Deep Learning for NLP: Feedforward Networks

COMP90042

Natural Language Processing

Lecture 7

Corrections on L3: page 21/22

Absolute Discounting

Context = *alleged*

- 5 observed n-grams
- 2 unobserved n-grams

			Lidstone smoothing, $\alpha = 0.1$		Discounting, $d = 0.1$	
	counts	unsmoothed probability	effective counts	smoothed probability	effective counts	smoothed probability
impropriety	8	0.4	7.826	0.391	7.9	0.395
offense	5	0.25	4.928	0.246	4.9	0.245
damage	4	0.2	3.961	0.198	3.9	0.195
deficiencies	2	0.1	2.029	0.101	1.9	0.095
outbreak	1	0.05	1.063	0.053	0.9	0.045
infirmity	0	0	0.097	0.005	0.25	0.013
cephalopods	0	0	0.097	0.005	0.25	0.013

8 - 0.1

(0.1 x 5) / 2

total amount of discounted probability mass (0.1 x 5) / 20

Corrections on L3: page 21/22

Backoff

- Absolute discounting redistributes the probability mass **equally** for all unseen n-grams
- Katz Backoff: redistributes the mass based on a **lower order** model (e.g. unigram)

$$P_{katz}(w_i|w_{i-1}) = \begin{cases} \frac{C(w_{i-1},w_i)-D}{C(w_{i-1})}, & \text{if } C(w_{i-1}, w_i) > 0 \\ \alpha(w_{i-1}) \times \frac{P(w_i)}{\sum_{w_j:C(w_{i-1},w_j)=0} P(w_j)}, & \text{otherwise} \end{cases}$$

unigram probability for w_i

sum unigram probabilities for all words that do not co-occur with context w_{i-1}

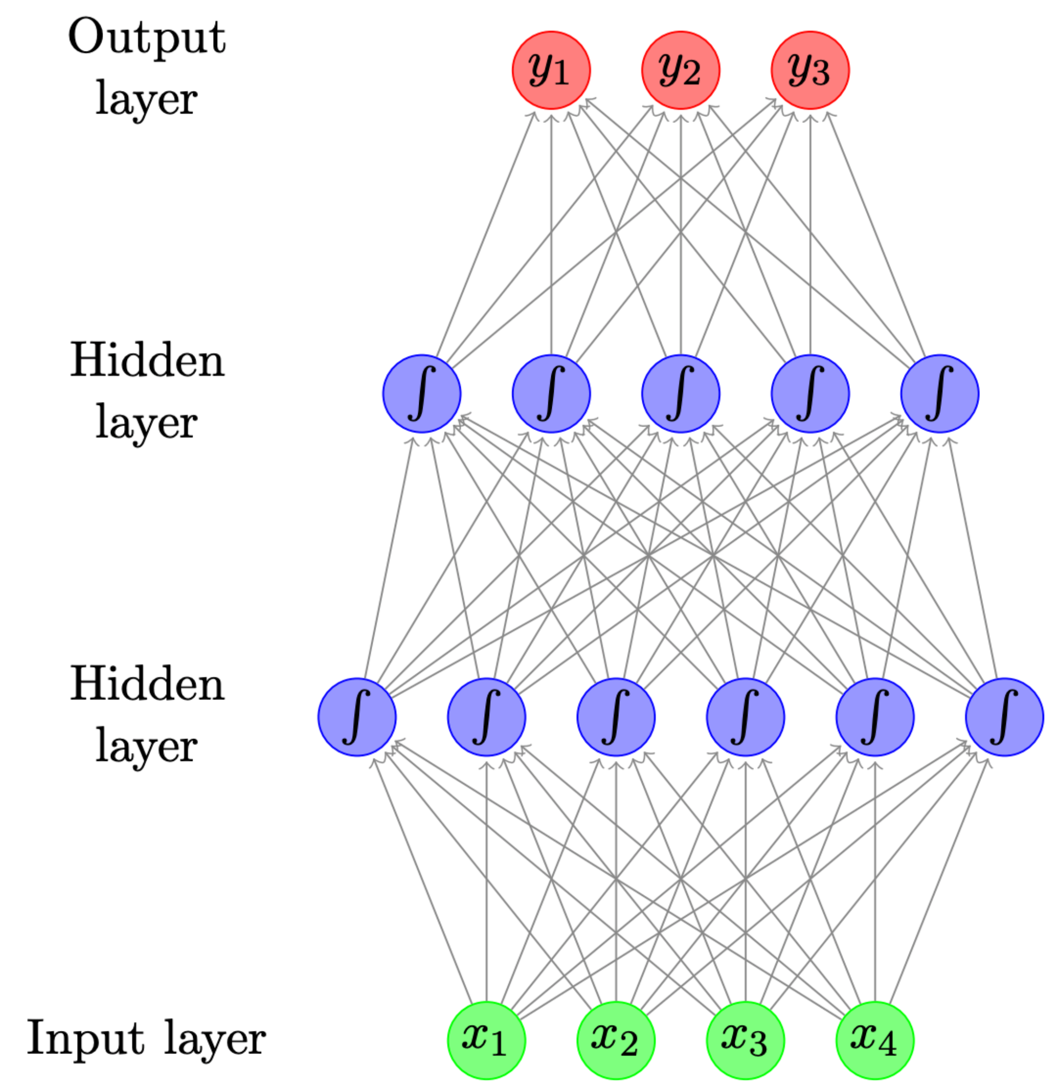
the amount of probability mass that has been discounted for context w_{i-1} ((0.1 x 5) / 20 in previous slide)

Deep Learning

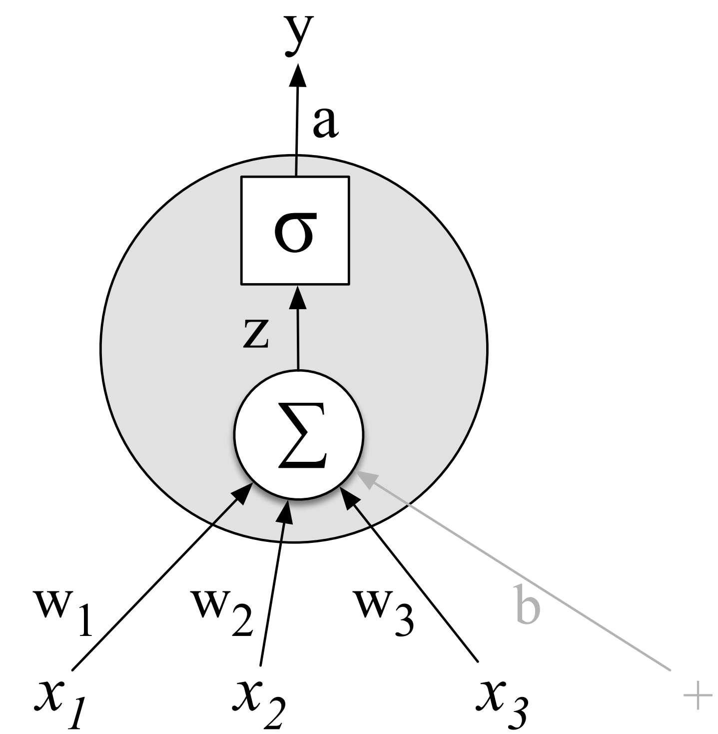
- A branch of machine learning
- Re-branded name for neural networks
- Neural networks: historically inspired by the way computation works in the brain
  - Consists of computation units called neurons
- Why deep? Many layers are chained together in modern deep learning models

Feed-forward NN

- Aka multilayer perceptrons
- Each arrow carries a weight, reflecting its importance
- Sigmoid function represents a non-linear function



NN Units



- Each “unit” is a function
  - given input x, computes real-value (scalar) h

$$h = \tanh\left(\sum_j w_j x_j + b\right)$$

  - scales input (with weights, w) and adds offset (bias, b)
  - applies non-linear function, such as logistic sigmoid, hyperbolic sigmoid (tanh), or rectified linear unit

Matrix Vector Notation

- Typically have several hidden units, i.e.

$$h_i = \tanh\left(\sum_j w_{ij} x_j + b_i\right)$$

- Each with its own weights (*w_i*) and bias term (*b_i*)
- Can be expressed using matrix and vector operators

$$\vec{h} = \tanh\left(W\vec{x} + \vec{b}\right)$$

- Where *W* is a matrix comprising the weight vectors, and *b* is a vector of all bias terms
- Non-linear function applied element-wise

Output Layer

- Binary classification problem (e.g. classify whether a tweet is positive or negative in sentiment):
  - sigmoid activation function (aka logistic function)
- Multi-class classification problem (e.g. classify the topics of a document)
  - softmax ensures probabilities > 0 and sum to 1

$$\left[\frac{\exp(v_1)}{\sum_i \exp(v_i)}, \quad \frac{\exp(v_2)}{\sum_i \exp(v_i)}, \quad \cdots \quad \frac{\exp(v_m)}{\sum_i \exp(v_i)}\right]$$

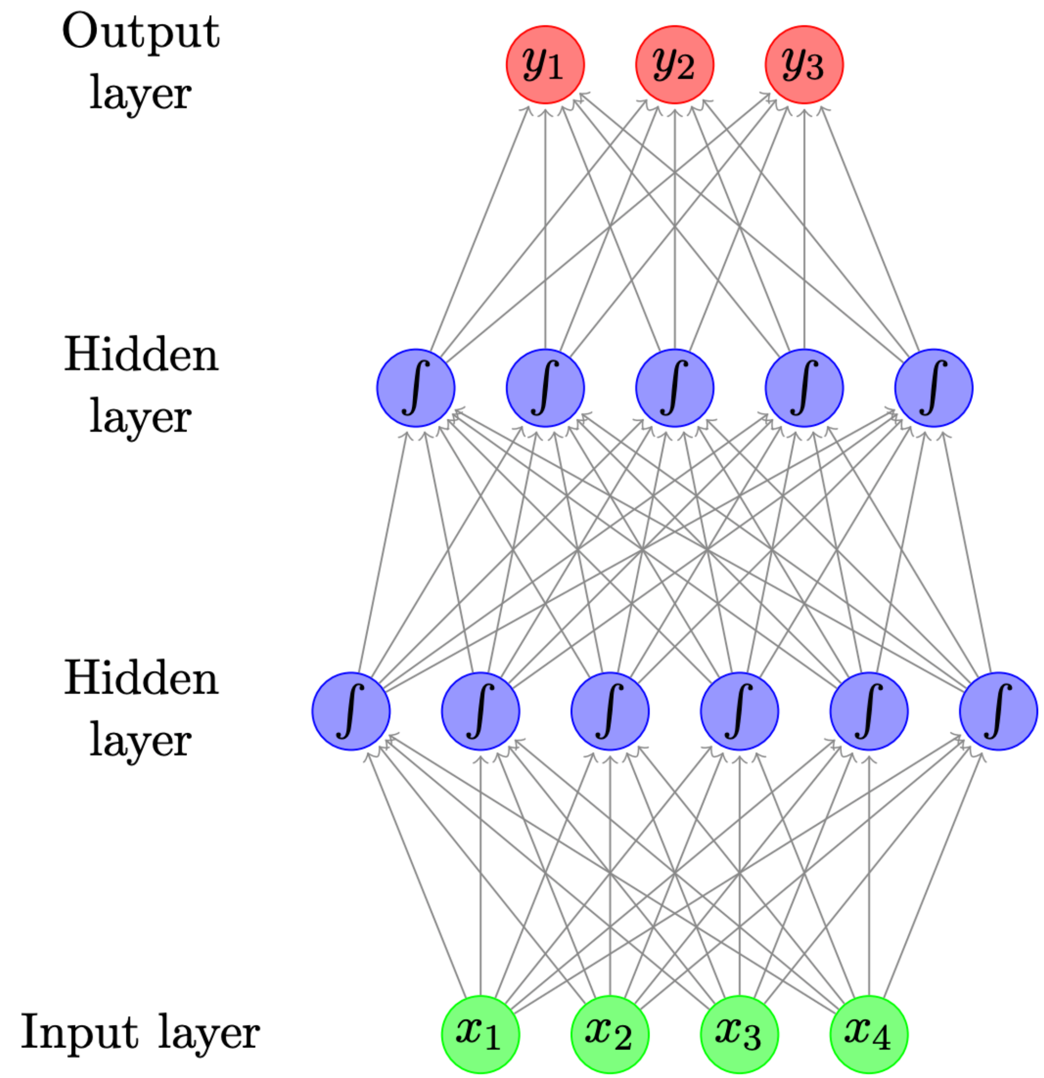
Feed-forward NN

$$\vec{h_1} = \tanh\left(W_1\vec{x} + \vec{b_1}\right)$$

$$\vec{h_2} = \tanh\left(W_2\vec{h_1} + \vec{b_2}\right)$$

$$\vec{y} = \mathrm{softmax}(W_3\vec{h_2})$$

- Matrices and biases = parameters of the model



Learning from Data

- How to learn the parameters from data?
- Consider how well the model “fits” the training data, in terms of the probability it assigns to the correct output

$$L = \prod_{i=0}^{m} P(y_i|x_i)$$

  - want to *maximise* total probability, L
  - equivalently *minimise* -log L with respect to parameters
- Trained using gradient descent
  - tools like *tensorflow, pytorch, dynet* use autodiff to compute gradients automatically

Topic Classification

- Given a document, classify it into a predefined set of topics (e.g. economy, politics, sports)
- Input: bag-of-words

	love	cat	dog	doctor
doc 1	0	2	3	0
doc 2	2	0	2	0
doc 3	0	0	0	4
doc 4	3	0	0	2

Topic Classification

$$\vec{h_1} = \tanh\left(W_1\vec{x} + \vec{b_1}\right)$$

$$\vec{h_2} = \tanh\left(W_2\vec{h_1} + \vec{b_2}\right)$$

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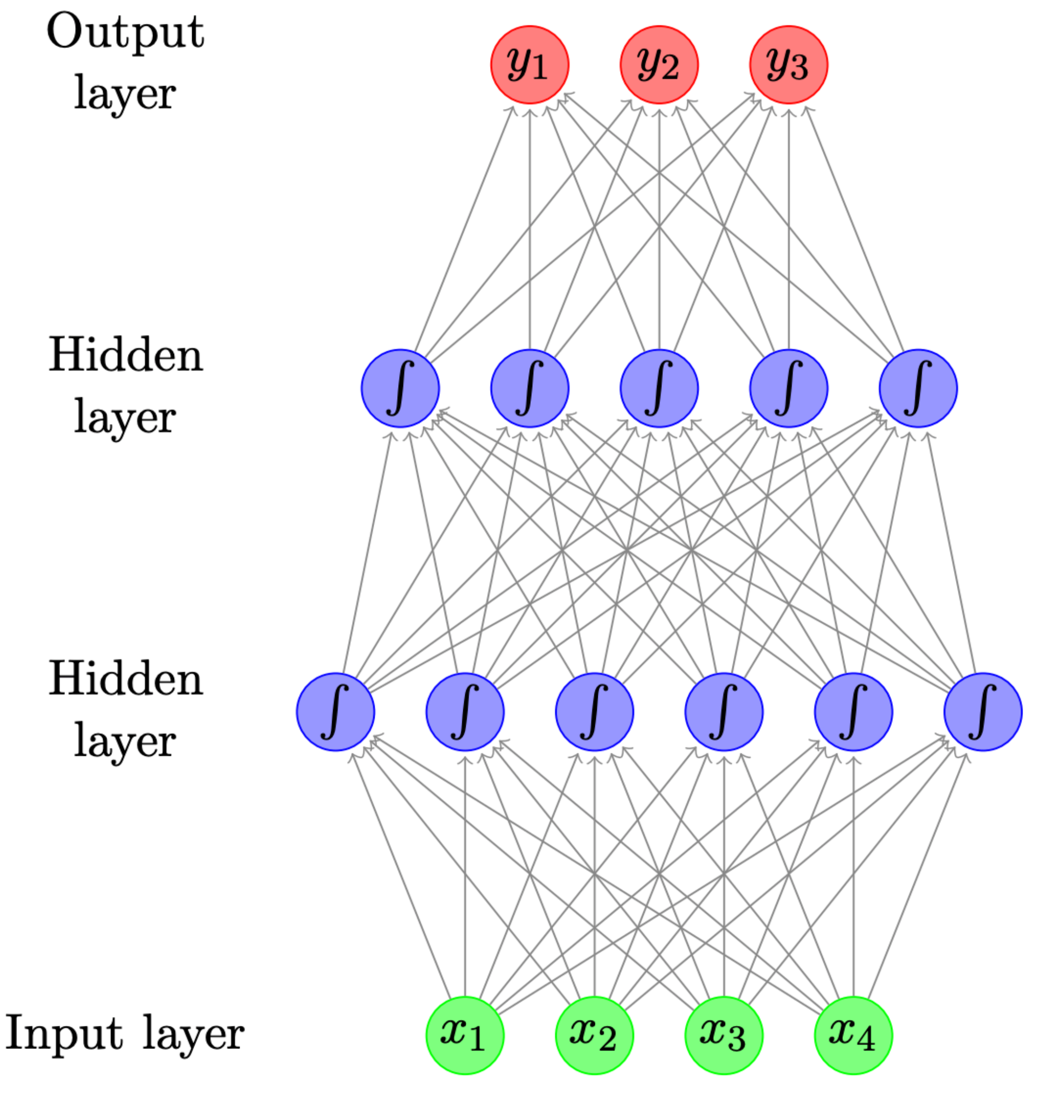

- x = [0, 2, 3, 0] for the first document
- y = [0.1, 0.6, 0.3]: probability distribution over the 3 classes

Topic Classification - Improvements

- + Bag of bigrams as input
- Preprocess text to lemmatise words and remove stopwords
- Instead of raw counts, we can weight words using TF-IDF or indicators (0 or 1 depending on presence of words)

Authorship Attribution

- Given a document, infer the identity of its author or characteristics of the author (e.g. gender, age, native language)
- Stylistic properties of text are more important than content words in this task
    - POS tags and function words (e.g. *on*, *of*, *the*, *and*)
- Good approximation of function words: top-300 most frequent words in a large corpus
- Input: bag of function words, bag of POS tags, bag of POS bigrams, trigrams
- Word weighting: density (e.g. ratio between no. of function words and content words in a window of text)
- Other features: distribution of distances between consecutive function words

Language model (Recap)

- Assign a probability to a sequence of words
- Framed as “sliding a window” over the sentence, predicting each word from finite context
  E.g., $n = 3$, a trigram model

$$P(w_1, w_2, .. w_m) = \prod_{i=1}^{m} P(w_i \,|\, w_{i-2} w_{i-1})$$

- Training (estimation) from frequency counts
  - Difficulty with rare events → smoothing

Language Models as Classifiers

LMs can be considered simple classifiers, e.g. trigram model

$$P\left(w_i \middle| \; w_{i-2} = \text{“}cow\text{”},\; \mathrm{w}_{\mathrm{i}-1} = \text{“}ea\mathrm{ts}\text{”}\right)$$

classifies the likely next word in a sequence.

Feed-forward NN Language Model

- Use neural network as a classifier to model
  $P\left(w_i \middle| \; w_{i-2} = \text{“}cow\text{”},\ \mathrm{w}_{\mathrm{i}-1} = \text{“}ea\mathrm{ts}\text{”}\right)$
  - input features = the previous two words
  - output class = the next word
- How to represent words? **Embeddings**

Word Embeddings

- Maps discrete word symbols to continuous vectors in a relatively low dimensional space
- Word embeddings allow the model to capture similarity between words
    - *dog* vs. *cat*
    - *walking* vs. *running*
- Alleviates data-sparsity problems

Topic Classification

$$\vec{h_1} = \tanh\left(W_1\vec{x} + \vec{b_1}\right)$$

$$\vec{h_2} = \tanh\left(W_2\vec{h_1} + \vec{b_2}\right)$$

$$\vec{y} = \text{softmax}(W_3\vec{h_2})$$

- x = [0, 2, 3, 0] for the first document
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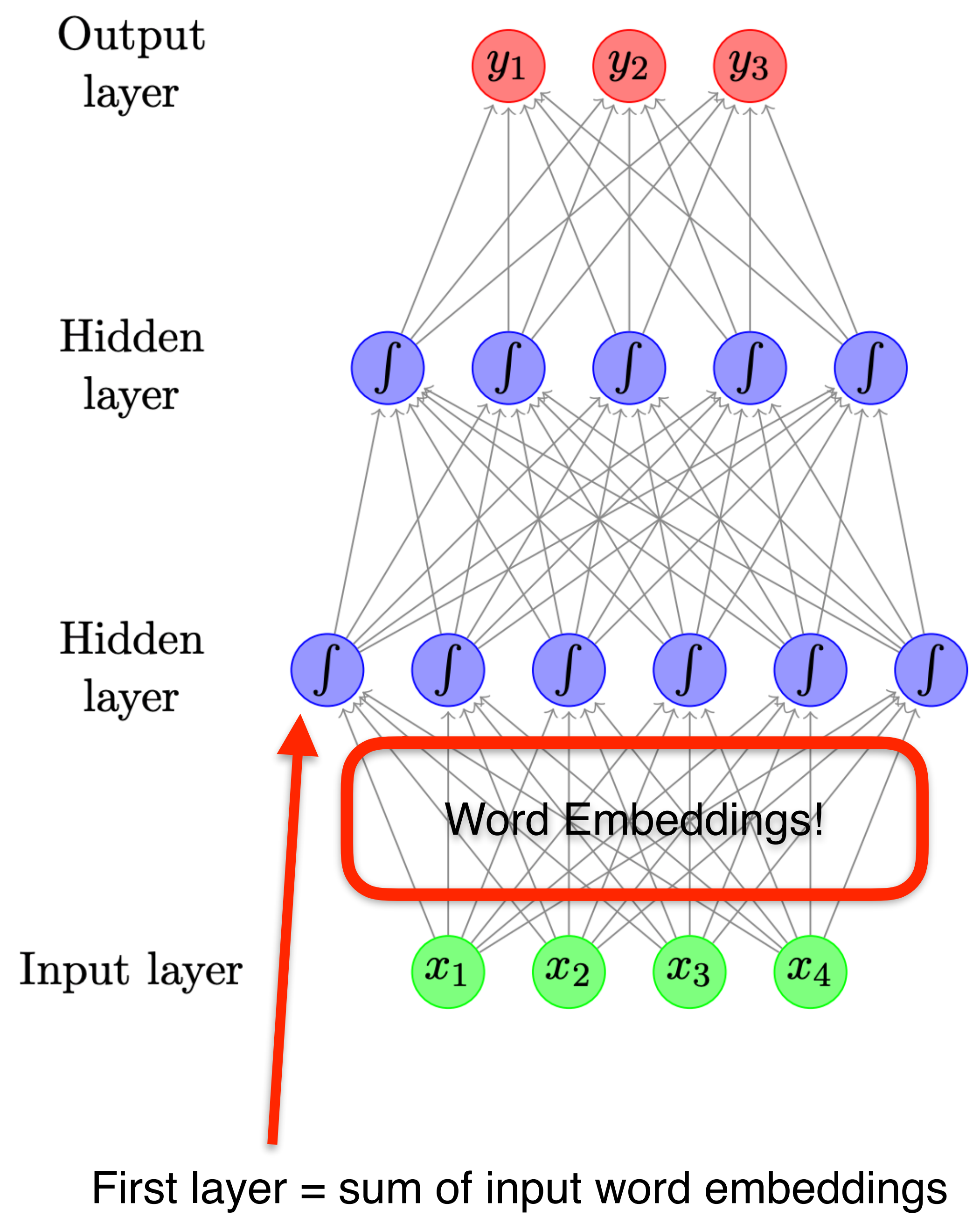
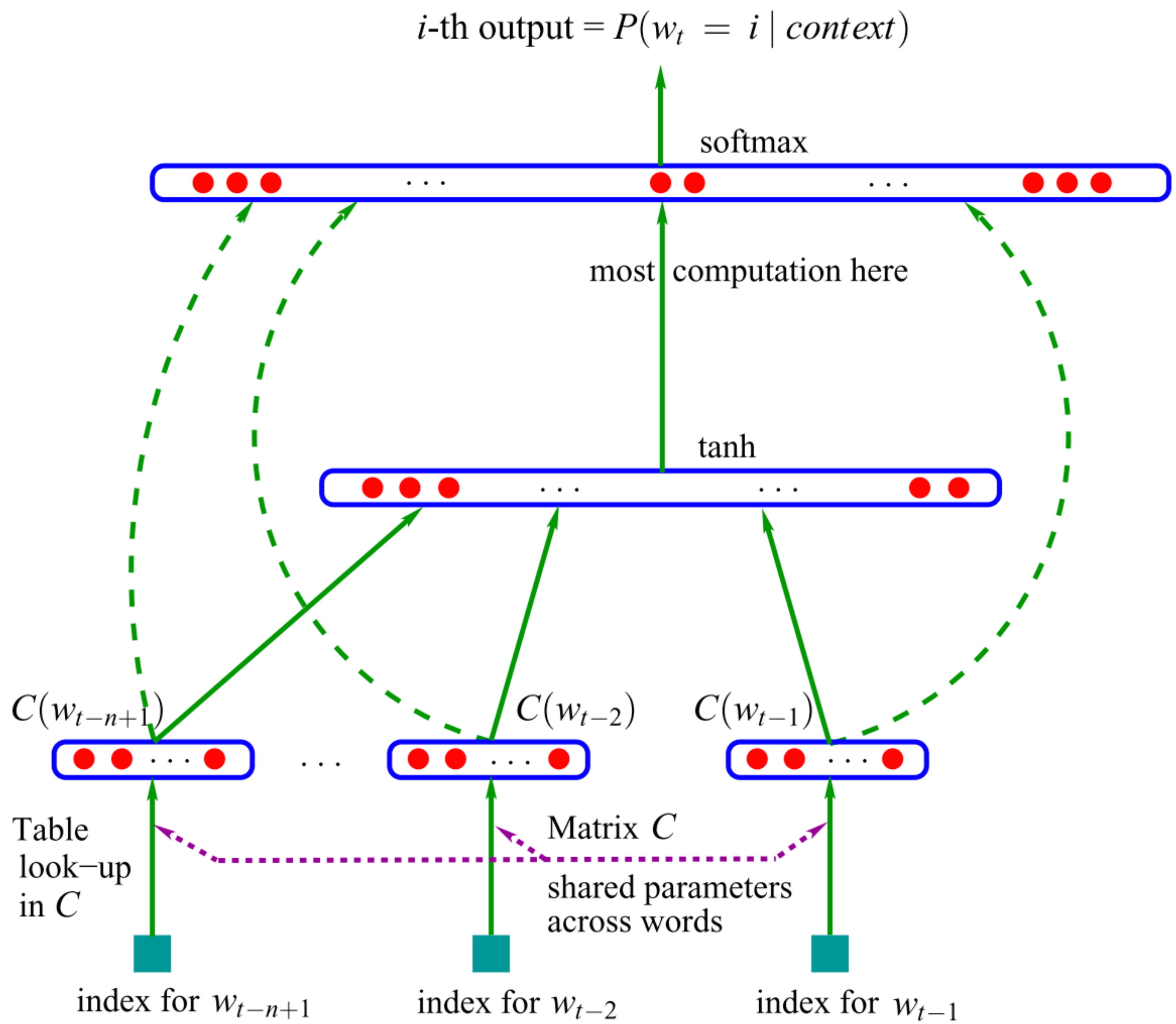


Language Model: Architecture



Bengio et al, 2003

Example

$$P(w_i = \text{“}grass\text{”} | w_{i-2} = \text{“}cow\text{”}, w_{i-1} = \text{“}eats\text{”})$$

- Lookup word embeddings for *cow* and *eats*

rabbit	grass	eats	hunts	cow
0.9	0.2	-3.3	-0.1	-0.5
0.2	-2.3	0.6	-1.5	1.2
-0.6	0.8	1.1	0.3	-2.4
1.5	0.8	0.1	2.5	0.4

- Concatenate them and feed it to the network

$$\vec{x} = \vec{v_{\text{cow}}} \oplus \vec{v_{\text{eats}}}$$

$$\vec{h_1} = tanh(W_1\vec{x} + \vec{b_1})$$

$$\vec{y} = \text{softmax}(W_2\vec{h_1})$$

Output

- *y* gives the probability distribution over all words in the vocabulary

0.01	0.80	0.05	0.10	0.04
rabbit	grass	eats	hunts	cow

$$P(w_i = \text{``}grass\text{''} | w_{i-2} = \text{``}cow\text{''}, w_{i-1} = \text{``}eats\text{''}) = 0.8$$

- Most parameters are in the word embeddings (size = d x |V|) and the output embeddings (size = |V| x d)

Example

$$P(w_i = \text{“}grass\text{”} | w_{i-2} = \text{“}cow\text{”}, w_{i-1} = \text{“}eats\text{”})$$

- Lookup word embeddings for *cow* and *eats*

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1.5	0.8	0.1	2.5	0.4

Word embeddings
d x |V|

- Concatenate them and feed it to the network

$$\vec{x} = v_{\vec{\text{cow}}} \oplus v_{\vec{\text{eats}}}$$

$$\vec{h_1} = tanh(W_1\vec{x} + \vec{b_1})$$

$$\vec{y} = \text{softmax}(W_2\vec{h_1})$$

Output word embeddings
|V| x d

Why Bother?

- Ngram LMs
  - cheap to train (just compute counts)
  - problems with sparsity and scaling to larger contexts
  - don’t adequately capture properties of words (grammatical and semantic similarity), e.g., film vs movie
- NNLMs more robust
  - force words through low-dimensional embeddings
  - automatically capture word properties, leading to more robust estimates
  - flexible: minor change to adapt to other tasks (tagging)

POS Tagging

- POS tagging can also be framed as classification:

$$P\left(t_i \middle| \; w_{i-1} = \text{“}cow\text{”},\ \mathrm{w_i} = \text{“}eats\text{”}\right)$$

classifies the likely POS tag for “eats”.

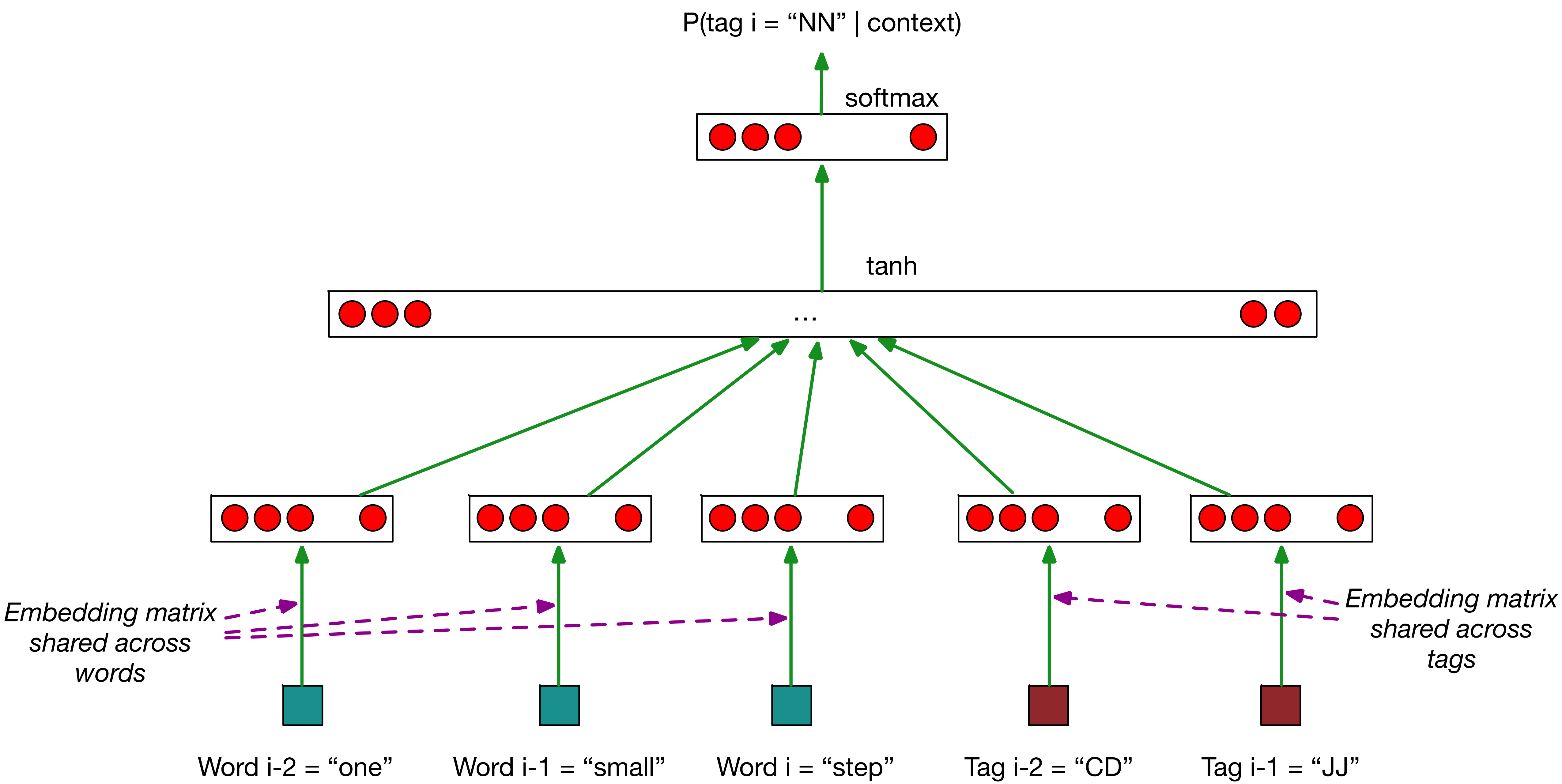
- Why not use a fancier classifier? (Neural net)
- NNLM architecture can be adapted to the task directly

Feed-forward NN for Tagging

- MEMM tagger takes as input:
  - recent words w_{i-2}, w_{i-1}, w_i
  - recent tags t_{i-2}, t_{i-1}
- And outputs: current tag t_i
- Frame as neural network with
  - 5 inputs: 3 x word embeddings and 2 x tag embeddings
  - 1 output: vector of size |T|, using softmax
- Train to minimise

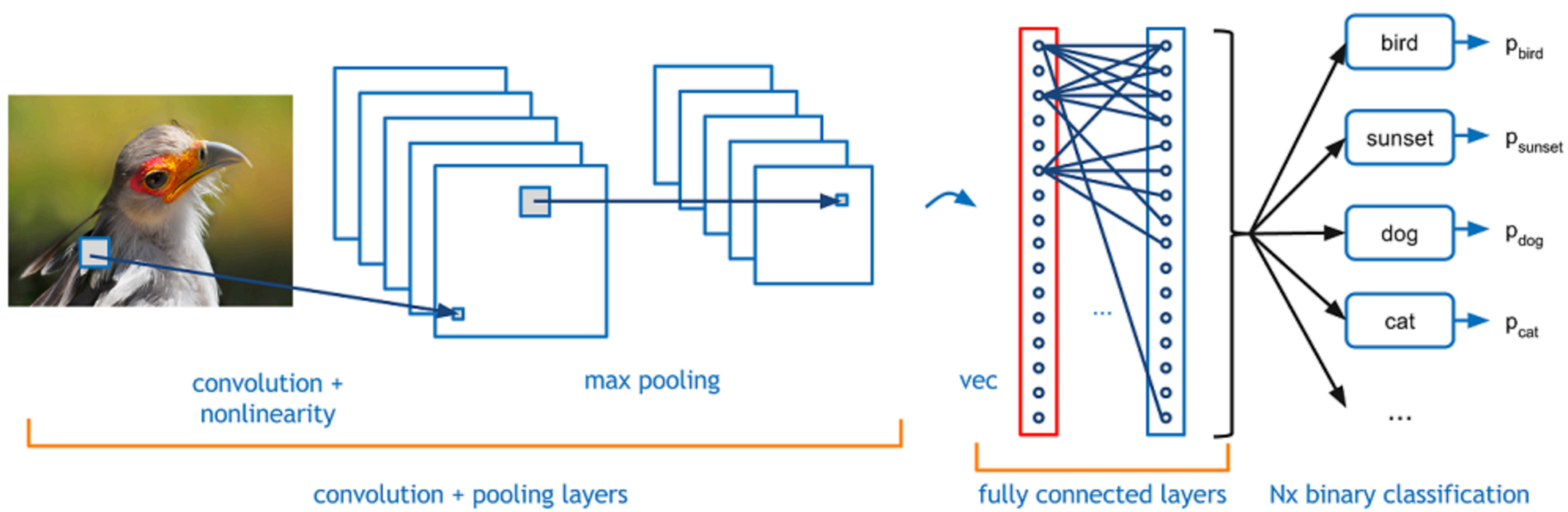
$$-\sum_i \log P(t_i \mid w_{i-2}, w_{i-1}, w_i, t_{i-2}, t_{i-1})$$

FF-NN for Tagging



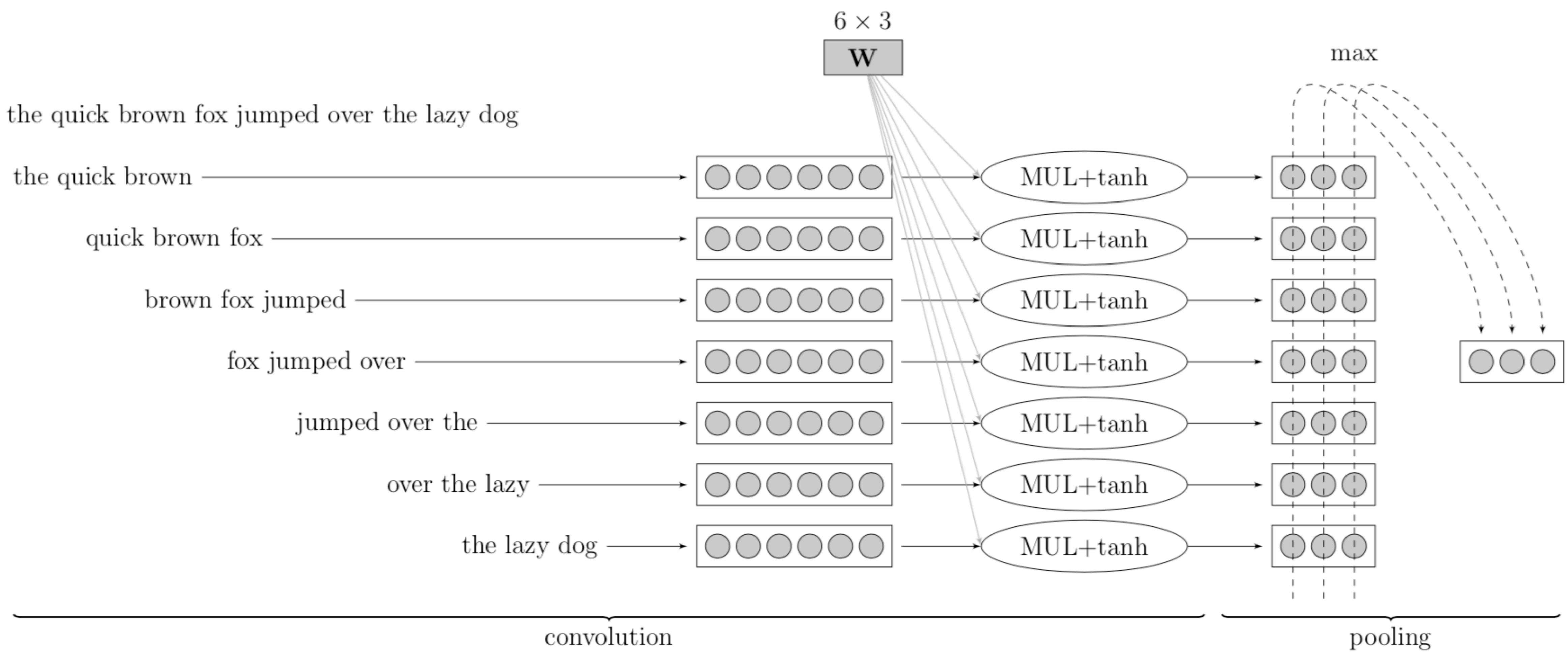
Convolutional Networks

- Commonly used in computer vision
- Identify indicative local predictors
- Combine them to produce a fixed-size representation



https://adeshpande3.github.io/A-Beginner%27s-Guide-To-Understanding-Convolutional-Neural-Networks/

Convolutional Networks for NLP



- Sliding window (e.g. 3 words) over sequence
- W = convolution filter (linear transformation+tanh)
- max-pool to produce a fixed-size representation

Final Words

- Neural networks
  - Robust to word variation, typos, etc
  - Excellent generalization
  - Flexible — customised architecture for different tasks
- Cons
  - Much slower than classical ML models… but GPU acceleration
  - Lots of parameters due to vocabulary size
  - Data hungry, not so good on tiny data sets
  - Pre-training on big corpora helps

Readings

- Feed-forward network: G15, section 4
- Convolutional network: G15, section 9