Sequence-to-sequence models: Part II

Seq2Seq / encoder-decoder models

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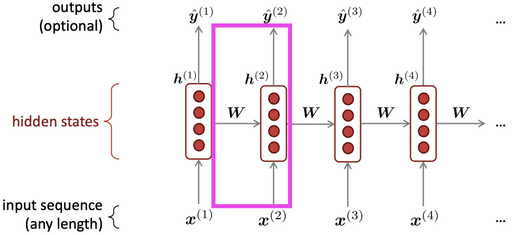
Outline

Recap: Recurrent Neural Networks

- RNNs [Hopfield, 1982; Rumelhart et al., 1985] are capable of conditioning the model on *all* previous tokens (in theory)



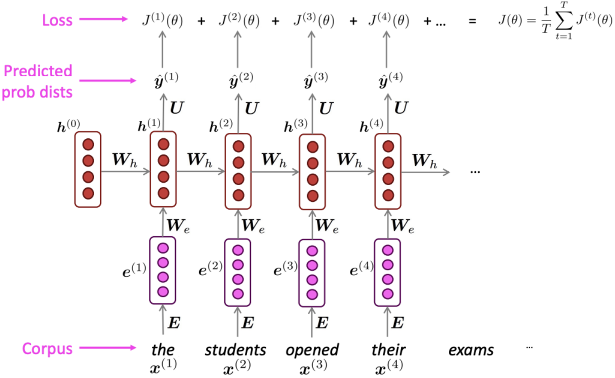
[1]

- Core idea: the hidden layer from previous timestep provides a form of memory or context that informs decisions to be made later in the sequence
- The same weights are applied at every timestep

[1] Manning et al. [2017]

Recap: Training RNN language models

- We use the cross-entropy loss between the output distribution $\hat{\boldsymbol{y}}^{(t)}$ and $\boldsymbol{y}^{(t)}$ (and average over the entire batch/corpus)
- We use teacher-forcing: input the previous words/tokens to predict the next

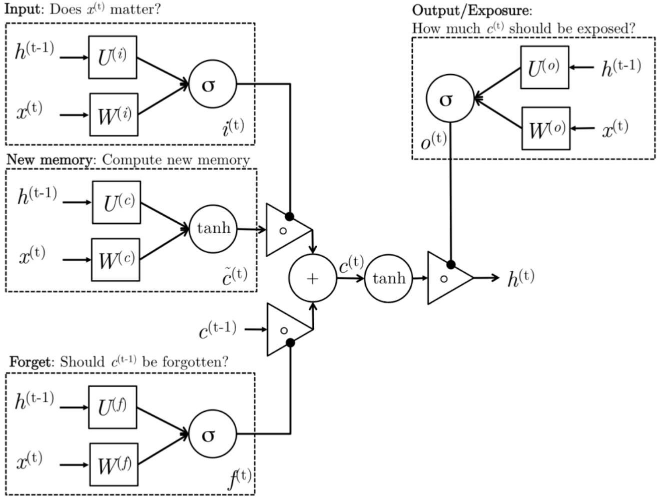


[2] Manning et al. [2017]

Recap: LSTMs

- "Vanilla" RNNs can be difficult to train
  - Vanishing/exploding gradients mean its hard to preserve memory over many timesteps
  - The hidden layers/states and weights are asked to do a *lot* of work
- Long short-term memory (LSTM) networks [Hochreiter and Schmidhuber, 1997; Gers et al., 2000] are the most commonly used extension to RNNs
  - In practice, could preserve information to about 100 timesteps rather than 7 in "vanilla" RNNs
  - See "Understanding LSTM Networks" [Olah, 2015] for a bit more of a deeper explanation and walkthrough

Recap: LSTM architecture



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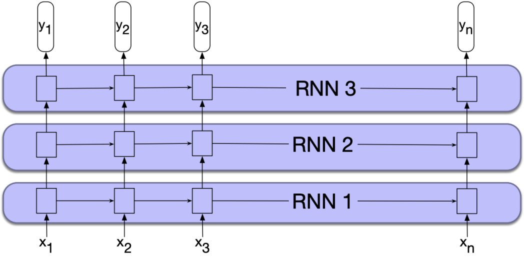
[3] Manning et al. [2017]

Stacked / Deep RNNs

- We can use the entire sequence of outputs from one RNN as the input of another RNN to create a stack of RNNs



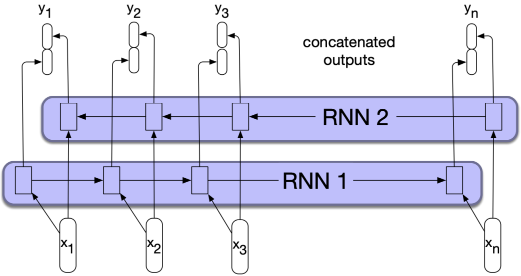
[4]

  - Outputs of one layer serves as input to a subsequent layer
  - Typically outperforms single-layer networks but increases training cost

[4] Jurafsky and Martin [2019, Chapter 9]

Bidirectional RNNs

- Run two separate RNNs: left-to-right (we've seen above) and right-to-left
- Then concatentate the hidden states from both RNNs
  - Alternatives: element-wise mean or sum

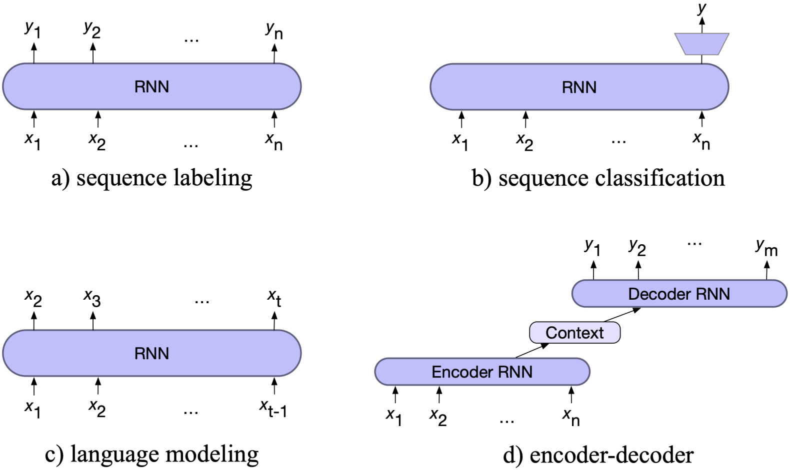


[5]

  - Effective if you have access to a full input sentence (to encode a sentence)
  - "BERT": Bidirectional Encoder Representations from Transformers

[5] Jurafsky and Martin [2019, Chapter 9]

RNN tasks

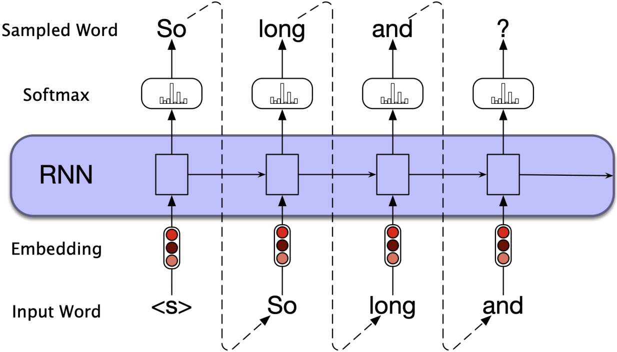


[6]

[6] Jurafsky and Martin [2019, Chapter 9]

Language modelling

- Causal language modelling / autogregressive generation: incremental generation of words by repeated sampling of the next word conditional on previous choices
  - <s>: beginning of sentence marker
  - </s>: end of sentence marker



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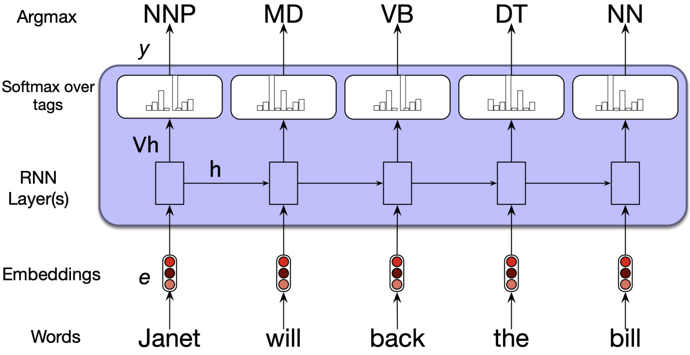
[7] Jurafsky and Martin [2019, Chapter 9]

Sequence labelling

- In sequence labelling, we aim to assign a label to each element in the sequence:
  - e.g. part-of-speech tagging, named entity recognition

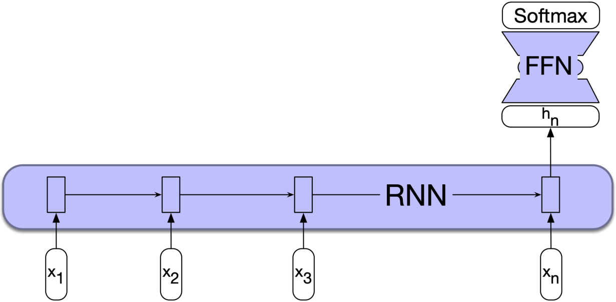


[8]

[8] Jurafsky and Martin [2019, Chapter 9]

Sequence classification

- In sequence classification, we use the RNN to classify the entire sequence (rather than the individual elements/tokens):
  - e.g. sentiment analysis, spam detection, document-level topic classification
- The loss comes from the final task, and we backpropagate through the entire network, i.e end-to-end training



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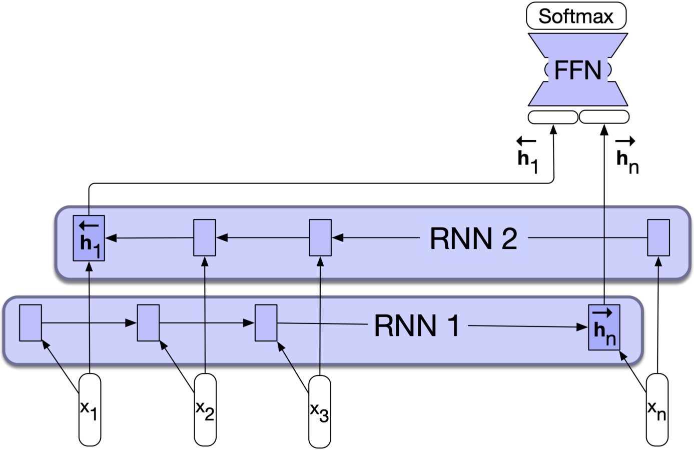
[9] Jurafsky and Martin [2019, Chapter 9]

Sequence classification (with bidirectional RNN)

- If we have access to the full sequence, a bidirectional RNN can provide a more effective encoding of the sequence



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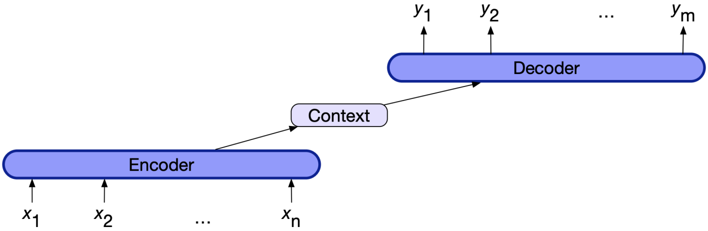
[10] Jurafsky and Martin [2019, Chapter 9]

Seq2Seq / Encoder-decoder RNN

- An architecture which takes in an input sequence and outputs a sequence that is of different length
  - Sequence labelling (part-of-speech tagging / named entity recognition) have two sequences that have the same length
- Some example use cases:
  - Machine translation, summarisation, question answering



[11]

[11] Jurafsky and Martin [2019, Chapter 9]

Seq2Seq architecture

- Able to generate context appropriate, arbitrary length output sequences *given* an input sequence
  - Encoder network: takes in input sequence to produce a contextualised representation of it
  - Decoder network: takes in the context produced to generate a text-specific output sequence
- For example, an RNN Seq2Seq model:
  - The *encoder RNN* produces a context

$$\boldsymbol{c} = f(\boldsymbol{h}^e_{1:n}) \tag{1}$$

    where $\boldsymbol{h}^e_{1:n} = \{\boldsymbol{h}^e_1, \ldots, \boldsymbol{h}^e_n\}$ are the hidden states of the encoder RNN
  - The *decoder RNN* accepts $\boldsymbol{c}$ and generates a sequence of hidden states $\boldsymbol{h}^d_{1:m}$ to form corresponding sequence of output states $\boldsymbol{y}_{1:m}$ (where possibly $m \neq n$)

Machine translation

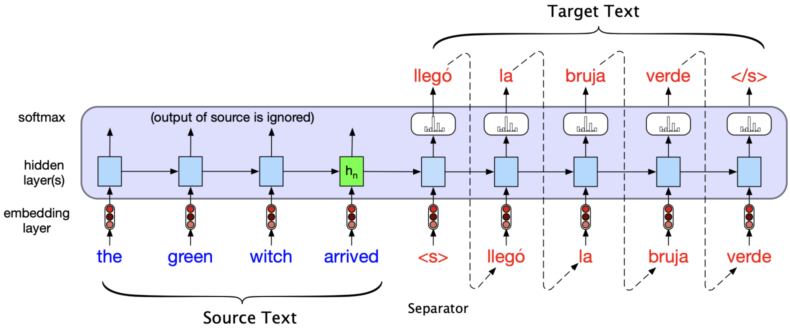
- Machine translation (MT) is the task of translating a sentence x in one language (source language) to a sentence y (target language)
- Early 1950s: MT research started but relied heavily on simple rule-based systems using word substitution
- 1990s-2010s: Statistical machine translation (SMT)
  - Want to find the "best" target sentence y given the source sentence x:

$$\text{argmax}_y p(y|x) = \text{argmax}_y p(x|y)p(y) \tag{2}$$

  - $p(x|y)$: translation model whose goal is to model how phrases are translated (trained with sentence pairs)
  - $p(y)$: language model whose goal is to write sensible sentences
- Systems were extremely complex which required lots of feature engineering and human effort to maintain
- Repeated effort for different language pairs

Seq2Seq for machine translation

- Neural machine translation (NMT): use a single end-to-end neural network
- Each training example is a pair of strings: `source, target`
  - Concatenate with a separator token, e.g. `<s>`, `<EOS>`, etc.



[12] Jurafsky and Martin [2019, Chapter 9]

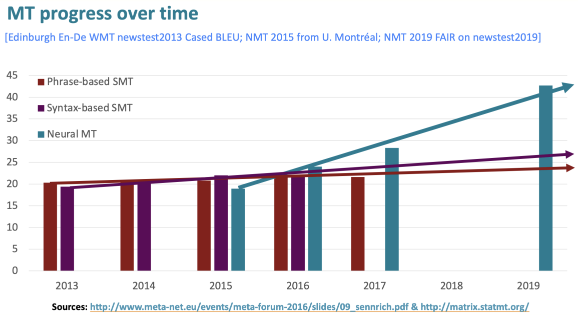
Seq2Seq for machine translation

- The sequence-to-sequence model for NMT is an example of a conditional language model
  - Language model: the decoder is predicting the next word in the target sentence y
  - Conditional: the predictions are also *conditioned* on some source sentence x
- NMT *directly* estimates $p(y|x)$:

$$p(y|x) = p(y_1|x) \cdot p(y_2|y_1, x) \cdot p(y_3|y_{1:2}, x) \cdots p(y_T|y_{1:T-1}, x) \tag{3}$$

Seq2Seq successes in machine translation

- BLEU: Bilingual Evaluation Understudy
  - Compares a machine-written translation to one or several human-written translation(s) and computes a similarity score based on *n*-gram precision
  - Adds a penalty for translations which are too short
- BLEU is useful but not perfect: there are many valid ways to translate a sentence



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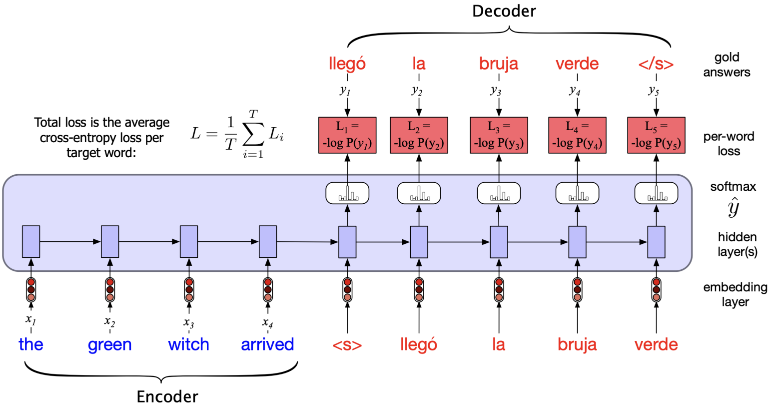
[13] Manning et al. [2017, Lecture 6]

Training Seq2Seq

- Use teacher-forcing and compute the average loss over the predicted sequence
- Encoder-decoder architectures are trained end-to-end



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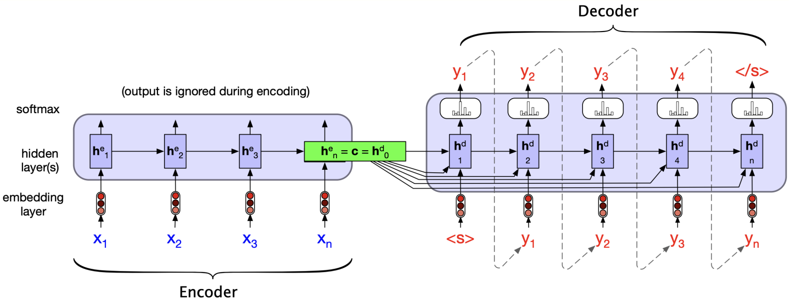
[14] Jurafsky and Martin [2019, Chapter 9]

Propagating the context

- Problem: the influence of the context, $\boldsymbol{c}$, decreases as the output sentence is generated
- Solution: Make $\boldsymbol{c}$ available at each step of the decoding process:

$$\boldsymbol{h}_t^d = g(\hat{\boldsymbol{y}}_{t-1}, \boldsymbol{h}_{t-1}^d, \boldsymbol{c}), \quad \text{for } t = 1, \ldots, m \tag{4}$$

where $\boldsymbol{c} = f(\boldsymbol{h}_{1:n}^e)$ and $\boldsymbol{h}_0^d = \boldsymbol{c}$



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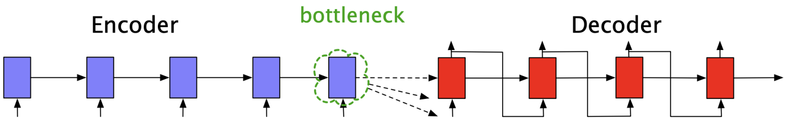
[15] Jurafsky and Martin [2019, Chapter 9]

Weaknesses of Seq2Seq

- Problem: the context $\boldsymbol{c}$ from the encoder must represent everything about the meaning of the source text
  - Information at different parts of the source text may not be equally represented in the context vector
- The attention mechanism is a solution: allows the decoder to access all hidden states in the encoder, not just $\boldsymbol{c}$



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[16] Jurafsky and Martin [2019, Chapter 9]

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