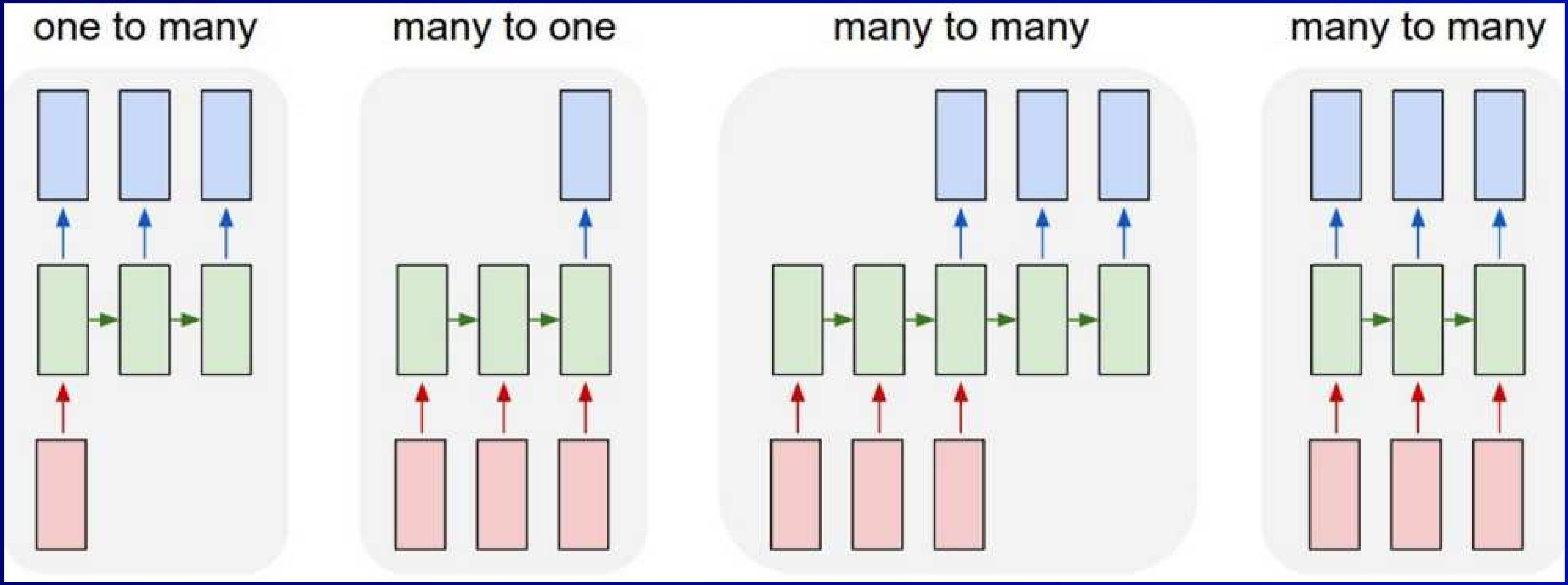
Natural Language Processing

Lecture 10
RNN sequence models and attention

2021

Sequence processing with RNNs

Depending on the way inputs, outputs and hidden/cell states are handled, RNNs can be used for a variety of sequence transformation and processing tasks:



(Figure from Karpathy [2015]).

Sequence processing with RNNs cont.

Perhaps the most basic is the many-to-many transformation of an $\langle \mathbf{x}_1, \dots, \mathbf{x}_n \rangle$ input sequence to the $\langle \mathbf{y}_1, \dots, \mathbf{y}_n \rangle$ sequence of corresponding outputs at each time step.

This type of architecture can be used e.g., for sequence tagging, when the outputs are distributions over the tags.

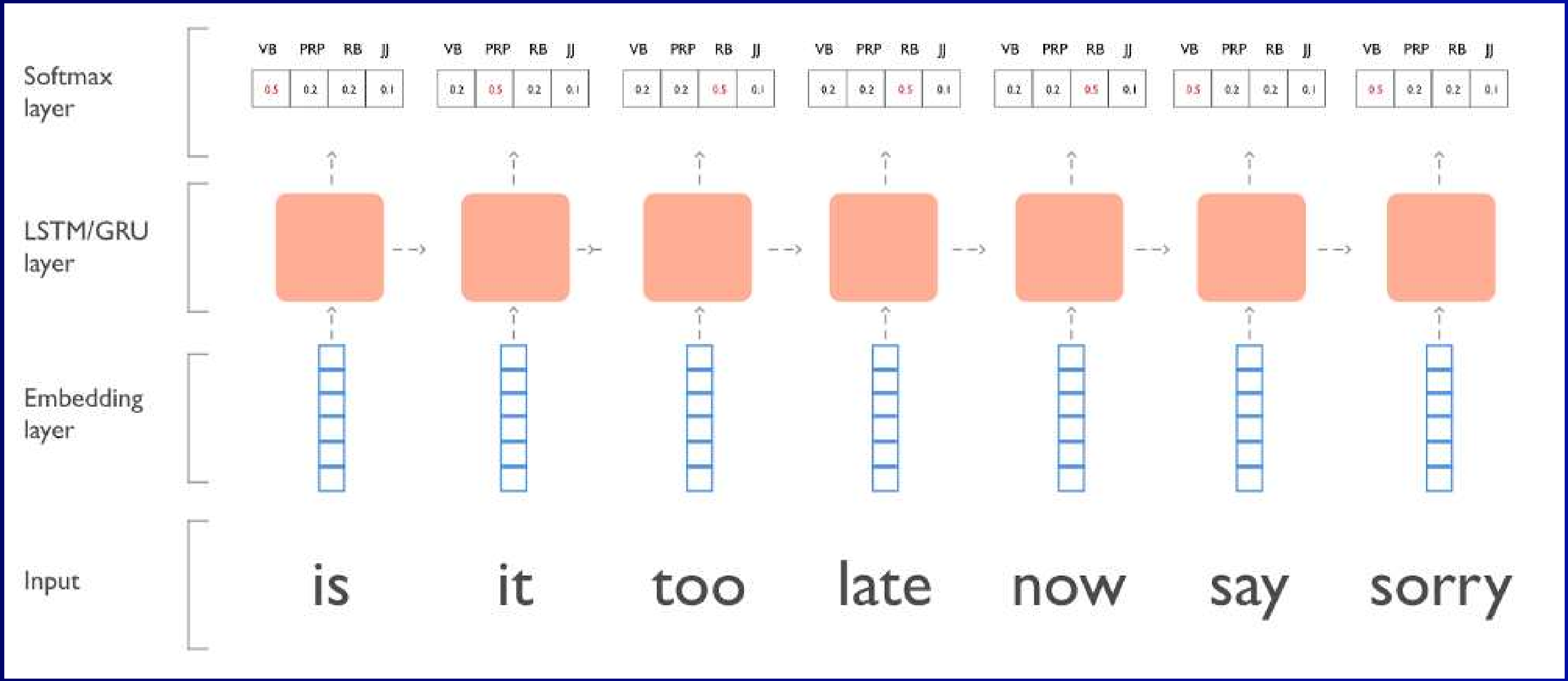
Language modeling can be considered a special case of sequence tagging, when the correct "tag" of each word in a text is simply the next word:

$$\mathbf{x} = \langle w_1, \dots, w_{n-1} \rangle,$$

$$\mathbf{y} = \langle w_2, \dots, w_n \rangle.$$

Sequence tagging

A simple tagging example: LSTM-based POS-tagger with word-embedding input and softmax output layers.



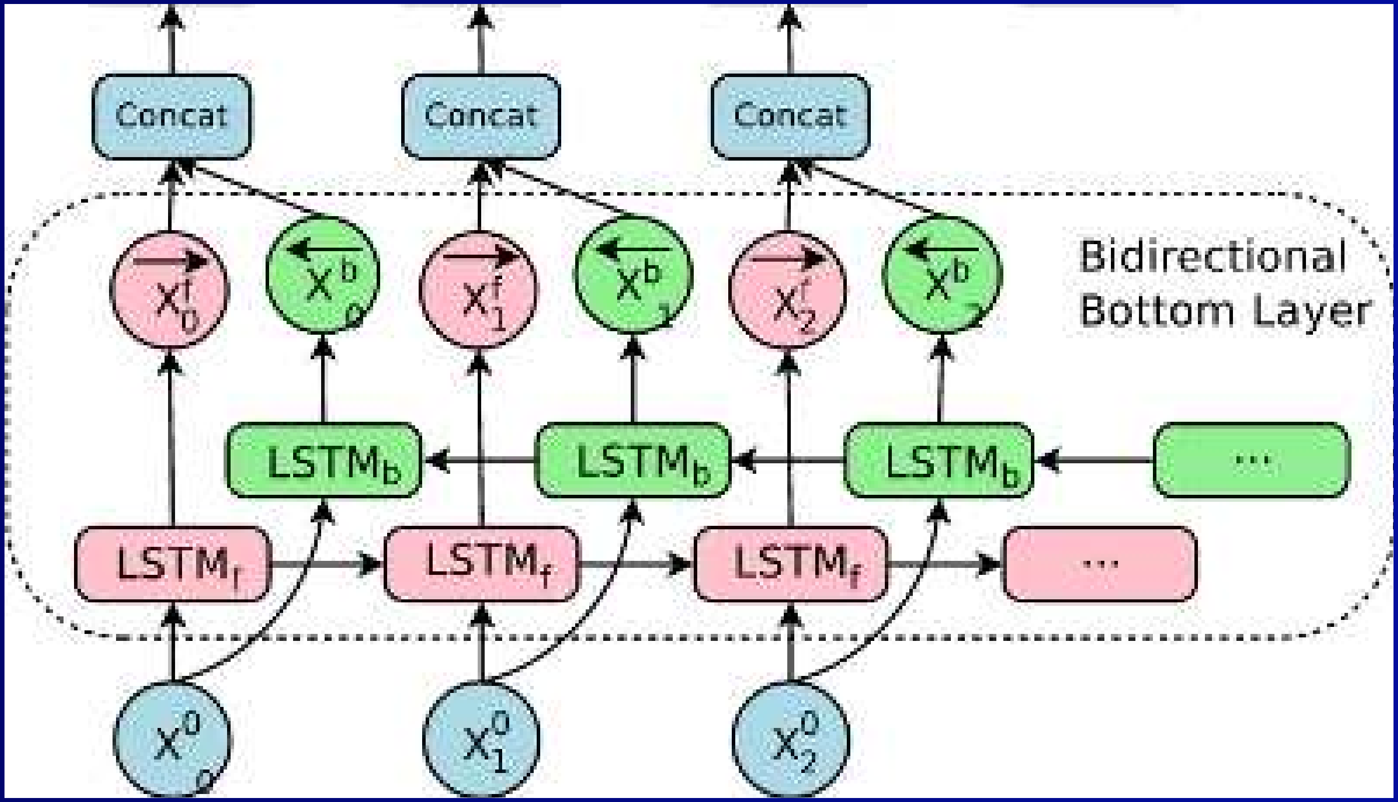
(Figure from Falcon [2018].)

Bidirectional RNNs

Language modeling as a sequence tagging task has a very particular property: models cannot have access to information about elements *after* the element to be tagged.

For other sequence tagging tasks this does not hold: context *after* the element is an important part of the input. But an RNN unit is inherently one-directional: hidden states can contain information only about inputs at earlier time steps. A widespread way of providing access to the full context is using RNNs in *both directions* and concatenate their hidden states at each element. This is a so-called *bidirectional RNN* layer.

Bidirectional RNNs cont.



Naturally, bidirectional RNN layers can be stacked similarly to ordinary, one-directional RNNs.

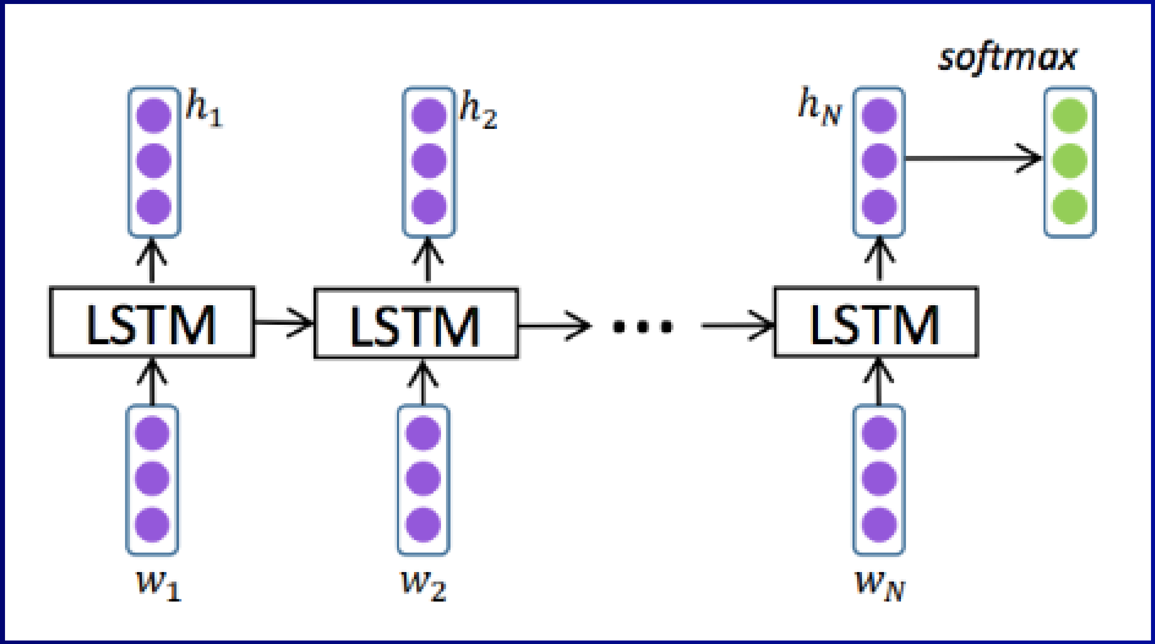
Seq2vec: sequence encoding

There are many tasks for which a variable-length input sequence has to be mapped to a fixed-length output, e.g., sequence classification tasks like sentiment classification.

How can one or several stacked RNNs be used to map the input sequence to a vector which is a useful representation of the whole input? The key is that RNN *hidden states* (plus the cell states of LSTMs) can represent the whole input sequence up to the given time step.

Seq2vec: sequence encoding cont.

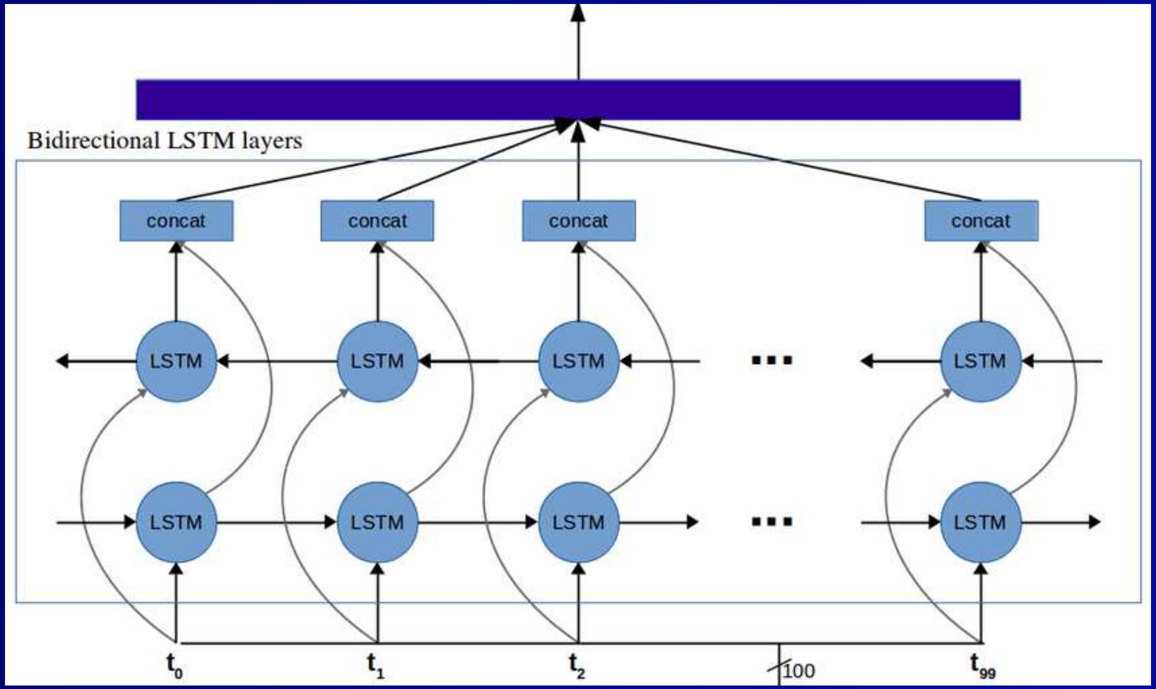
In the case of one-directional RNN(s), the obvious solution is to use the *last hidden state* (possibly together with the cell state in case of LSTMs) to represent the whole input sequence. E.g., for classification:



(Figure from Minaee et al. [2019].)

Seq2vec: sequence encoding cont.

The (combined) hidden states of bi-RNNs, in contrast, contain information about the entire input at each time step, so it makes more sense to aggregate all of them, e.g., by taking their average or using max pooling.



(Figure adapted from Faust et al. [2018].)

Vec2seq: sequence generation

Sequence generation based on a fixed size vector is analogous to language generation with a language model, but in this case generation is *conditional*: we want to model sequence probabilities

$$P(\langle y_1, \ldots, y_n \rangle \mid \mathbf{x})$$

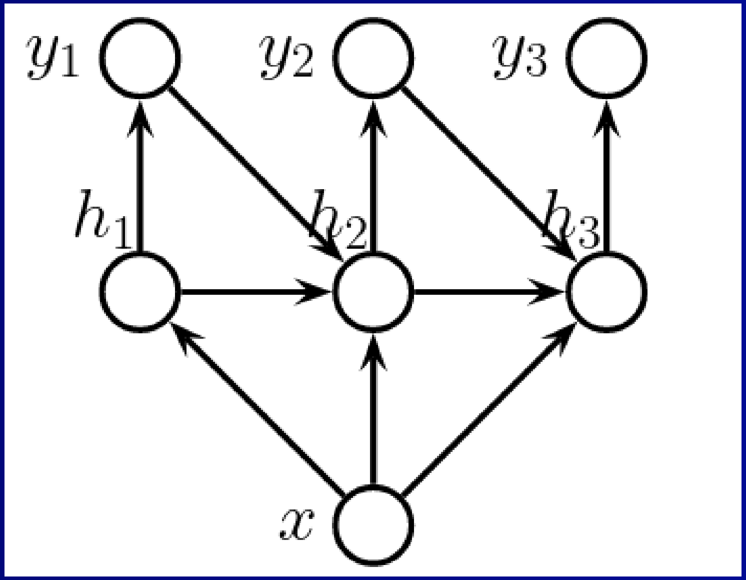
where $\mathbf{x}$ is a fixed length vector. Similarly to RNN-based *uncoditional* language models, we can reduce the problem to modeling the individual

$$P(y_n | \langle y_1, \ldots, y_{n-1} \rangle, \mathbf{x})$$

continuation probabilities with RNNs.

Vec2seq: sequence generation cont.

The standard RNN-based language model architecture can be reused with a single modification: the RNN hidden states are also conditioned on the condition vector $\mathbf{x}$. The model has the following conditional independence structure:



(Figure from Murphy [2021].)

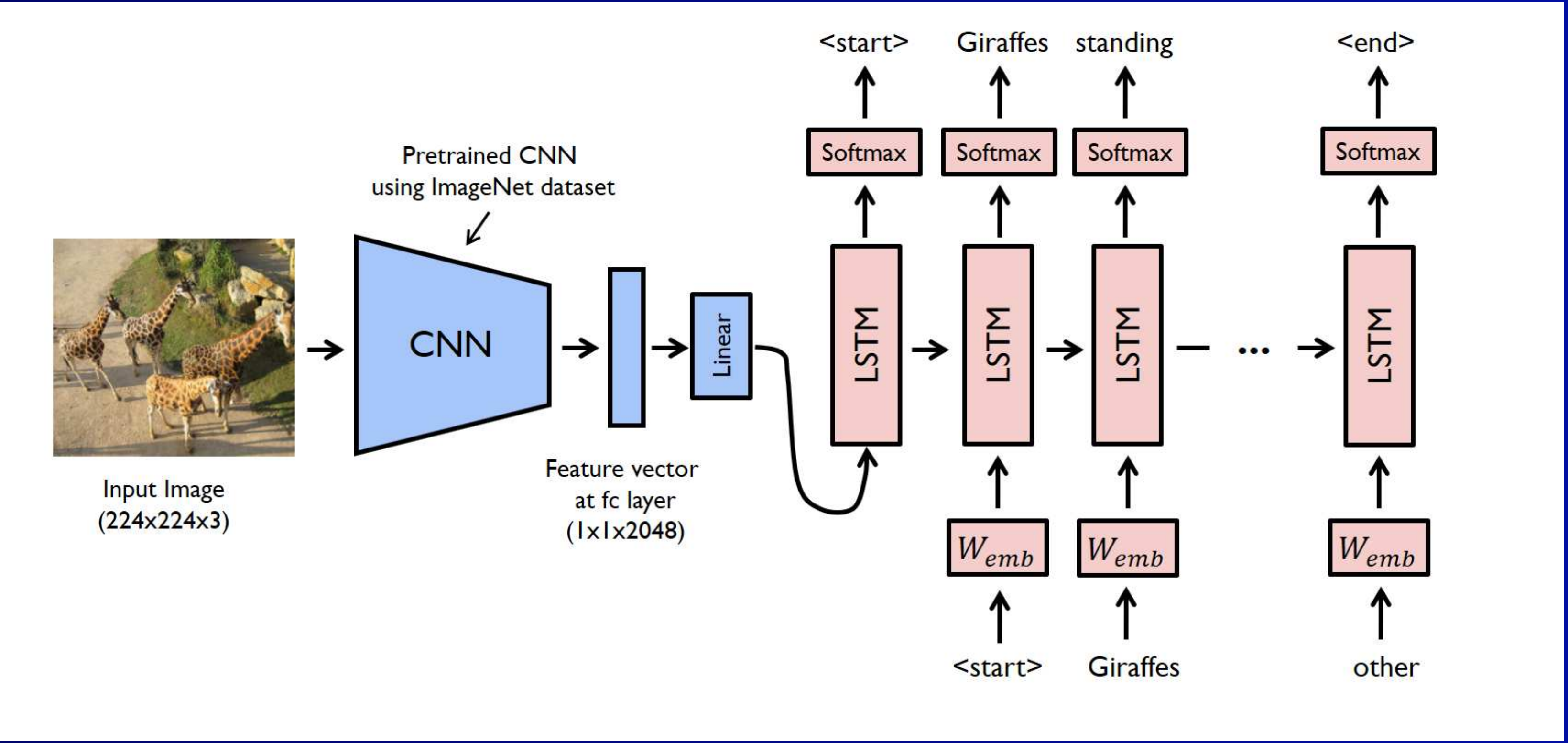
Vec2seq: sequence generation cont.

On the neural architecture level, conditioning the RNN hidden states on $\mathbf{x}$ can be implemented in several ways:

- use $\mathbf{x}$ (directly or after a transformation) as the *initial hidden state* of the RNN (also as the initial cell state for LSTMs);
- use $\mathbf{x}$ (directly or transformed) as the *input* at the *first time step*;
- use $\mathbf{x}$ (directly or transformed) as the *input* at *each time step* (in addition to the already generated sequence elements).

Vec2seq: sequence generation cont.

The first two solutions are the most widely used, e.g., the following image captioning model uses the image's feature vector as the first LSTM input:



(Figure from Yunjey Choi's PyTorch tutorial.)

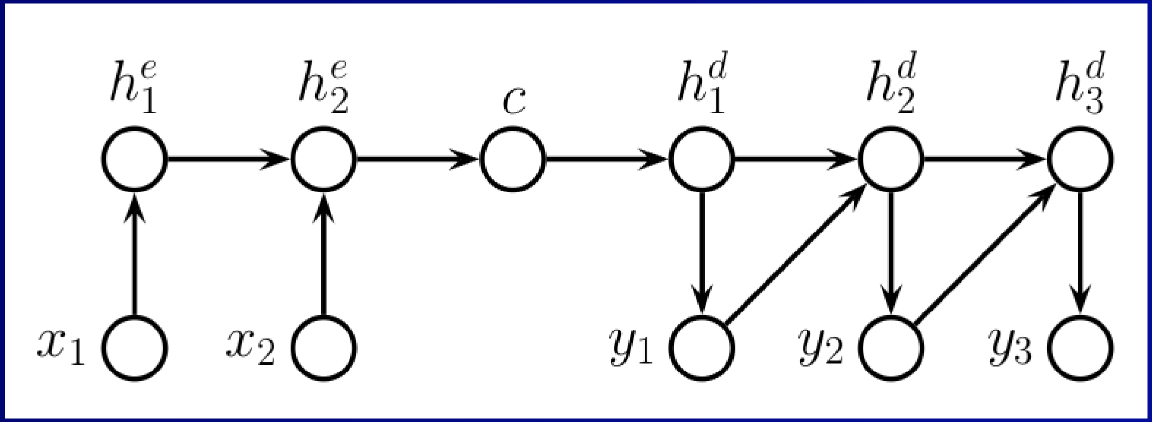
Vec2seq: sequence generation cont.

The training of Vec2seq models is, again, analogous to that of unconditional language models:

- The dominant strategy is *teacher forcing*: the training dataset's sequences are used as RNN input, the predicted continuation probabilities are used only for calculating the loss (negative log likelihood).
- As in the unconditional case, teacher forcing leads to *exposure bias* (an unhealthy gap between the training and inference setting), so alternative training strategies such as *scheduled sampling* are also used.

RNN-based Seq2seq

By combining an RNN Seq2vec with an RNN Vec2seq module we can build a Seq2seq model which transforms a variable-length input sequence into another *unaligned* sequence by first *encoding* the input into a fixed-size vector representation and then *decoding* this vector into another sequence. The probabilistic structure of the combined model is:



(Figure from Murphy [2021].)

RNN-based Seq2seq cont.

Historically, RNN-based Seq2seq models were among the most successful applications of RNNs (more concretely, of LSTM variants). Applications included

- machine translation (LSTM Seq2seq models were the first neural MT models competitive with and later superior to traditional phrase-based solutions),
- summarization,
- question answering, and
- dialogue systems.

RNN-based Seq2seq cont.

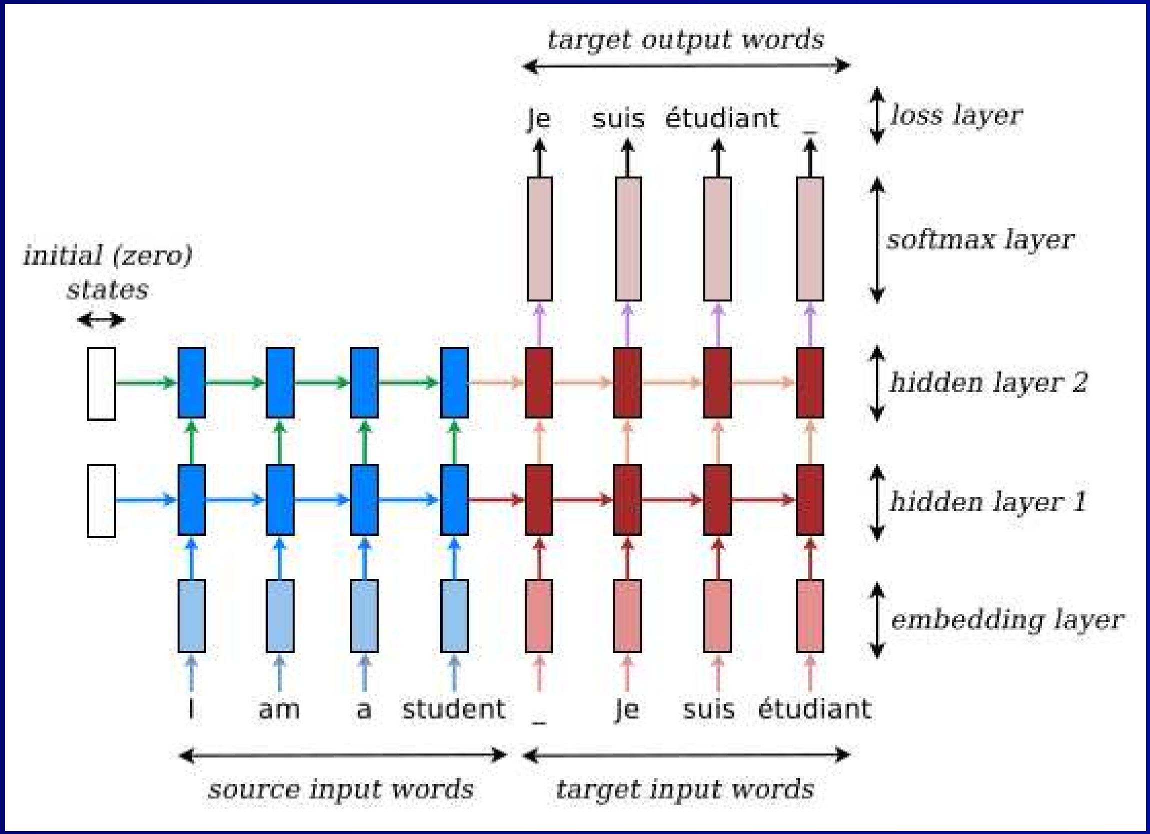
Architecturally, these models are typically

- embedding-based,
- use several LSTM layers in both the encoder and the decoder,
- initialize the hidden state and the cell state of the decoder with the (last or aggregated) hidden states and cell states of the encoder,
- are trained, as usual, with teacher forcing and negative log likelihood loss.

While the decoder cannot contain backward RNNs (for obvious reasons), the encoder often contains bidirectional RNN layers.

RNN-based Seq2seq cont.

A typical machine translation model:



(Figure from Luong [2016].)

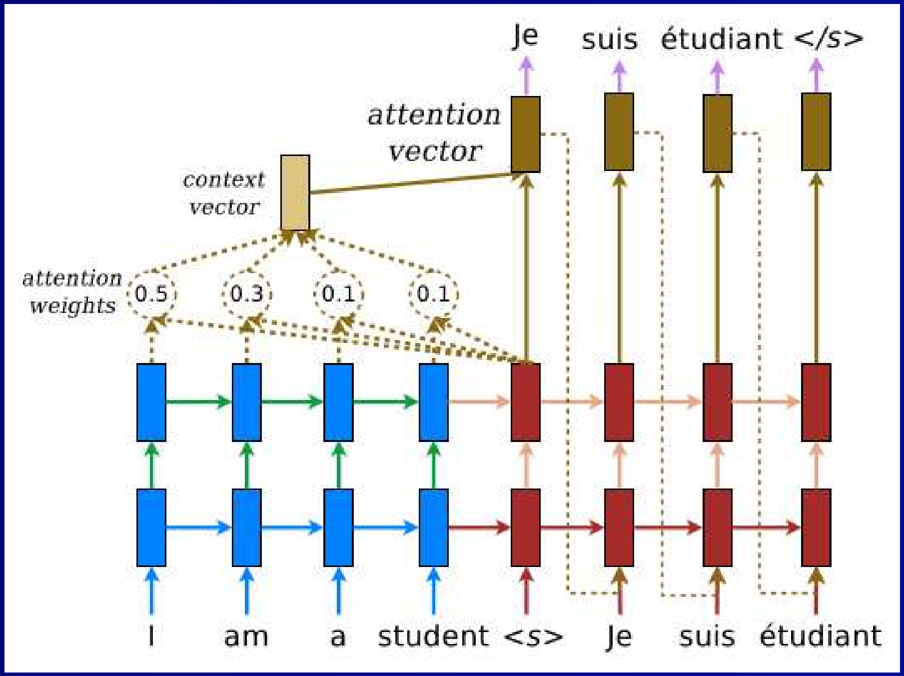
Attention

In basic RNN Seq2seq models, as we have seen, the decoder could access the encoded input sequence only in the form of the fixed-size vector representation(s) produced by the encoder.

Significantly, this fixed-size "summary" did not depend on *where* the decoder was in the decoding process, even though we know that for typical Seq2seq tasks, e.g. for translation, different parts of the input are relevant at different decoding stages.
Even if the fixed size vector was produced by pooling the whole sequence of encoder hidden states, the decoder's context has no influence on the pooling.

Attention cont.

Attention mechanisms solve the problem by providing access to *dynamically pooled* versions of the encoder hidden states at each decoding time step, *based on the encoder's context*, i.e., the h^d_{t-1} hidden state:



(Figure from Luong [2016].)

Attention cont.

Concretely, attention mechanisms *score* the $\mathbf{h}^e = \langle h_1^e \dots, h_n^e \rangle$ encoder hidden states based on the h_{t-1}^d decoder context using an $s(\cdot, \cdot)$ scoring function, and produce a weighted sum with the softmax of the scores:

$$\mathbf{s}(\mathbf{h}^e, h_{t-1}^d) = \langle s(h_1^e, h_{t-1}^d), \dots, s(h_n^e, h_{t-1}^d) \rangle,$$

$$\mathcal{A}(\mathbf{h}^e, h_{t-1}^d) = \mathrm{softmax}(\mathbf{s}(\mathbf{h}^e, h_{t-1}^d)) \cdot \mathbf{h}^e.$$

Attention: scoring functions

There are two main types of attention according to the type of scoring function they use:

- *Additive* or *MLP* or *Bahdanau* attention: the score is calculated by a simple feedforward network with one hidden layer:

$$s_{add}(\mathbf{a}, \mathbf{b}) = \mathbf{v}^\intercal \tanh(\mathbf{W_1 a} + \mathbf{W_2 b}),$$

  where $\mathbf{v}$, $\mathbf{W}_1$ and $\mathbf{W}_2$ are learned parameters.
- *Multiplicative* or *Luong* attention: the score is calculated as

$$s_{mult}(\mathbf{a}, \mathbf{b}) = \mathbf{a}^\intercal \mathbf{W} \mathbf{b},$$

  where $\mathbf{W}$ is, again, learned.

Dot product attention

Dot product scoring is an important, simple multiplicative scoring variant, in which $\mathbf{W}$ is identity, i.e.,

$$s_{dot}(\mathbf{a}, \mathbf{b}) = \frac{\mathbf{a} \cdot \mathbf{b}}{\sqrt{d}},$$

where d is the dimensionality of $\mathbf{a}$ and $\mathbf{b}$, and the division with $\sqrt{d}$ ensures that the scores have 0 mean and 1 variance if the $\mathbf{a}$ and $\mathbf{b}$ inputs have.

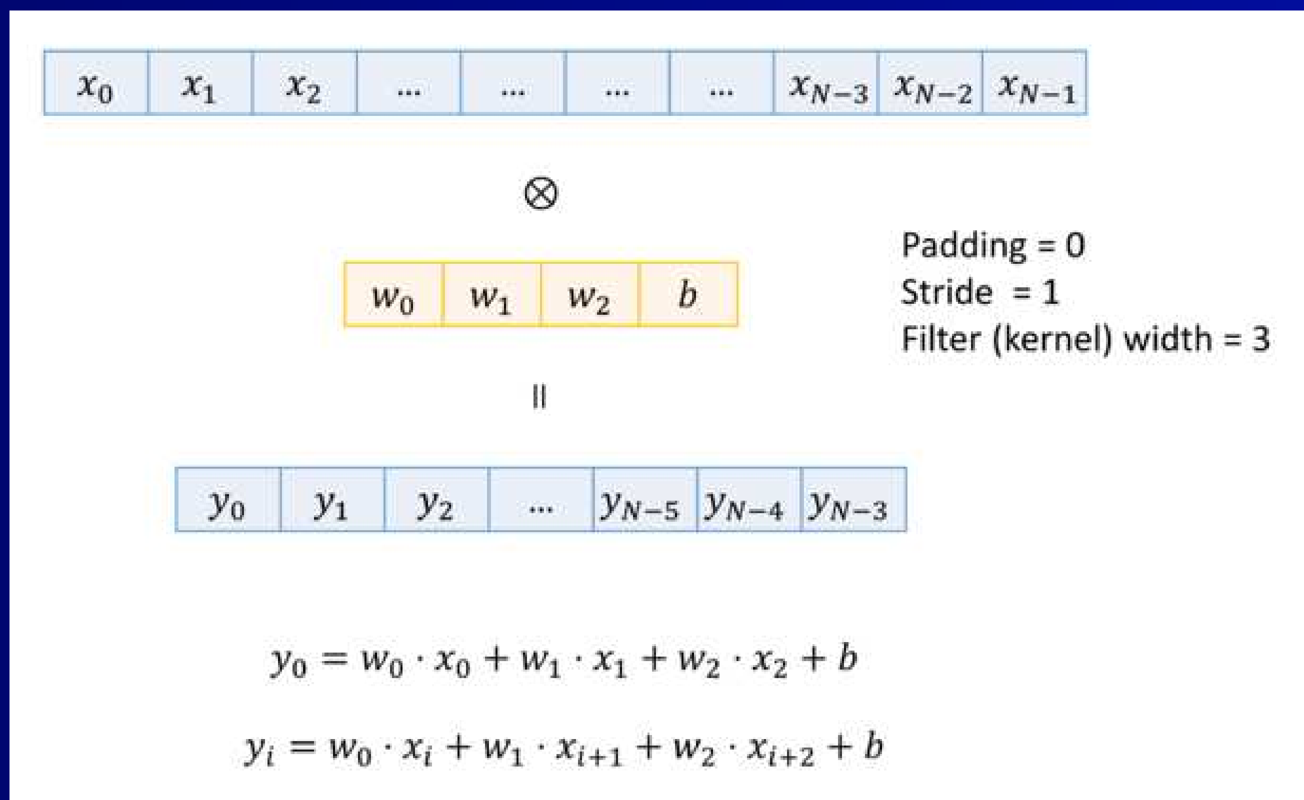
Performance gains from attention

Adding attention mechanisms to RNN Seq2seq architectures typically results in sizable performance gains, Luong [2016, 63], e.g., reports 11% perplexity and 20% BLEU score improvement on a translation taskq.

As a result, state-of-the-art RNN Seq2seq models virtually always contain some type of attention mechanism.

Prologue: CNNs as sequence models

Although our discussion has concentrated on RNNs, convolutional networks are rather competitive in many NLP tasks. They use 1d convolutions:



Prologue: CNNs as sequence models

...and 1d (typically max- or average) pooling layers. In fact, the surprisingly well performing fastText classification model uses pooling *without* convolution:[1]

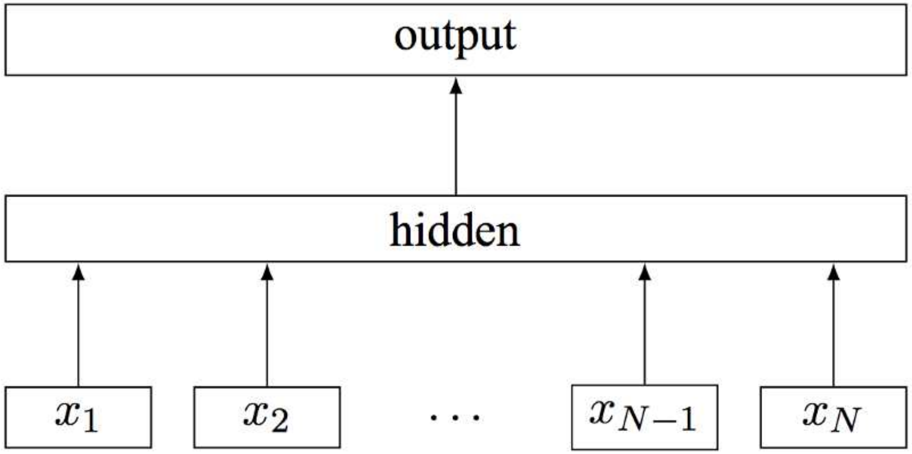


Figure 1: Model architecture of `fastText` for a sentence with N ngram features $x_1, \dots, x_N$. The features are embedded and averaged to form the hidden variable.

[1] Figure from Joulin et al. [2016].

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