Natural Language Processing

COMP 4630 | Winter 2025

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Overview

- Text to tokens
- Tokens to embeddings
- Embeddings to predictions
- References and suggested reading:
    - Scikit-learn book: Chapter 16
    - Deep Learning Book: Chapter 12

Tokenization

- Consider the sentence:

> *"The cat sat on the mat."*

- This can be split up into individual words or **tokens**:

> *["The", "cat", "sat", "on", "the", "mat", "."]*

- ❓ what other ways could we tokenize this sentence?
- ❓ what about punctuation, capitalization, etc.?

RNN + tokens: predict the next character

- Just like predicting the next day's weather or stock price, we can predict the next character in a sentence using an RNN
- Input tokens: `['T', 'h', 'e', ' ', 'c', 'a', 't', ' ', 's', 'a', 't', ' ', 'o', 'n', ' ', 't', 'h', 'e', ' ', 'm', 'a', 't', '.']`
- Numeric representation: `[20, 8, 5, 0, 3, 1, 20, 0, 19, 1, 20, 0, 15, 14, 0, 20, 8, 5, 0, 13, 1, 20, 2]`
- We could train an RNN model to predict the next character
- For more info check out Andrej Karpathy's blog post, one of the sources for the Scikit-learn chapter

Repeatedly predicting the next character

- To predict whole sentences from a starting point, we can predict the next character and append it to the input, then predict again
- In practice this tends to get stuck in loops:
  Input: `"to be or not"`
  Output: `"to be or not to be or not to be or not..."`
- ❓ how might we avoid this?
- ❓ could we just predict the next whole word instead?

Controlled chaos: softmax temperature

- The softmax is defined as:

$$\mathrm{softmax}(\mathbf{z})_i = \frac{\exp(z_i)}{\sum_{j=1}^{n} \exp(z_j)}$$

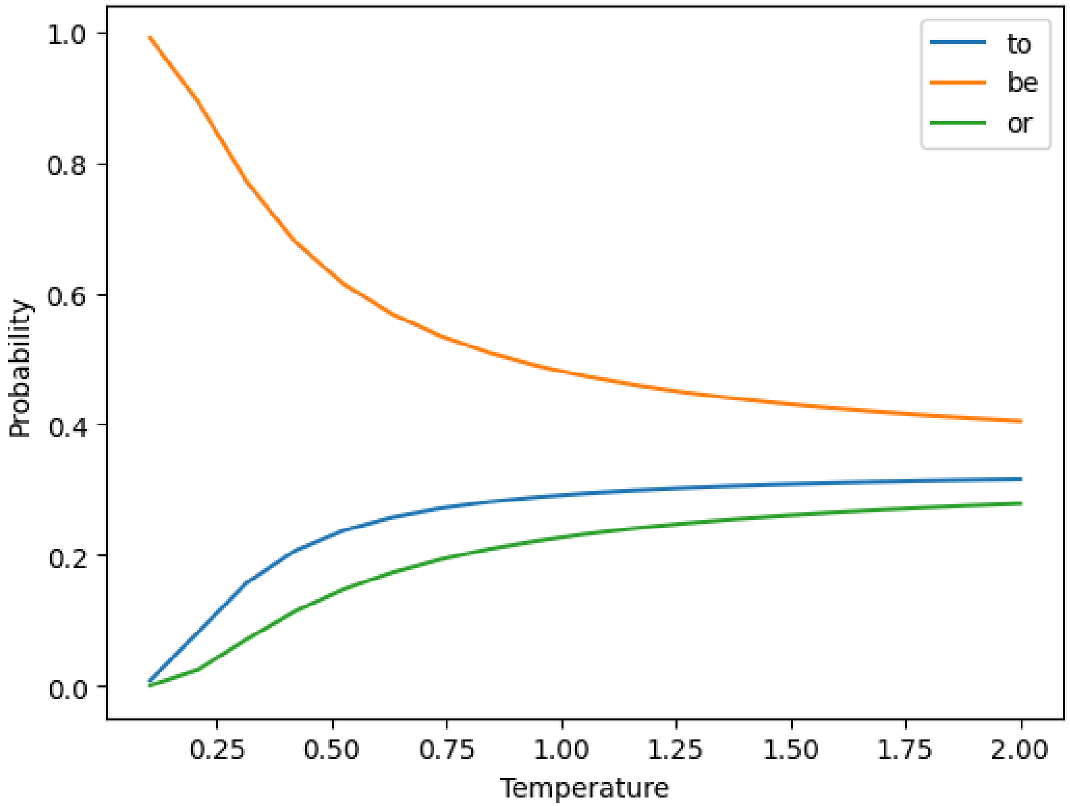
  where $\mathbf{z}$ is a vector of **logits**, or log probabilities

- This estimates the probability of class i out of n classes
- Adding a temperature parameter T:

$$\mathrm{softmax}(\mathbf{z}/T)_i = \frac{\exp(z_i/T)}{\sum_{j=1}^{n} \exp(z_j/T)}$$

Temperature Example

- Vocab = `["to", "be", "or"]`
- Assume that the "logits" $z_i = [2.1, 1.0, 0.5]$
- **Sample** the next word from the resulting distribution



In the beginning, there were n-grams

- A simple way to represent text is as a bag of n-grams
- unigram: single words (aka "Bag of Words"):

> *["the", "cat", "sat", "on", "the", "mat"]*

- bigram: pairs of words:

> *["the cat", "cat sat", "sat on", "on the", "the mat"]*

- trigram: triples of words:

> *["the cat sat", "cat sat on", "sat on the", "on the mat"]*

Predictive text with n-grams

- Given a sequence of tokens, we can predict the probability of the nth token given the previous $n-1$ tokens:

$$P(x_1, \ldots, x_\tau) = P(x_1, \ldots, x_{\tau-1}) \prod_{t=n}^{\tau} P(x_t | x_{t-n+1}, \ldots, x_{t-1})$$

- Each of these conditional probabilities can be estimated from the frequency of the n-grams in a **corpus**
- The most likely next word is the one with the highest probability
- ❓ What are some limitations of this approach?

n-grams challenges

- n-grams lose the meaning of words:
  - "The cat sat on the mat"
  - "The dog sat on the rug"
- Also subject to the **curse of dimensionality**
  - Vocabulary $\mathbb{V}$ with size $|\mathbb{V}|$ leads to $|\mathbb{V}|^n$ possible n-grams
  - Most n-grams will not be present in the corpus!
- ❓ Can you think of an n-gram modification that could help this problem?

Side note: The curse of dimensionality

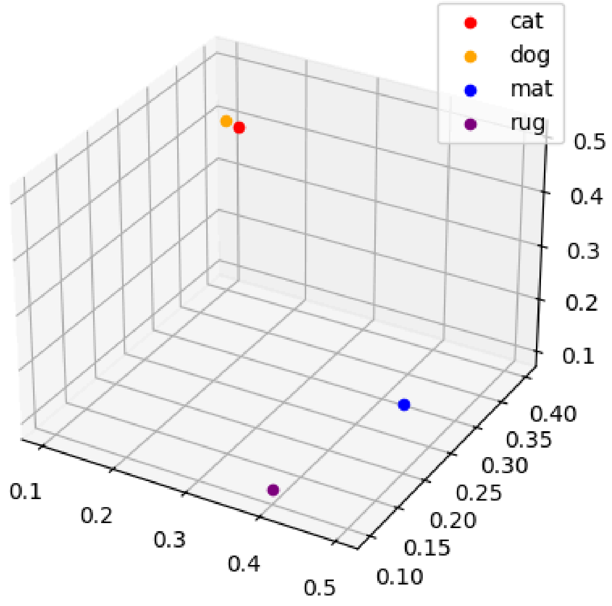
- Data is often represented as n samples with p features each
- As p increases, the number of samples required to cover the space increases exponentially
- Also called $p \gg n$ problem

Figure 5.9 from the Deep Learning Book

Word embeddings

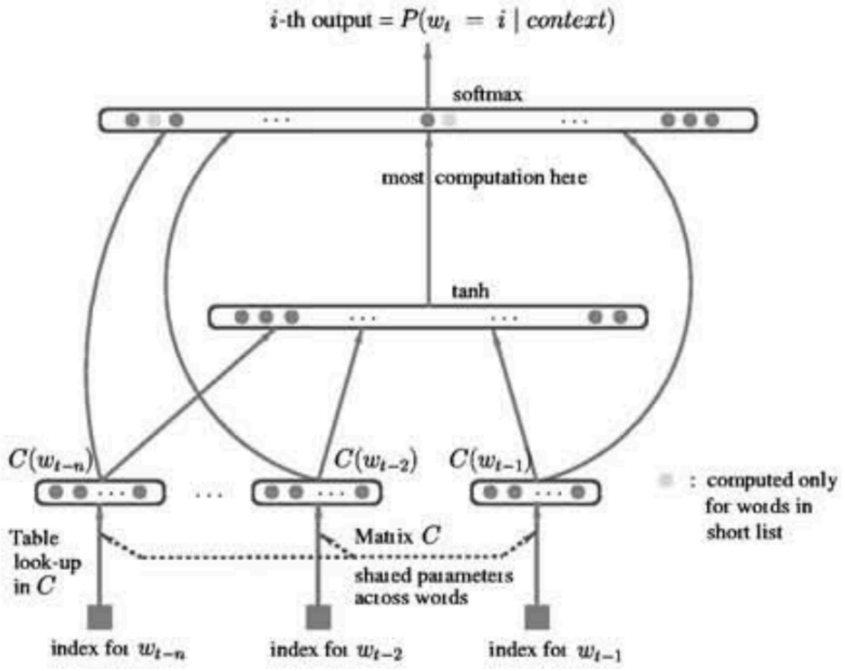
- Alternative solution: represent individual words as vectors, or **embeddings**
- ❓ How are these embeddings defined?

Word	Embedding
cat	`[0.2, 0.3, 0.5]`
dog	`[0.1, 0.4, 0.4]`
mat	`[0.5, 0.2, 0.2]`
rug	`[0.4, 0.1, 0.1]`



Learning word embeddings

- ~~Wednesday~~ Friday we'll discuss the influential **Word2Vec** paper, but it wasn't the first time embeddings were learned as part of a network
- The concept was first presented successfully by Bengio in 2001



So we have embeddings, now what?

- We can use these embeddings as input to a neural network
- Applications:
  - **Sentiment analysis**: is a review/tweet/comment positive or negative?
  - **Named entity recognition**: who/what is mentioned in a text?
  - **Machine translation**: convert text from one language to another
  - **Predictive text**: what word comes next?
  - **Text generation**: create new text based on a given input

Sentiment analysis

General pipeline:

- Standardize and tokenize the text
- Add an embedding layer (trainable or pre-trained)
- Add a recurrent layer, such as a GRU
- Add a dense layer with sigmoid activation

To Colab!

Sequence to Sequence models

Back to RNNs

- RNNs predict the future based on the past
- This is exactly what we want for predicting stock prices, weather, etc
- ❓ what if we want to predict the next word in a sentence?
- ❓ what about translating a sentence from one language to another?

> *Time flies like an arrow; fruit flies like a banana.*

- ❓ Can you think of a way to get RNNs to see the future?

Bidirectional RNNs

- Simple approach: just reverse the sequence

$$\mathbf{h}_t = \mathbf{W}_x^{(f)T}\mathbf{x}_t + \mathbf{W}_h^T\mathbf{h}_{t-1} + \mathbf{b}^{(f)}$$
$$\mathbf{g}_t = \mathbf{W}_x^{(b)T}\mathbf{x}_t + \mathbf{W}_g^T\mathbf{g}_{t+1} + \mathbf{b}^{(b)}$$
$$\hat{\mathbf{y}}_t = \mathbf{h}_t + \mathbf{g}_t$$

- ❓ Drawbacks?

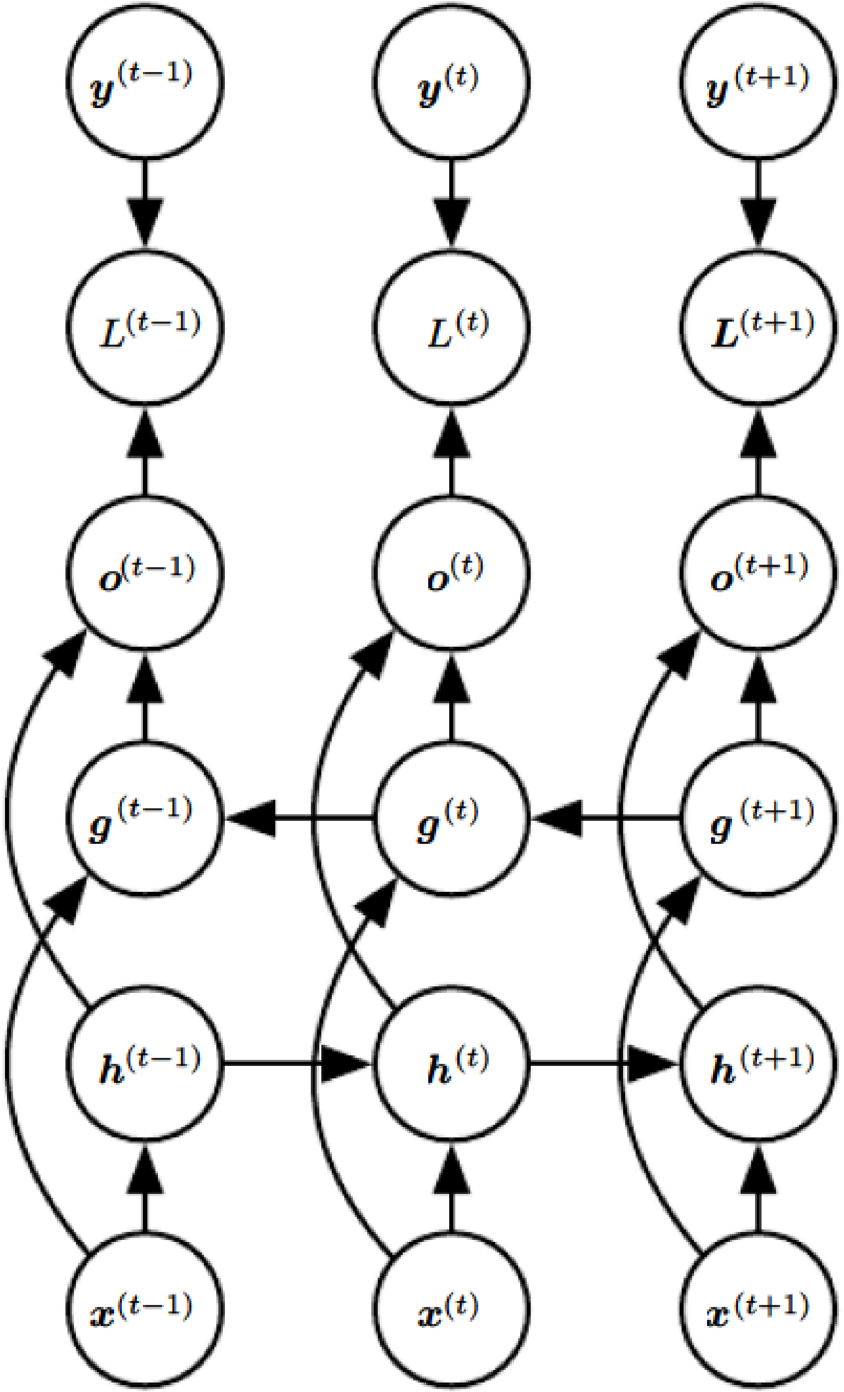


Figure 10.11 from the Deep Learning Book

Pretrained Embeddings and transfer learning

- Embeddings like Word2Vec have been trained on large corpora
- Surely this provides a great starting point for our models!
  - ❓ why might we want to use pretrained embeddings?
  - ❓ what are some potential drawbacks?
- ELMo was introduced in 2018 specifically to address the limitations of Word2Vec and GloVe (another popular embedding)

> *"Our representations differ from traditional word type embeddings in that each token is assigned a representation that is a function of the entire input sentence. We use vectors derived from a bidirectional LSTM that is trained with a coupled language model objective on a large text corpus"*

Subword Tokenization

- Word embeddings are great, but still have limitations
- ELMo uses **character** tokenization to handle out-of-vocabulary words
- In between characters and words are **subwords**
  - `"This warm weather is enjoyable"`
  - `"This", "warm", "weath", "er", "is", "enjoy", "able"`
- Byte Pair Encoding is the most common subword tokenization method, used by GPT and BERT
- ❓ What are some advantages of subword tokenization?

Machine Translation

English	Spanish
My mother did nothing but weep	Mi madre no hizo nada sino llorar
Croatia is in the southeastern part of Europe	Croacia está en el sudeste de Europa
I would prefer an honorable death	Preferiría una muerte honorable
I have never eaten a mango before	Nunca he comido un mango

- ❓ What kind of challenges can you think of?
- ❓ How might you approach this problem?

Encoder-Decoder Models

- RNNs can convert an arbitrary length **sequence** into a fixed length **vector**
- RNNs can convert a fixed length **vector** into an arbitrary length **sequence**
- Why not use two RNNs to convert a **sequence** to a **sequence**?
- The output head is a softmax layer with one node for **each word** in the target vocabulary $\mathbb{V}$
  - ❓ What problems can you think of with this approach?
  - ❓ How might you address these problems?

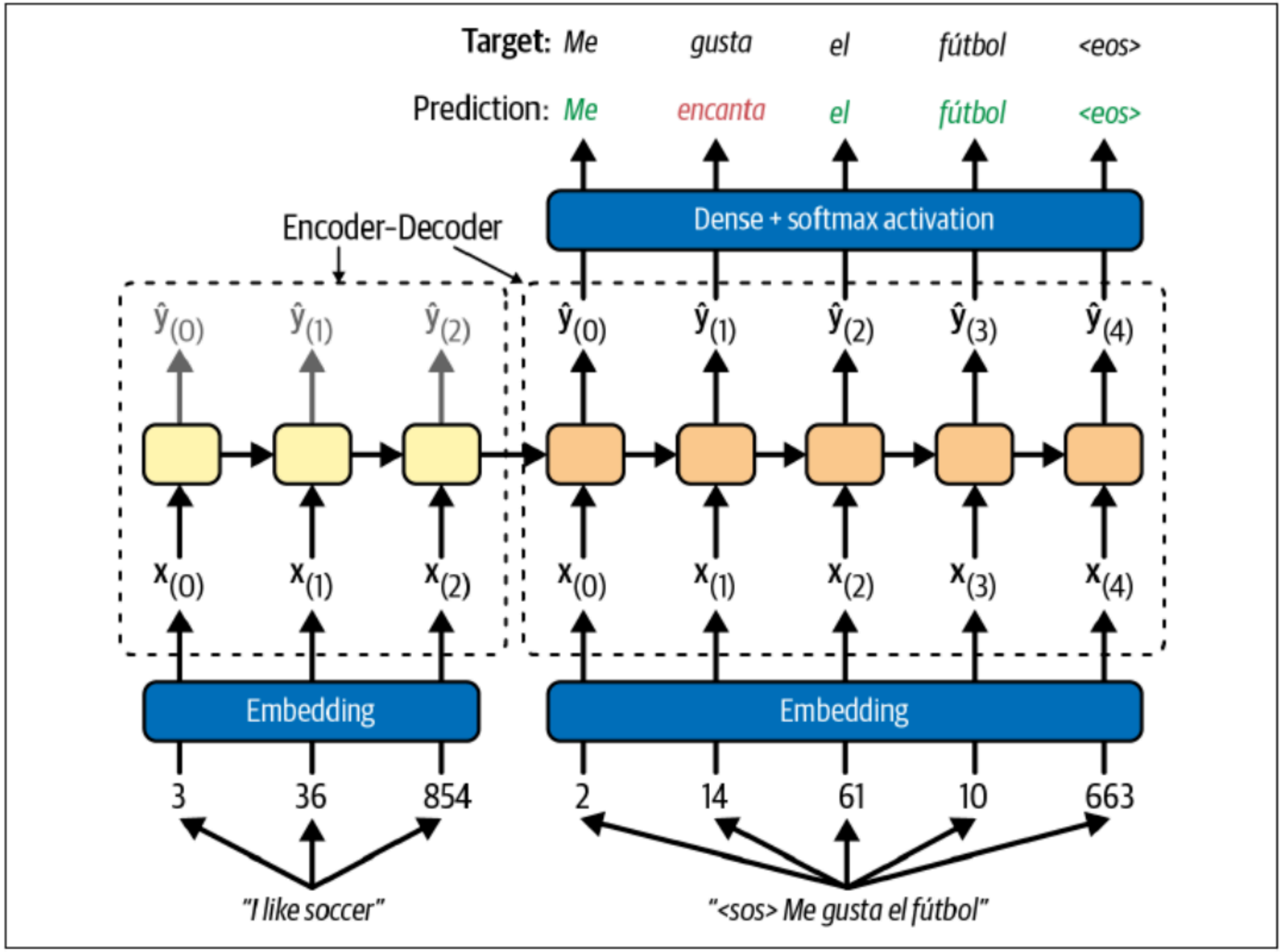


Figure 16-3. A simple machine translation model

Teacher Forcing

- This model uses **teacher forcing** to train the decoder
- It feels like cheating, but this involves feeding the **correct output** to the decoder at each time step
- This speeds up training and can improve performance
- Avoids the whole backpropagation through time thing and makes training of RNNs parallelizable
- ❓ How would this work with LSTM/GRU cells?
- ❓ What are the implications at inference time?

Coming up next: Attention mechanisms and Transformers