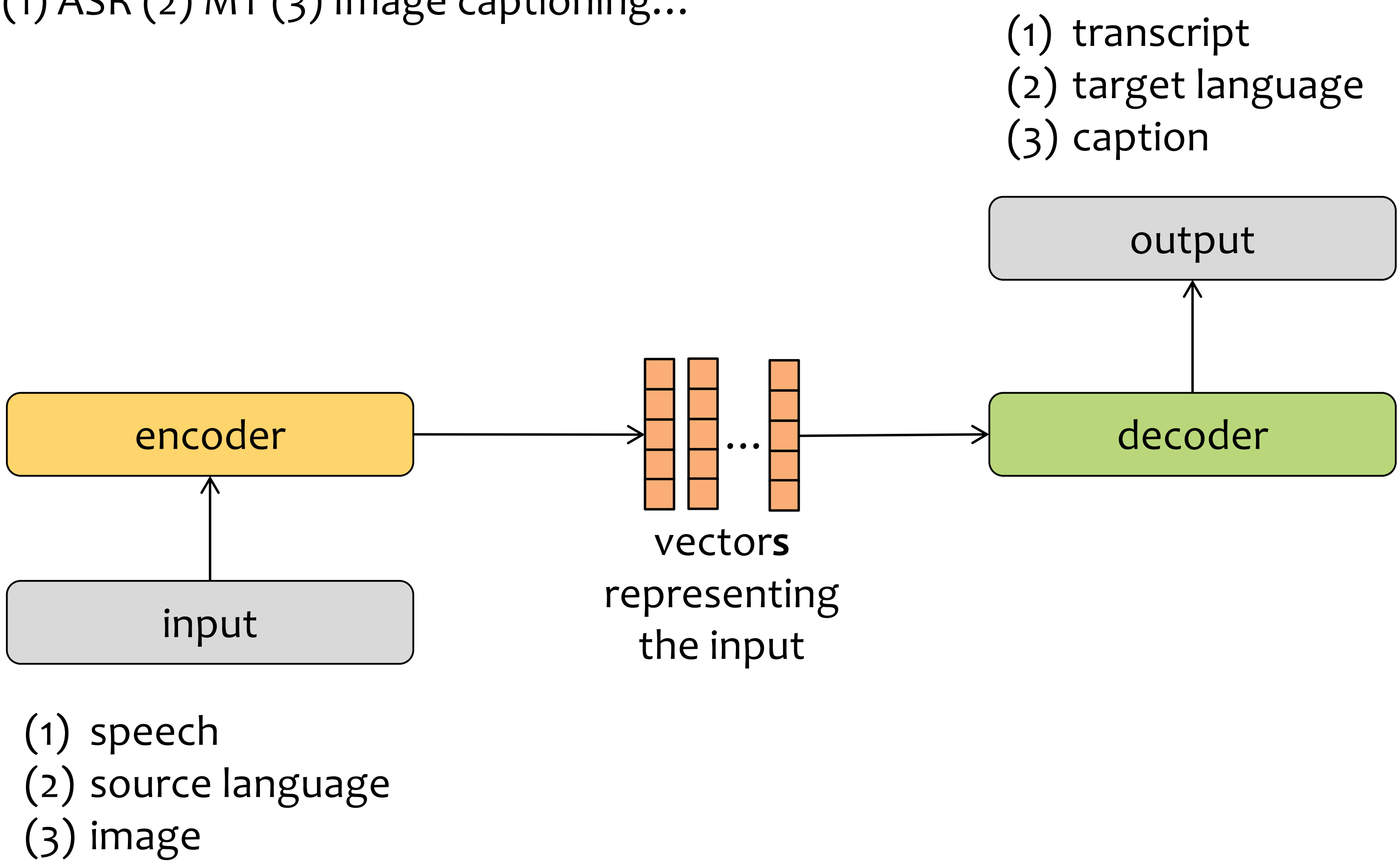

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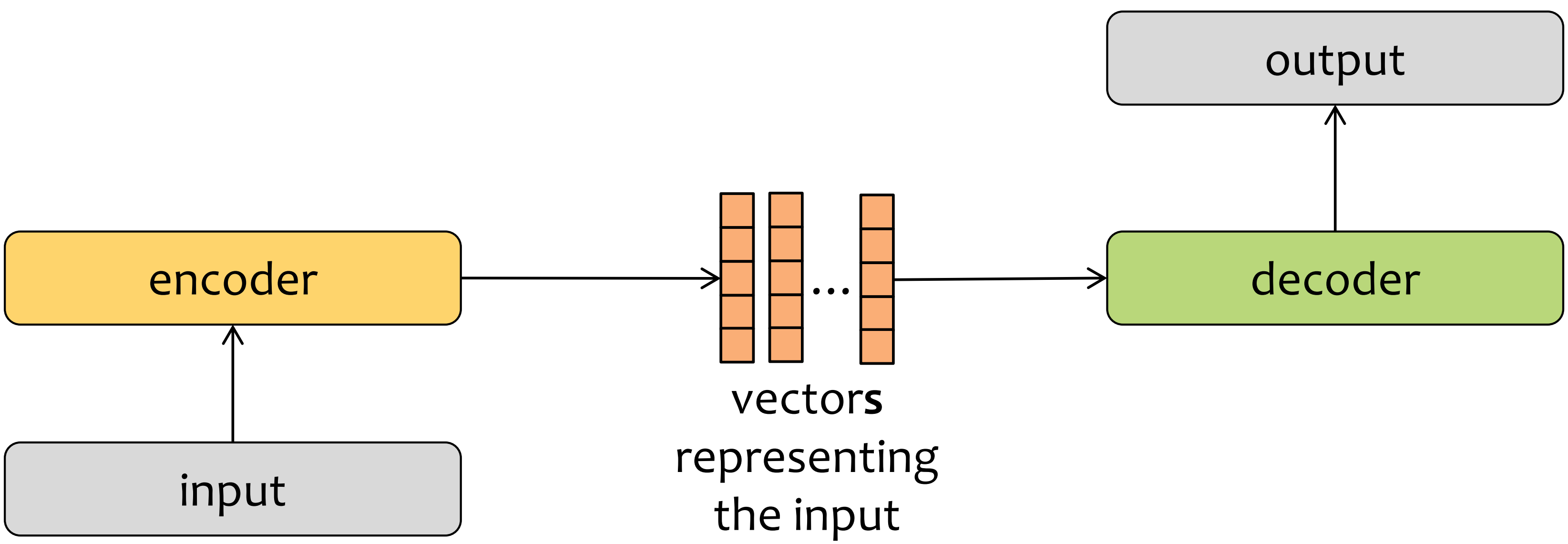

(1) speech
(2) source language
(3) image

- A seq2seq model is one flavor of the (more general) encoder-decoder architecture.
- Image captioning (or video captioning) provides an example in which the input is not a sequence, and the encoder must handle its 2D (or 3D) input.

Comparing RNN, RNN-LM, seq2seq

Question:
Fill in the blank: A recurrent neural network (RNN) is a ____.
A. discriminative model
B. generative model

Answer:

Question:
Fill in the blank: An RNN-LM is a ____.
A. discriminative model
B. generative model

Answer:

Question:
Fill in the blank: A seq2seq model is a ____.
A. discriminative model
B. generative model

Answer: