Vision & Language

Recurrent Neural Networks: Neural Image Captioning

First Assignment

- Due soon…!

Course Project

- Chat group on Campuswire – Introduce yourselves if nothing more…
- Start forming your group and start working on a one-page to two-page project proposal
- Groups from 1 to 3 students. (You can work on your own)
- Project effort should be equivalent to at least one of the assignments – keep in mind this semester ends a bit short – so think of your project as your Assignment #4 (for grad students), Assignment #3 (for undergrad students).
- So Project should be like an Assignment #4 – but it is yours. I won't push you to do anything but it should hopefully be relevant to the class topic – vision and language. e.g. not prediction of the weather using ML – or email spam classification.

Last Class

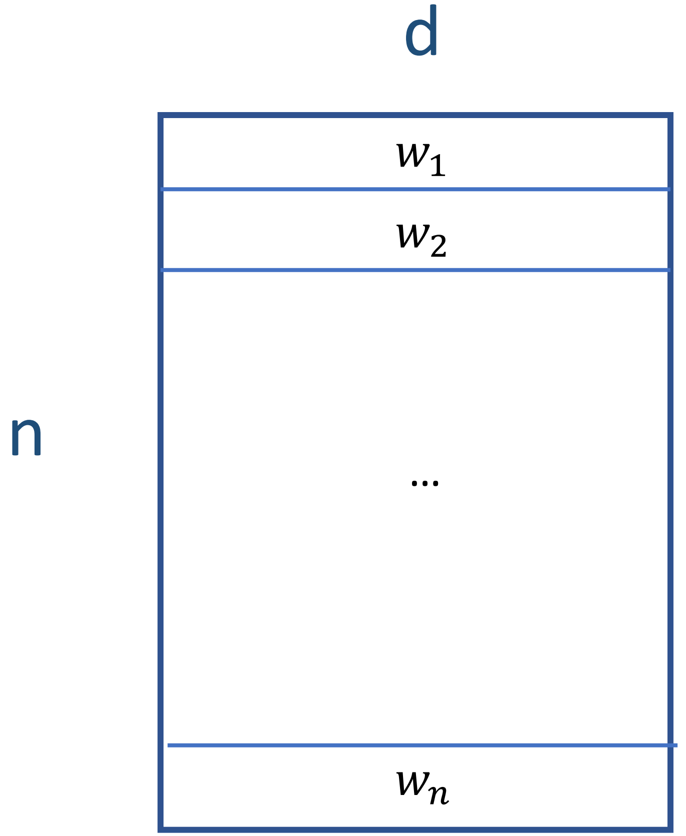
- Intro to NLP
- Why is NLP hard
- Common NLP Tasks
- The bag of words representation
- The bag of n-grams representation
- Distributional Semantics – word embeddings
- Continuous Bag of Words (CBOW) – Word2Vec

Today

- Recap on Word Embeddings (CBOW)
- More on Tokenization
- Recurrent Neural Network – Transition Cell
- Recurrent Neural Network (Unrolled)
- Understanding Issues with Batching…
- Variations with gated connections: LSTMs and GRUs
- Stacked and Bidirectional RNNs
- Use in vision and language: Neural Image Captioning

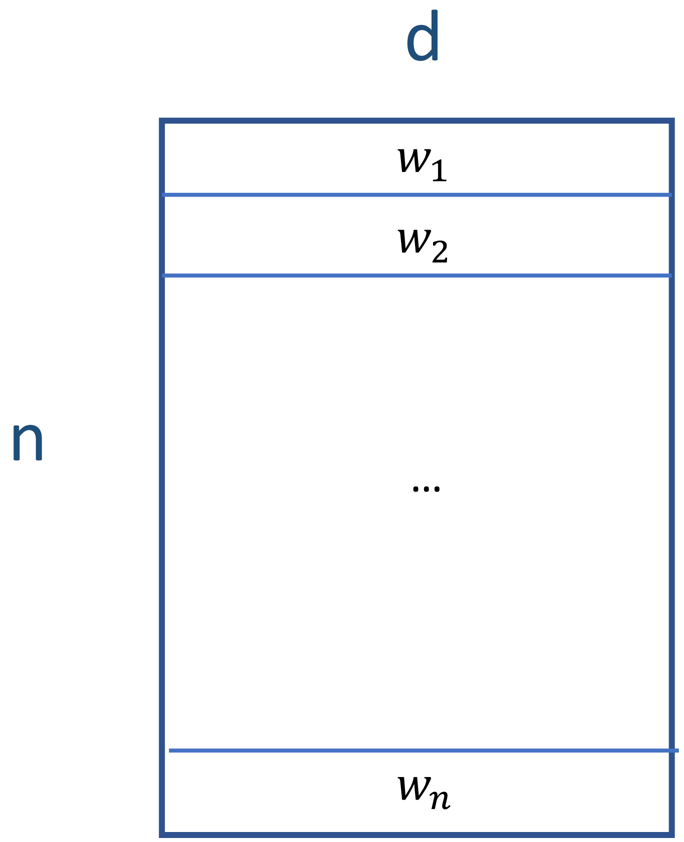
Word2Vec – CBOW Version

- First, create a huge matrix of word embeddings initialized with random values – where each row is a vector for a different word in the vocabulary.

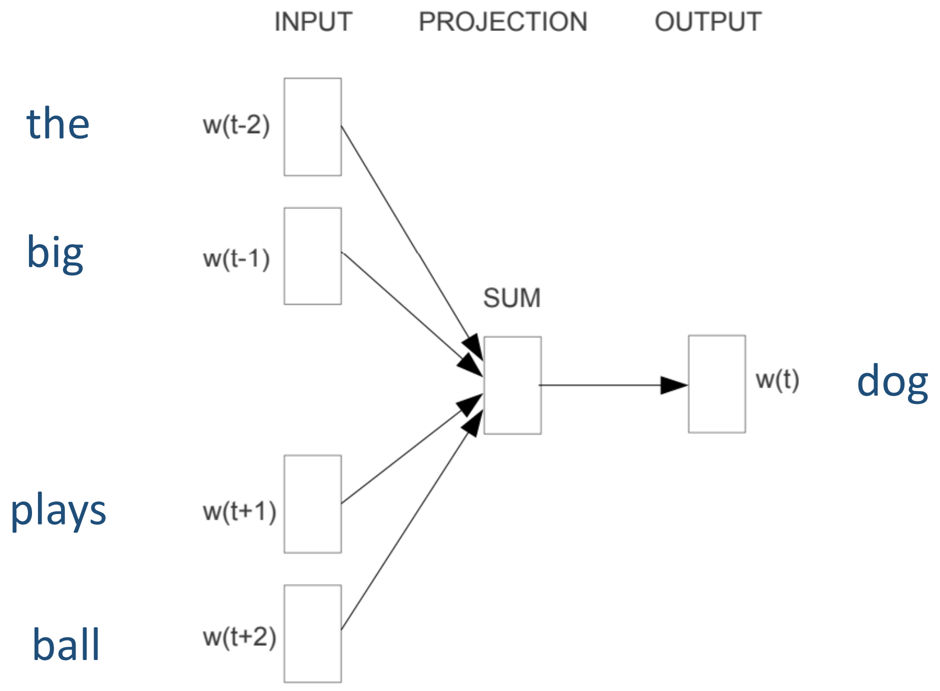


Word2Vec – CBOW Version

- Then, collect a lot of text, and solve the following regression problem for a large corpus of text:



"the big dog plays ball"



CBOW

Practical Issues - Tokenization

- For each text representation we usually need to separate a sentence into tokens – we have assumed words in this lecture (or pairs of words) – but tokens could also be characters and anything in-between.

- Word segmentation can be used as tokenization.
    - In the assignment I was lazy I just did “my sentence”.split(“ “) and called it a day.
    - However, even English is more difficult than that because of punctuation, double spaces, quotes, etc. For English I would recommend you too look up the great word tokenization tools in libraries such as Python’s NLTK and Spacy before you try to come up with your own word tokenizer.

Issues with Word based Tokenization

- We already mentioned that tokenization can be hard even when word-based for other languages that don't use spaces in-between words.

- Word tokenization can also be bad for languages where the words can be "glued" together like German or Turkish.
  - Remember fünfhundertfünfundfünfzig? It wouldn't be feasible to have a word embedding for every number in the German language.

- It is problematic to handle words that are not in the vocabulary e.g. a common practice is to use a special <OOV> (out of vocabulary) token for those words that don't show up in the vocabulary.

Tokenization can be complex

- Think of Japanese
  - Three vocabularies/sets of symbols:
    Katakana and Hiragana symbols represent syllables / sounds
    く= ku, ぎ = gi, ナ = na, ア= a
    Kanji represent ideas / words (Chinese characters).
    日 = day, sun, 大 = big, 凸= convex 凹 = concave
  - They can be combined – e.g. tomorrow = 明日
  - Each symbol also has some structure within the symbols. They are not independently created. e.g. bright= 明るい , rising sun = 旭
  - And of course there are no spaces in between the characters.

Solution: Sub-word Tokenization

- Byte-pair Encoding Tokenization (BPE)
  - Start from small strings and based on substring counts iteratively use larger sequences until you define a vocabulary that maximizes informative subtokens. That way most will correspond to words at the end.
- Byte-level BPE Tokenizer
  - Do the same but at the byte representation level not at the substring representation level.

Tokenizers

Rust passing | license Apache-2.0 | downloads/week 169k

Provides an implementation of today's most used tokenizers, with a focus on performance and versatility.

Main features:

- Train new vocabularies and tokenize, using today's most used tokenizers.
- Extremely fast (both training and tokenization), thanks to the Rust implementation. Takes less than 20 seconds to tokenize a GB of text on a server's CPU.
- Easy to use, but also extremely versatile.
- Designed for research and production.
- Normalization comes with alignments tracking. It's always possible to get the part of the original sentence that corresponds to a given token.
- Does all the pre-processing: Truncate, Pad, add the special tokens your model needs.

huggingface/tokenizers

BPE Tokenization Overview

Neural Machine Translation of Rare Words with Subword Units

Rico Sennrich and **Barry Haddow** and **Alexandra Birch**
School of Informatics, University of Edinburgh
{rico.sennrich,a.birch}@ed.ac.uk,bhaddow@inf.ed.ac.uk

- Learn BPE operations (python code on the right) – from the paper.
- Use said operations to construct your sub-word vocabulary.
- Treat each sub-word token as a “word” in any models we will discuss.

Algorithm 1 Learn BPE operations

```
import re, collections

def get_stats(vocab):
  pairs = collections.defaultdict(int)
  for word, freq in vocab.items():
    symbols = word.split()
    for i in range(len(symbols)-1):
      pairs[symbols[i],symbols[i+1]] += freq
  return pairs

def merge_vocab(pair, v_in):
  v_out = {}
  bigram = re.escape(' '.join(pair))
  p = re.compile(r'(?<!\S)' + bigram + r'(?!\S)')
  for word in v_in:
    w_out = p.sub(''.join(pair), word)
    v_out[w_out] = v_in[word]
  return v_out

vocab = {'l o w </w>' : 5, 'l o w e r </w>' : 2,
         'n e w e s t </w>':6, 'w i d e s t </w>':3}
num_merges = 10
for i in range(num_merges):
  pairs = get_stats(vocab)
  best = max(pairs, key=pairs.get)
  vocab = merge_vocab(best, vocab)
  print(best)
```

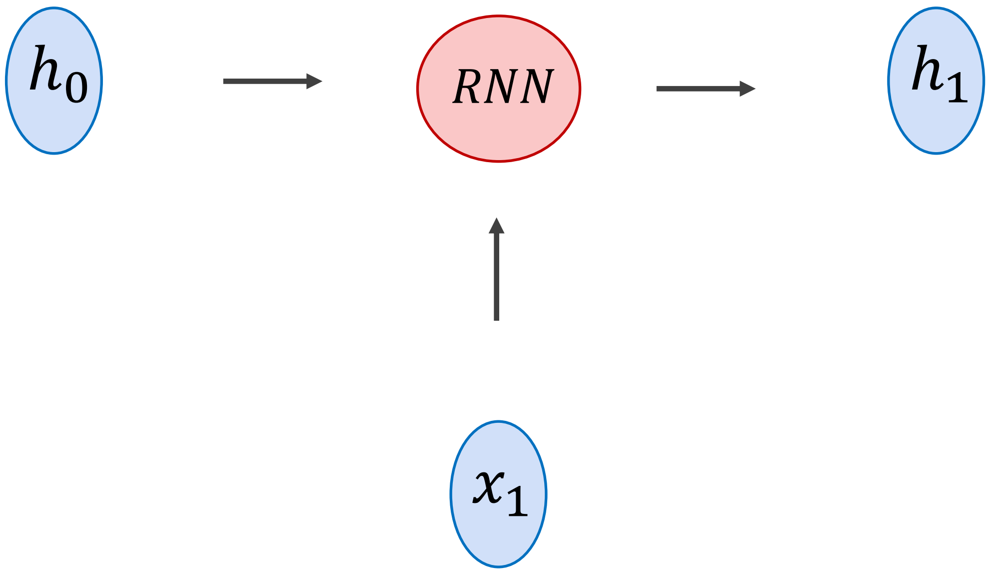
$$
\begin{array}{lcl}
\text{r }\cdot & \rightarrow & \text{r}\cdot \\
\text{l o} & \rightarrow & \text{lo} \\
\text{lo w} & \rightarrow & \text{low} \\
\text{e r}\cdot & \rightarrow & \text{er}\cdot
\end{array}
$$

Figure 1: BPE merge operations learned from dictionary {‘low’, ‘lowest’, ‘newer’, ‘wider’}.

Recurrent Neural Networks

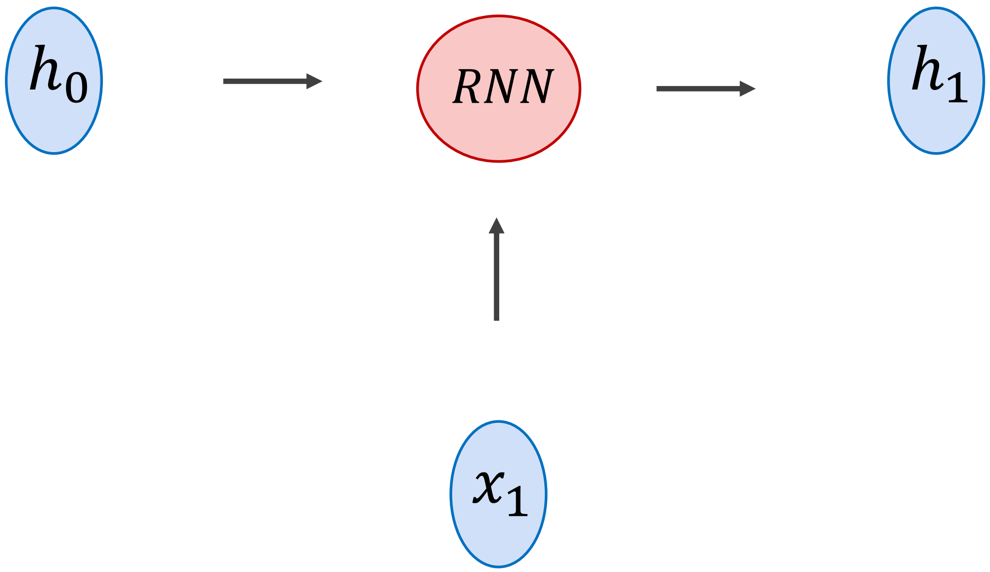
- These are models for handling sequences of things.
- Each input is not a vector but a sequence of input vectors.
- e.g. Each input can be a "word embedding" or any "word" representation – we will use in our first examples one-hot encoded tokens but in practice continuous dense word embeddings are used.

Recurrent Neural Network Cell

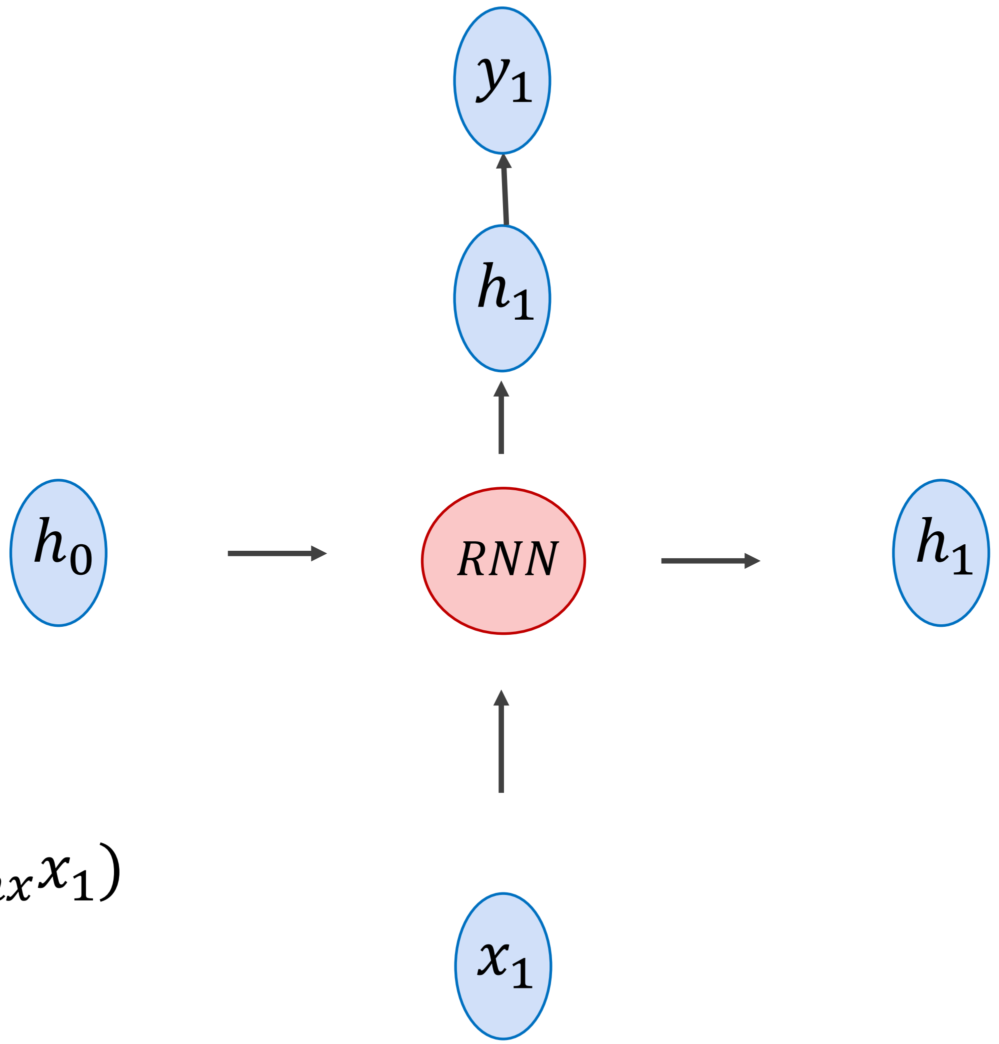


Recurrent Neural Network Cell

$$h_1 = \tanh(W_{hh}h_0 + W_{hx}x_1)$$



Recurrent Neural Network Cell



$$h_1 = \tanh(W_{hh}h_0 + W_{hx}x_1)$$

$$y_1 = \text{softmax}(W_{hy}h_1)$$

Recurrent Neural Network Cell

$$y_1 = [0.1, 0.05, 0.05, 0.1, 0.7]$$

$$h_1 = [0.1 \quad 0.2 \; 0 \; -0.3 \; -0.1\,]$$

$$h_0 = [0\;0\;0\;0\;0\;0\;0\,]$$

RNN

$$h_1 = [0.1 \quad 0.2 \; 0 \; -0.3 \; -0.1\,]$$

$$h_1 = \tanh(W_{hh}h_0 + W_{hx}x_1)$$

$$x_1 = \; [0\;0\;1\;0\;0]$$

$$y_1 = \text{softmax}(W_{hy}h_1)$$

Recurrent Neural Network Cell

$y_1 = [0.1, 0.05, 0.05, 0.1, 0.7]$ → **e (0.7)**

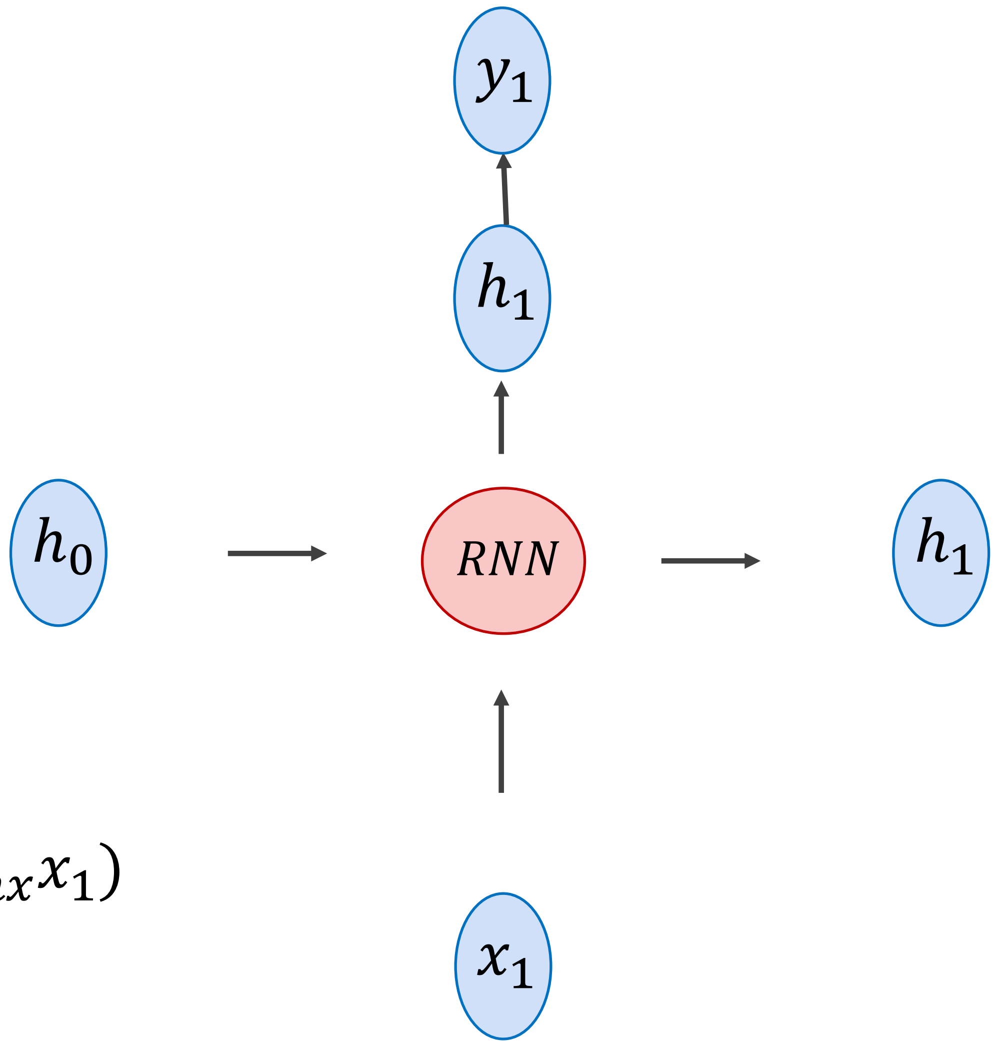
$h_1 = [0.1 \quad 0.2 \; 0 \quad -0.3 \quad -0.1\,]$

$h_0 = [0\;0\;0\;0\;0\;0\;0\,]$ → RNN → $h_1 = [0.1 \quad 0.2 \; 0 \quad -0.3 \quad -0.1\,]$

$x_1 = \; [0\;0\;1\;0\;0]$

a b **c** d e

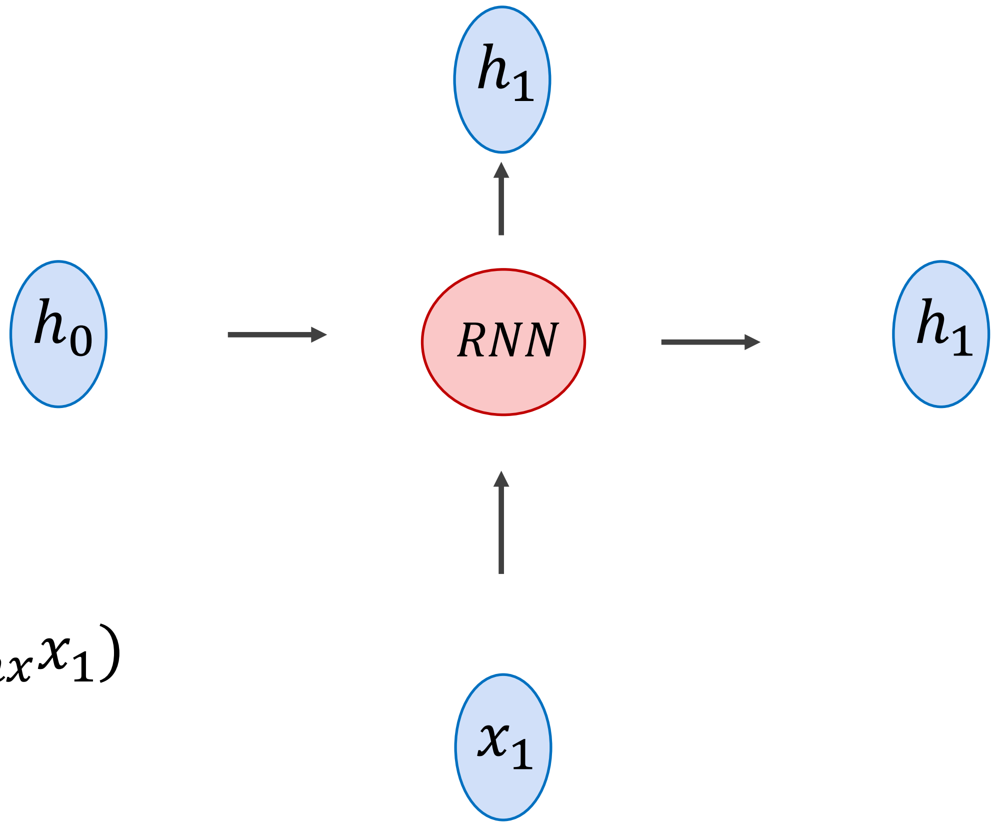
Recurrent Neural Network Cell



$$h_1 = \tanh(W_{hh}h_0 + W_{hx}x_1)$$

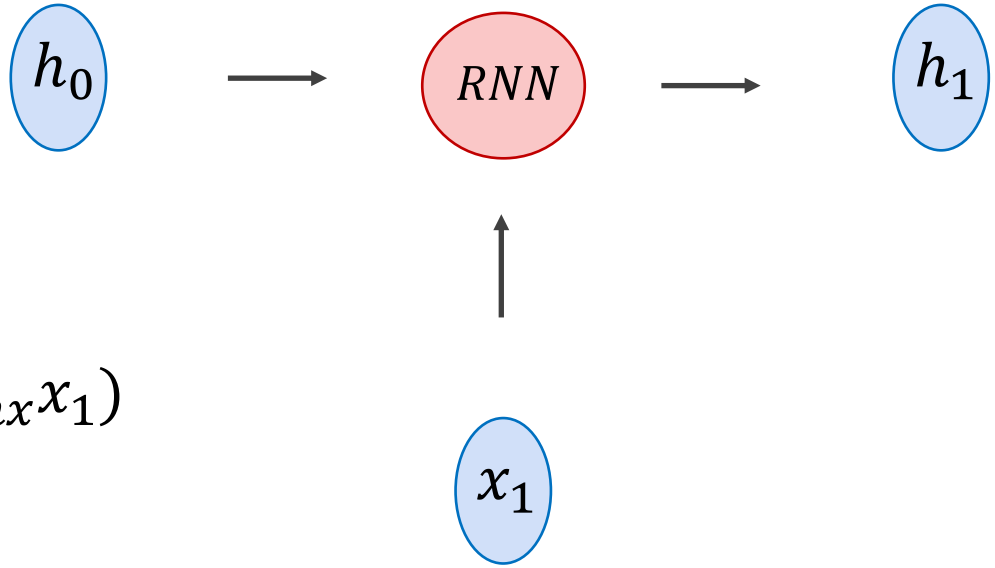
$$y_1 = \text{softmax}(W_{hy}h_1)$$

Recurrent Neural Network Cell



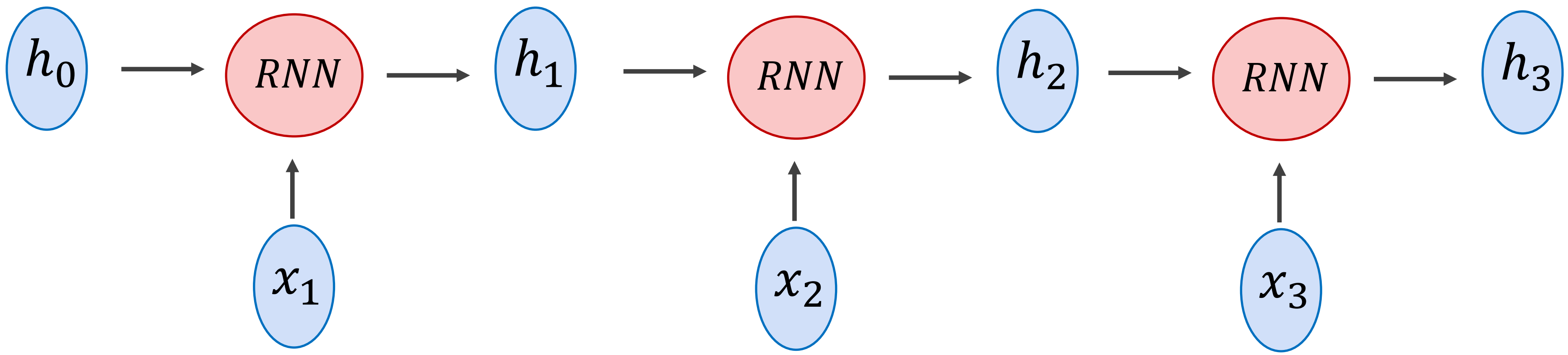
$$h_1 = \tanh(W_{hh} h_0 + W_{hx} x_1)$$

Recurrent Neural Network Cell

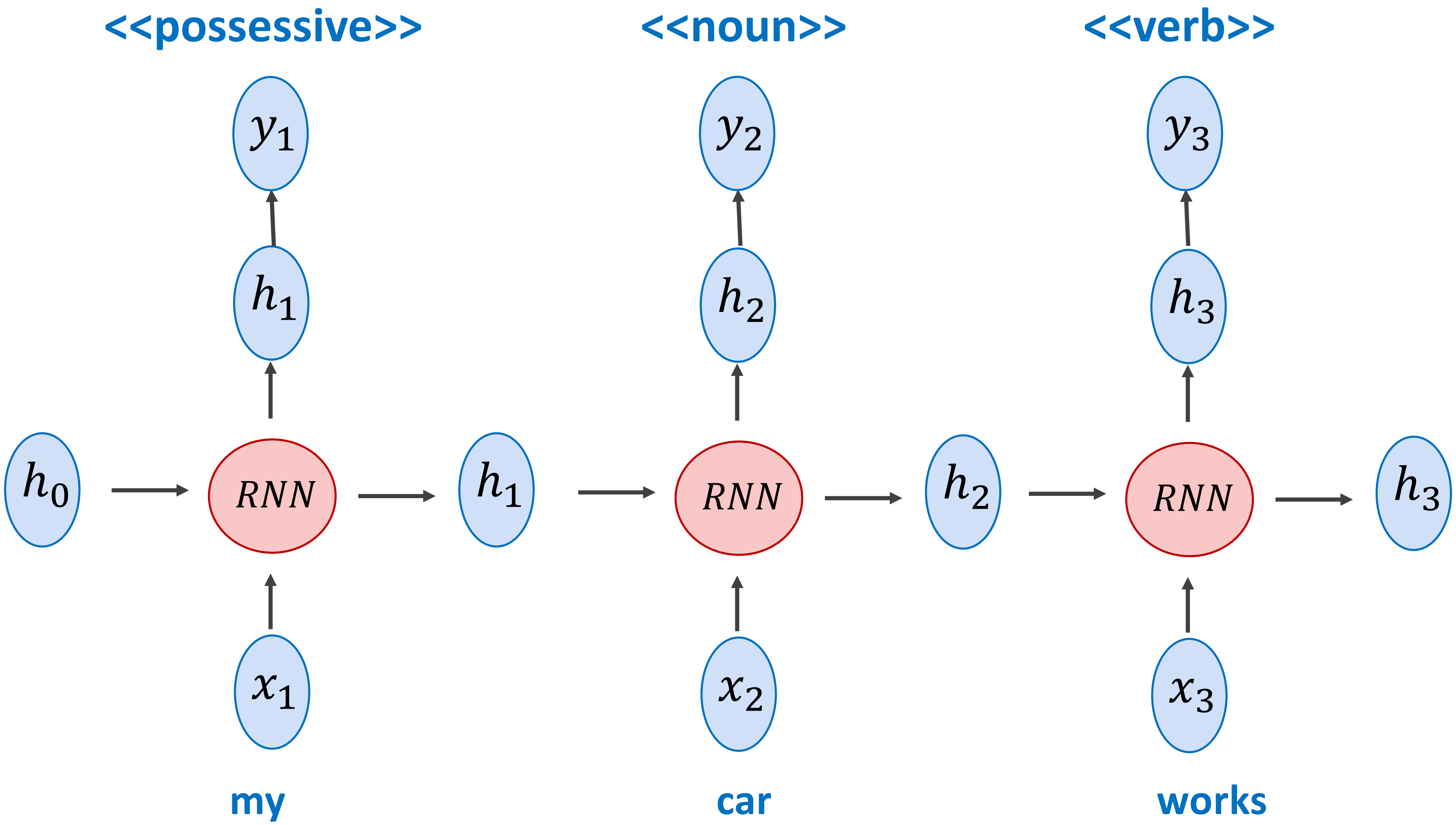


$$h_1 = \tanh(W_{hh}h_0 + W_{hx}x_1)$$

(Unrolled) Recurrent Neural Network



How can it be used? – e.g. Tagging a Text Sequence
One-to-one Sequence Mapping Problems



How can it be used? – e.g. Tagging a Text Sequence
One-to-one Sequence Mapping Problems

Training examples don’t need to be the same length!

input	output
my car works	<<possessive>> <<noun>> <<verb>>
my dog ate the assignment	<<possessive>> <<noun>> <<verb>> <<pronoun>> <<noun>>
my mother saved the day	<<possessive>> <<noun>> <<verb>> <<pronoun>> <<noun>>
the smart kid solved the problem	<<pronoun>> <<qualifier>> <<noun>> <<verb>> <<pronoun>> <<noun>>

How can it be used? – e.g. Tagging a Text Sequence
One-to-one Sequence Mapping Problems

Training examples don’t need to be the same length!

input	output
L(my car works) = 3	**L (<<possessive>> <<noun>> <<verb>>) = 3**
L(my dog ate the assignment) = 5	**L (<<possessive>> <<noun>> <<verb>> <<pronoun>> <<noun>>) = 5**
L(my mother saved the day) = 5	**L (<<possessive>> <<noun>> <<verb>> <<pronoun>> <<noun>>) = 5**
L(the smart kid solved the problem) = 6	**L (<<pronoun>> <<qualifier>> <<noun>> <<verb>> <<pronoun>> <<noun>>) = 6**

How can it be used? – e.g. Tagging a Text Sequence
One-to-one Sequence Mapping Problems

Training examples don't need to be the same length!

If we assume a vocabulary of a 1000 possible words and 20 possible output tags

input	output
T: 1000 x 3	T: 20 x 3
T: 1000 x 5	T: 20 x 5
T: 1000 x 5	T: 20 x 5
T: 1000 x 6	T: 20 x 6

How can it be used? – e.g. Tagging a Text Sequence
One-to-one Sequence Mapping Problems

Training examples don't need to be the same length!

If we assume a vocabulary of a 1000 possible words and 20 possible output tags

input	output
T: 1000 x 3	T: 20 x 3
T: 1000 x 5	T: 20 x 5
T: 1000 x 5	T: 20 x 5
T: 1000 x 6	T: 20 x 6

How do we create batches if inputs and outputs have different shapes?

How can it be used? – e.g. Tagging a Text Sequence
One-to-one Sequence Mapping Problems

Training examples don't need to be the same length!

If we assume a vocabulary of a 1000 possible words and 20 possible output tags

input	**output**
T: 1000 x 3	**T: 20 x 3**
T: 1000 x 5	**T: 20 x 5**
T: 1000 x 5	**T: 20 x 5**
T: 1000 x 6	**T: 20 x 6**

How do we create batches if inputs and outputs have different shapes?

Solution 1: Forget about batches, just process things one by one.

How can it be used? – e.g. Tagging a Text Sequence
One-to-one Sequence Mapping Problems

Training examples don't need to be the same length!

If we assume a vocabulary of a 1000 possible words and 20 possible output tags

input	output
T: 1000 x 3	T: 20 x 3
T: 1000 x 5	T: 20 x 5
T: 1000 x 5	T: 20 x 5
T: 1000 x 6	T: 20 x 6

How do we create batches if inputs and outputs have different shapes?

Solution 2: Zero padding. We can put the above vectors in **T: 4 x 1000 x 6**

How can it be used? – e.g. Tagging a Text Sequence
One-to-one Sequence Mapping Problems

Training examples don't need to be the same length!

If we assume a vocabulary of a 1000 possible words and 20 possible output tags

input	output
T: 1000 x 3	T: 20 x 3
T: 1000 x 5	T: 20 x 5
T: 1000 x 5	T: 20 x 5
T: 1000 x 6	T: 20 x 6

How do we create batches if inputs and outputs have different shapes?

Solution 3: Advanced. Dynamic Batching or Auto-batching
https://dynet.readthedocs.io/en/latest/tutorials_notebooks/Autobatching.html

How can it be used? – e.g. Tagging a Text Sequence
One-to-one Sequence Mapping Problems

Solution 4: Pytorch stacking, padding, and sorting combination

pad_sequence

`torch.nn.utils.rnn.pad_sequence(sequences, batch_first=False, padding_value=0)` [SOURCE]

Pad a list of variable length Tensors with `padding_value`

`pad_sequence` stacks a list of Tensors along a new dimension, and pads them to equal length. For example, if the input is list of sequences with size `L x *` and if batch_first is False, and `T x B x *` otherwise.

B is batch size. It is equal to the number of elements in `sequences`. *T* is length of the longest sequence. *L* is length of the sequence. * is any number of trailing dimensions, including none.

Example

```
>>> from torch.nn.utils.rnn import pad_sequence
>>> a = torch.ones(25, 300)
>>> b = torch.ones(22, 300)
>>> c = torch.ones(15, 300)
>>> pad_sequence([a, b, c]).size()
torch.Size([25, 3, 300])
```

• NOTE

This function returns a Tensor of size `T x B x *` or `B x T x *` where *T* is the length of the longest sequence. This function assumes trailing dimensions and type of all the Tensors in sequences are same.

Parameters

- **sequences** (*list*[*Tensor*]) – list of variable length sequences.
- **batch_first** (*bool, optional*) – output will be in `B x T x *` if True, or in `T x B x *` otherwise
- **padding_value** (*python:float, optional*) – value for padded elements. Default: 0.

Returns

Tensor of size `T x B x *` if `batch_first` is `False`. Tensor of size `B x T x *` otherwise

How can it be used? – e.g. Tagging a Text Sequence
One-to-one Sequence Mapping Problems

Solution 4: Pytorch stacking, padding, and sorting combination

pack_sequence

`torch.nn.utils.rnn.pack_sequence(`*`sequences, enforce_sorted=True`*`)` [SOURCE]

Packs a list of variable length Tensors

`sequences` should be a list of Tensors of size `L x *`, where *L* is the length of a sequence and * is any number of trailing dimensions, including zero.

For unsorted sequences, use *enforce_sorted = False*. If `enforce_sorted` is `True`, the sequences should be sorted in the order of decreasing length. `enforce_sorted = True` is only necessary for ONNX export.

Example

```
>>> from torch.nn.utils.rnn import pack_sequence
>>> a = torch.tensor([1,2,3])
>>> b = torch.tensor([4,5])
>>> c = torch.tensor([6])
>>> pack_sequence([a, b, c])
PackedSequence(data=tensor([ 1,  4,  6,  2,  5,  3]), batch_sizes=tensor([ 3,  2,  1]))
```

Parameters

- **sequences** (*list*[*Tensor*]) – A list of sequences of decreasing length.
- **enforce_sorted** (*bool, optional*) – if `True`, checks that the input contains sequences sorted by length in a decreasing order. If `False`, this condition is not checked. Default: `True`.

Returns

a `PackedSequence` object

Pytorch RNN

RNN

CLASS `torch.nn.RNN(*args, **kwargs)` [SOURCE]

Applies a multi-layer Elman RNN with $tanh$ or $ReLU$ non-linearity to an input sequence.

For each element in the input sequence, each layer computes the following function:

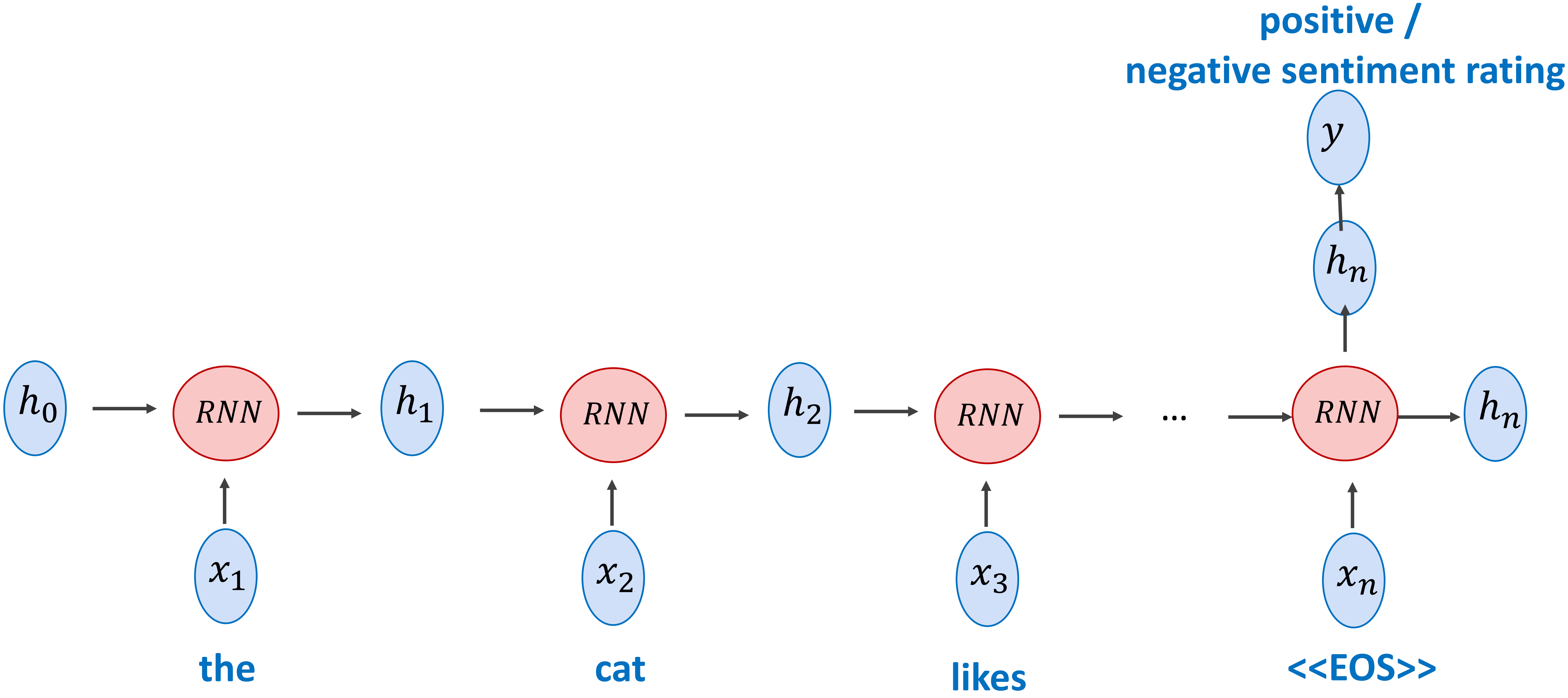
$$h_t = \tanh(W_{ih} x_t + b_{ih} + W_{hh} h_{(t-1)} + b_{hh})$$

where h_t is the hidden state at time *t*, x_t is the input at time *t*, and $h_{(t-1)}$ is the hidden state of the previous layer at time *t-1* or the initial hidden state at time *0*. If `nonlinearity` is `'relu'`, then *ReLU* is used instead of *tanh*.

Inputs: input, h_0

- **input** of shape (*seq_len, batch, input_size*): tensor containing the features of the input sequence. The input can also be a packed variable length sequence. See `torch.nn.utils.rnn.pack_padded_sequence()` or `torch.nn.utils.rnn.pack_sequence()` for details.

How can it be used? – e.g. Scoring the Sentiment of a Text Sequence
Many-to-one Sequence to score problems



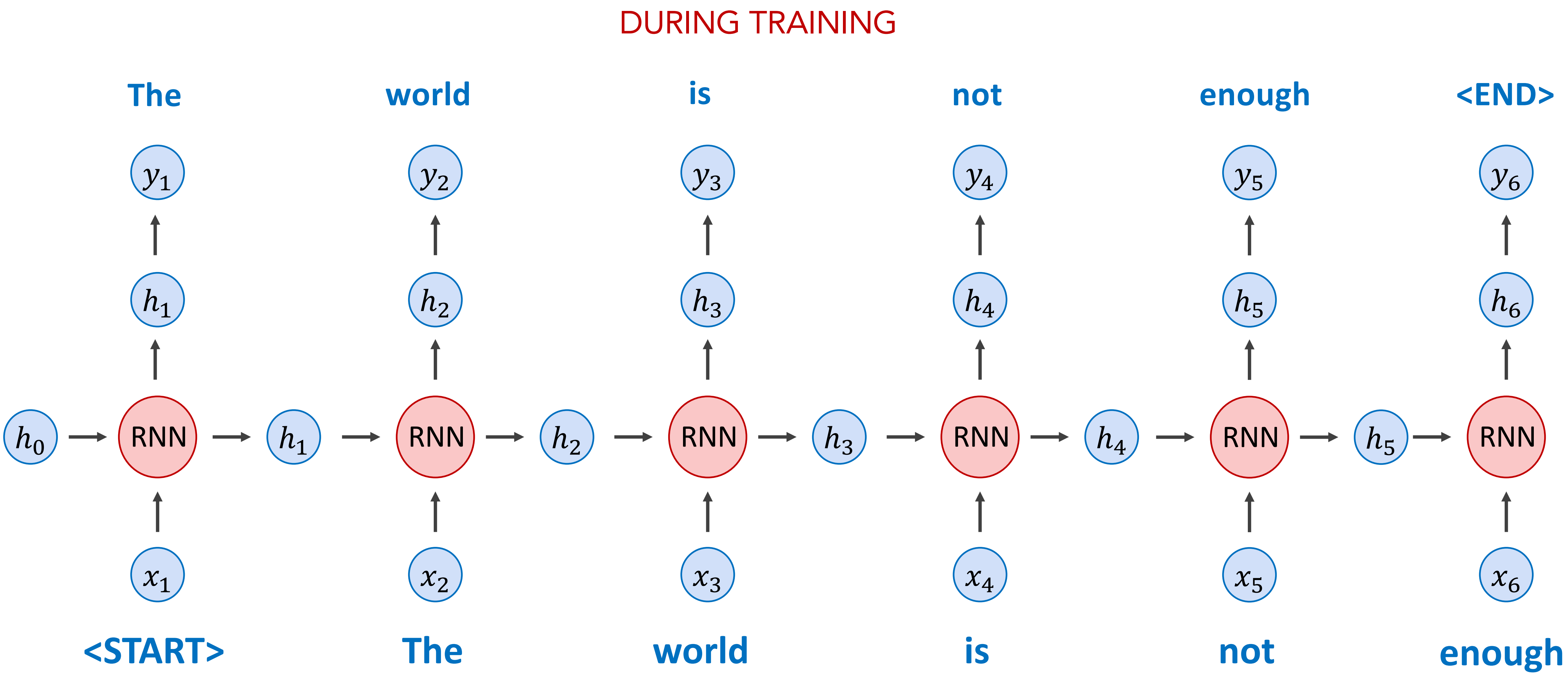
How can it be used? – e.g. Sentiment Scoring
Many to one Mapping Problems

Input training examples don't need to be the same length!
In this case outputs can be.

input	output
this restaurant has good food	Positive
this restaurant is bad	Negative
this restaurant is the worst	Negative
this restaurant is well recommended	Positive

How can it be used? – e.g. Text Generation

Auto-regressive model – Sequence to Sequence during Training, Auto-regressive during test



How can it be used? – e.g. Text Generation
Auto-regressive Models

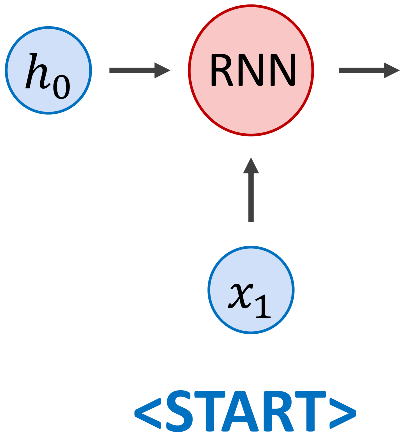
Input training examples don’t need to be the same length!
In this case outputs can be.

input	output
<START> this restaurant has good food	this restaurant has good food <END>
<START> this restaurant is bad	this restaurant is bad <END>
<START> this restaurant is the worst	this restaurant is the worst <END>
<START> this restaurant is well recommended	this restaurant is well recommended <END>

How can it be used? – e.g. Text Generation

Auto-regressive model – Sequence to Sequence during Training, Auto-regressive during test

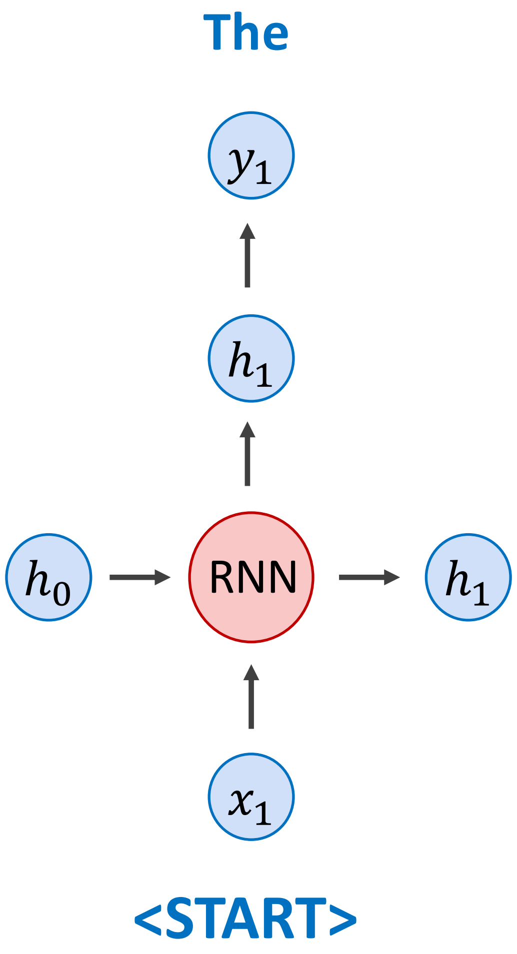
DURING TESTING



How can it be used? – e.g. Text Generation

Auto-regressive model – Sequence to Sequence during Training, Auto-regressive during test

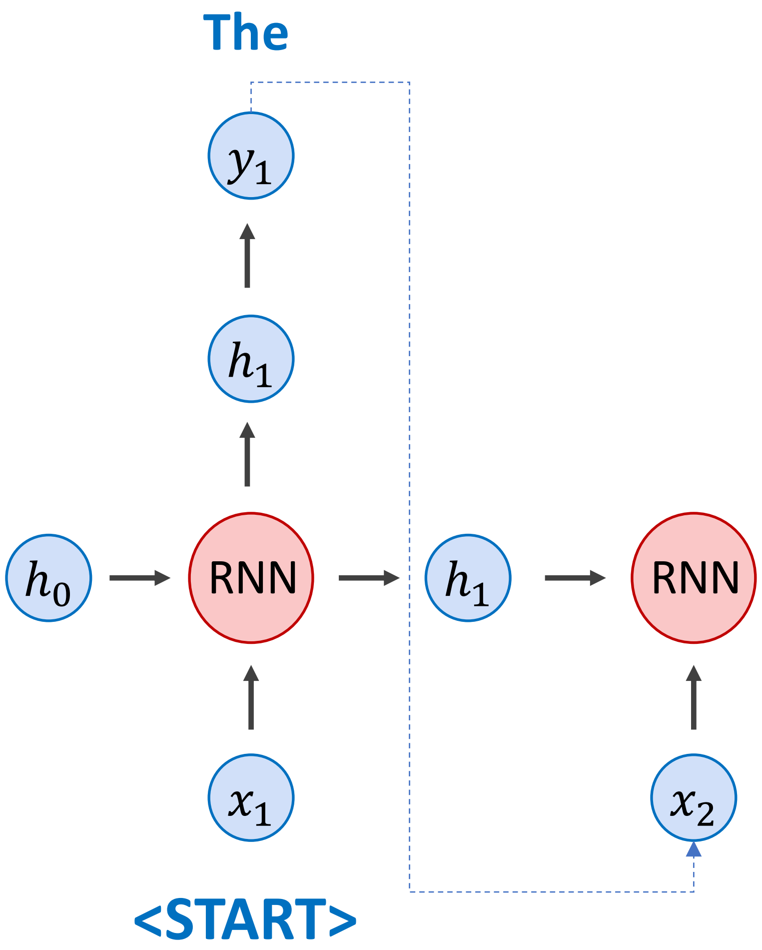
DURING TESTING



How can it be used? – e.g. Text Generation

Auto-regressive model – Sequence to Sequence during Training, Auto-regressive during test

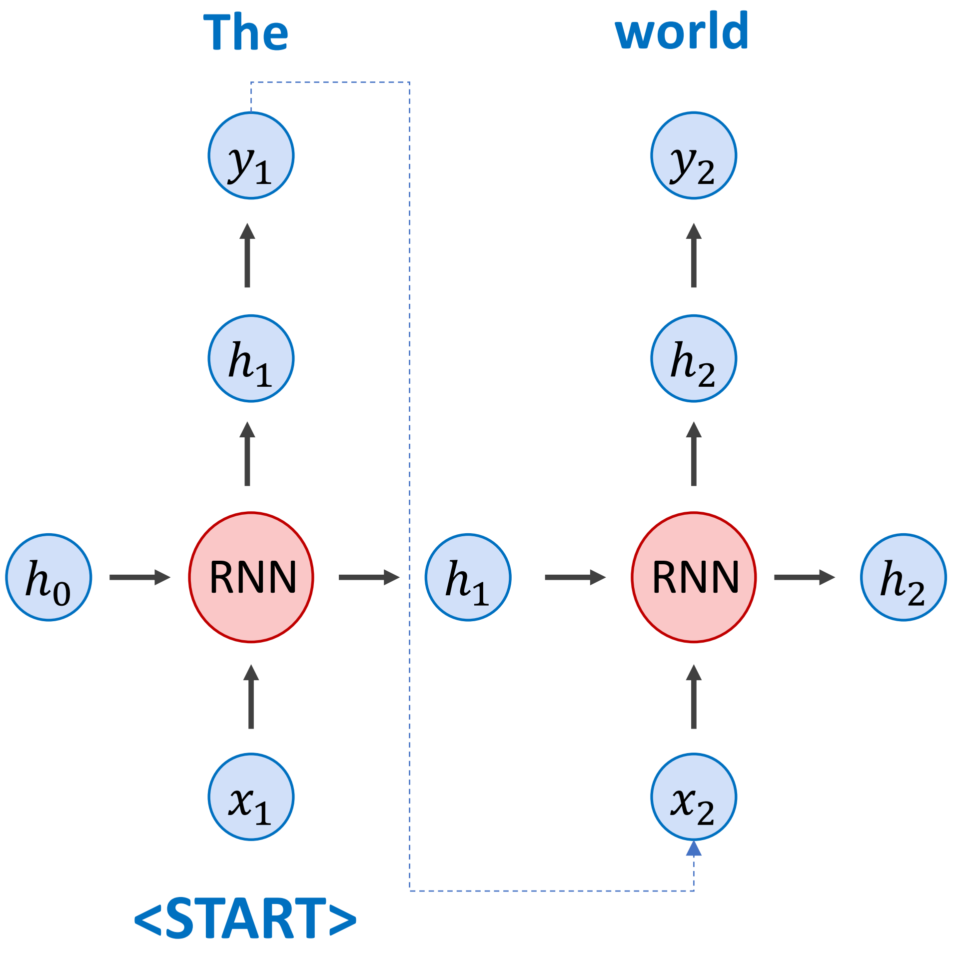
DURING TESTING



How can it be used? – e.g. Text Generation

Auto-regressive model – Sequence to Sequence during Training, Auto-regressive during test

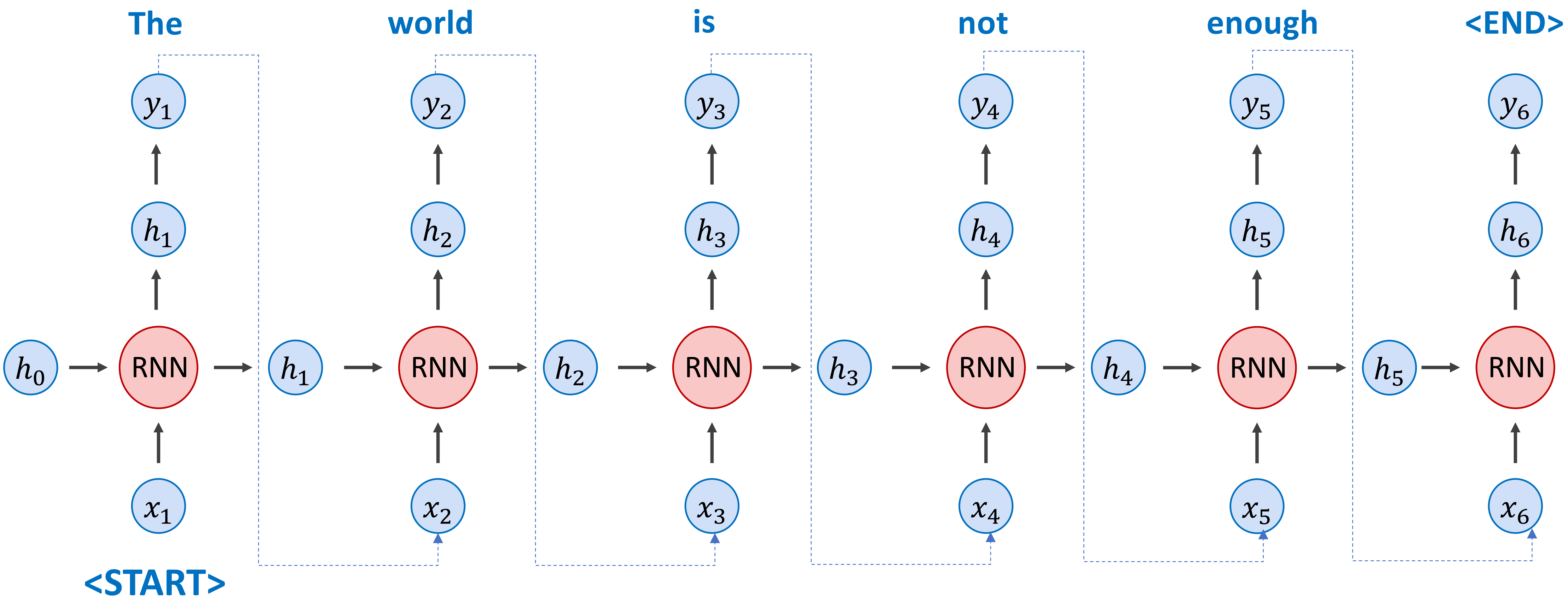
DURING TESTING



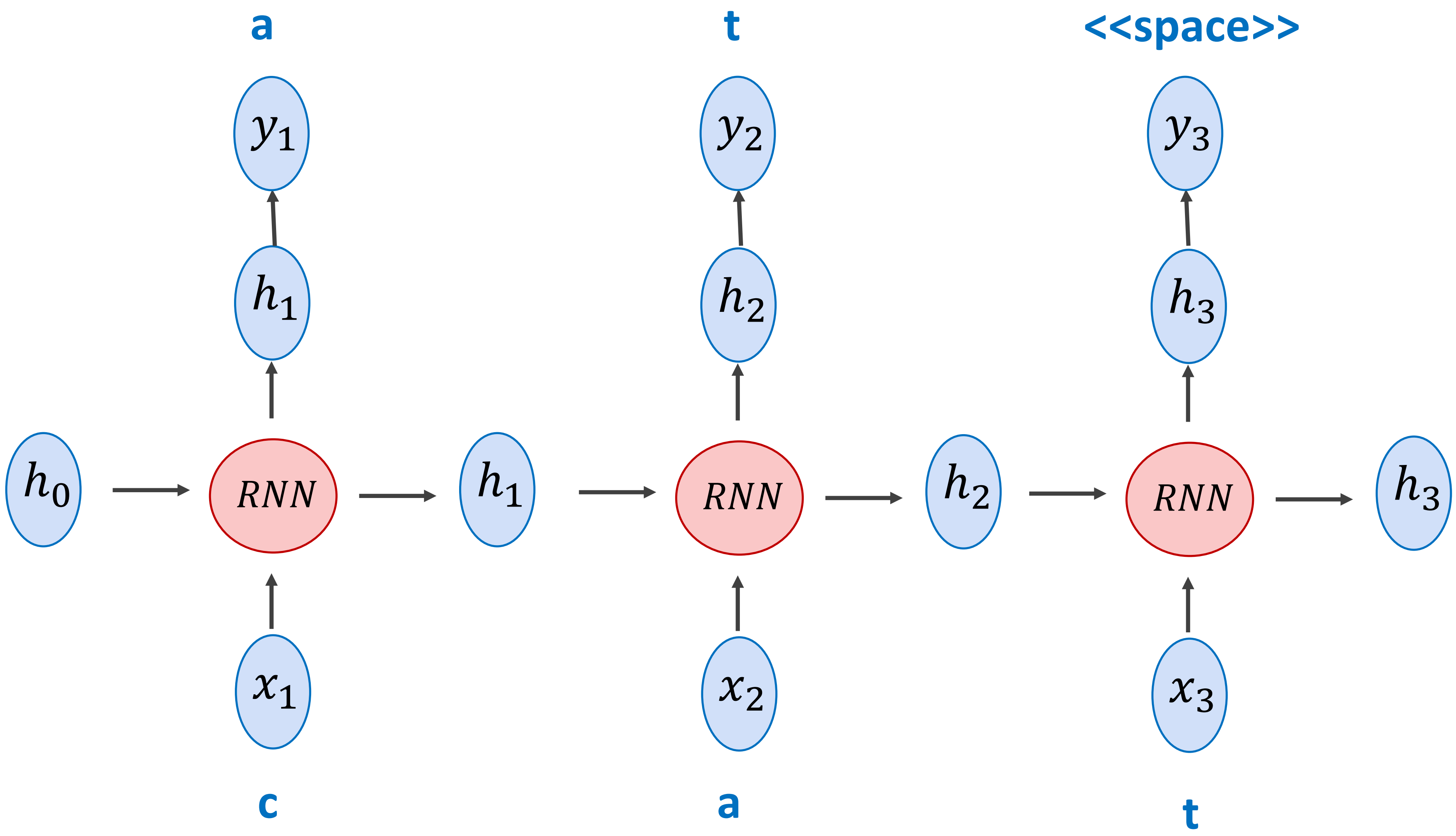
How can it be used? – e.g. Text Generation

Auto-regressive model – Sequence to Sequence during Training, Auto-regressive during test

DURING TESTING



Character-level Models



Generating Sequences With Recurrent Neural Networks

Alex Graves
Department of Computer Science
University of Toronto
graves@cs.toronto.edu

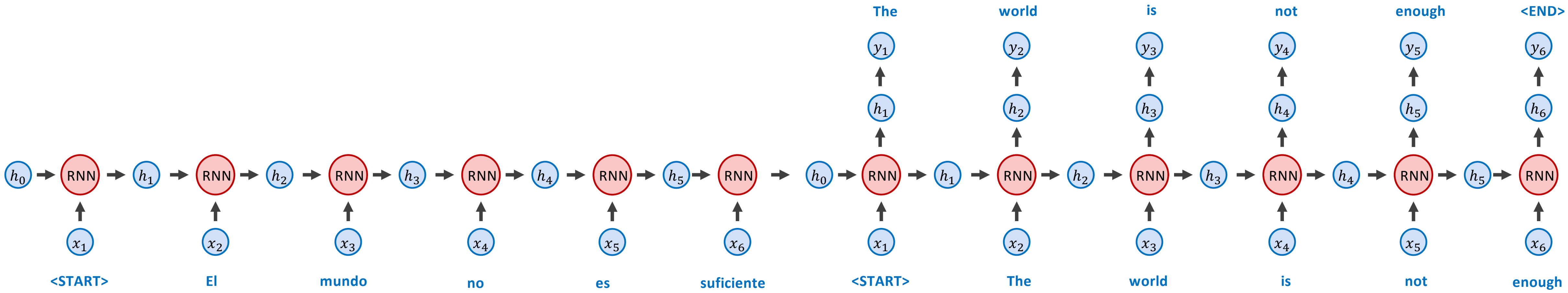
Abstract

This paper shows how Long Short-term Memory recurrent neural networks can be used to generate complex sequences with long-range structure, simply by predicting one data point at a time. The approach is demonstrated for text (where the data are discrete) and online handwriting (where the data are real-valued). It is then extended to handwriting synthesis by allowing the network to condition its predictions on a text sequence. The resulting system is able to generate highly realistic cursive handwriting in a wide variety of styles.

How can it be used? – e.g. Machine Translation

Sequence to Sequence – Encoding – Decoding – Many to Many mapping

DURING TRAINING



How can it be used? – e.g. Machine Translation
Sequence to Sequence Models

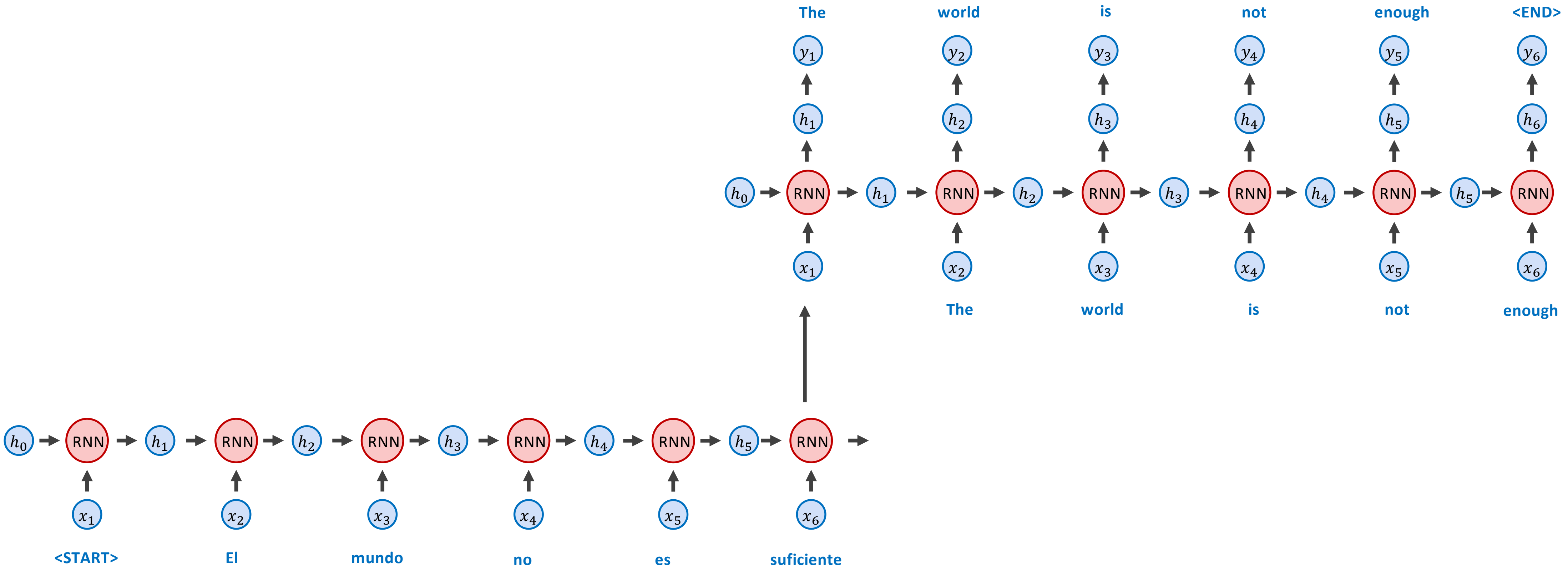
Input training examples don’t need to be the same length!
In this case outputs can be.

input	**output**
<START> este restaurante tiene buena comida	**this restaurant has good food <END>**
<START> this restaurant has good food	
<START> el mundo no es suficiente	**the world is not enough <END>**
<START> the world is not enough	

How can it be used? – e.g. Machine Translation

Sequence to Sequence – Encoding – Decoding – Many to Many mapping

DURING TRAINING – (Alternative)



Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation

Kyunghyun Cho
Bart van Merriënboer **Caglar Gulcehre**
Université de Montréal
firstname.lastname@umontreal.ca

Dzmitry Bahdanau
Jacobs University, Germany
d.bahdanau@jacobs-university.de

Fethi Bougares **Holger Schwenk**
Université du Maine, France
firstname.lastname@lium.univ-lemans.fr

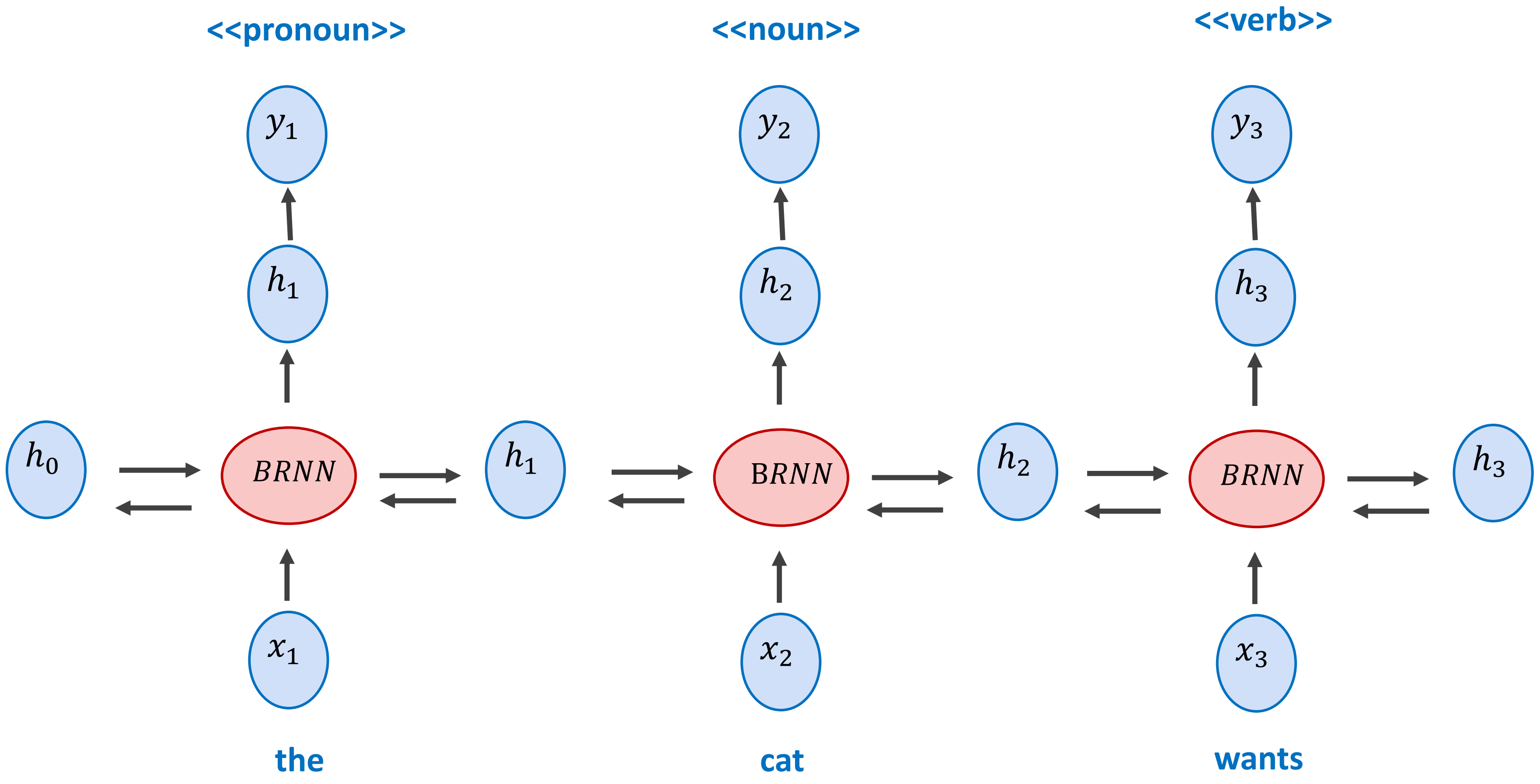
Yoshua Bengio
Université de Montréal, CIFAR Senior Fellow
find.me@on.the.web

NEURAL MACHINE TRANSLATION BY JOINTLY LEARNING TO ALIGN AND TRANSLATE

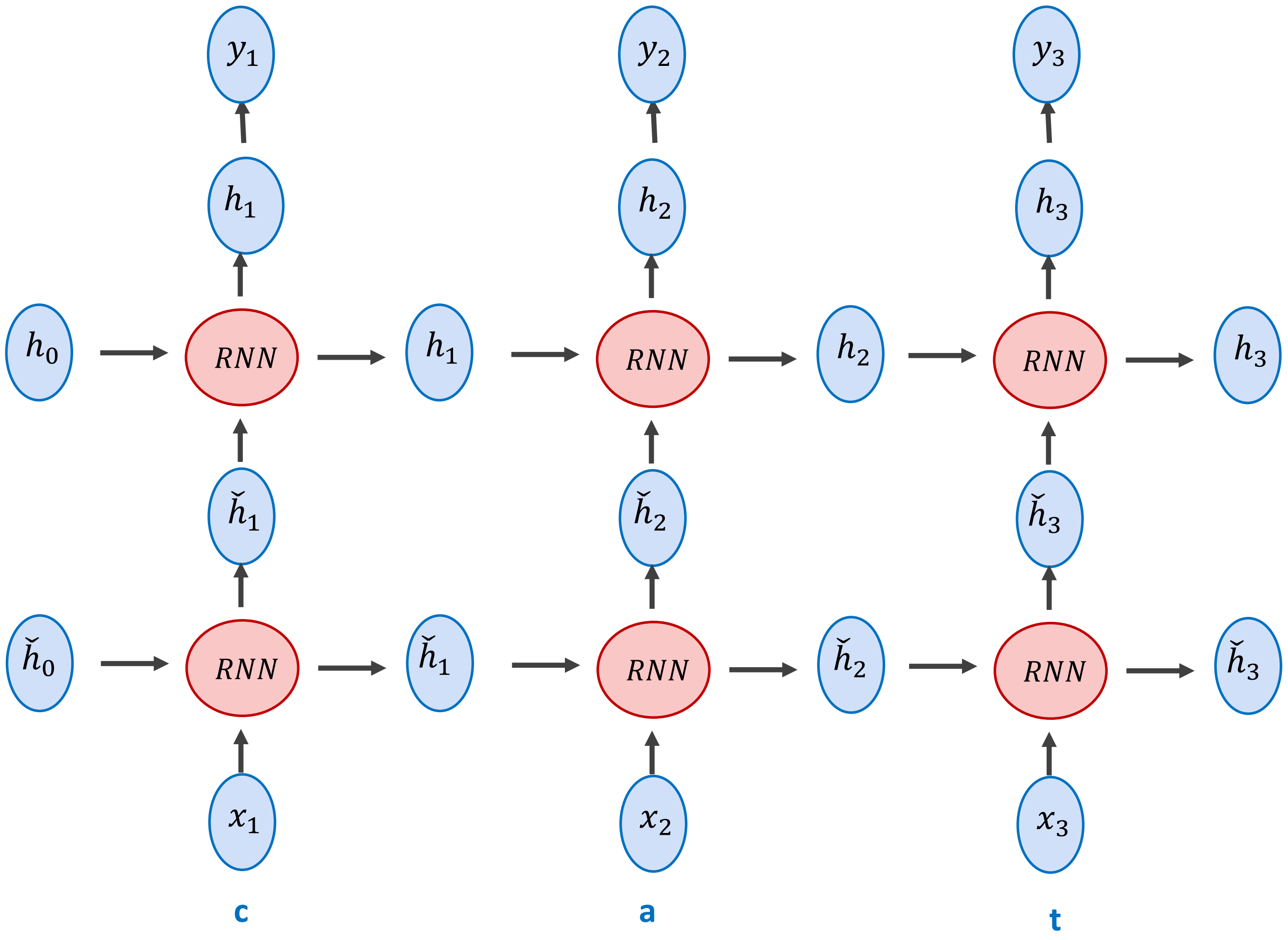
Dzmitry Bahdanau
Jacobs University Bremen, Germany

KyungHyun Cho **Yoshua Bengio***
Université de Montréal

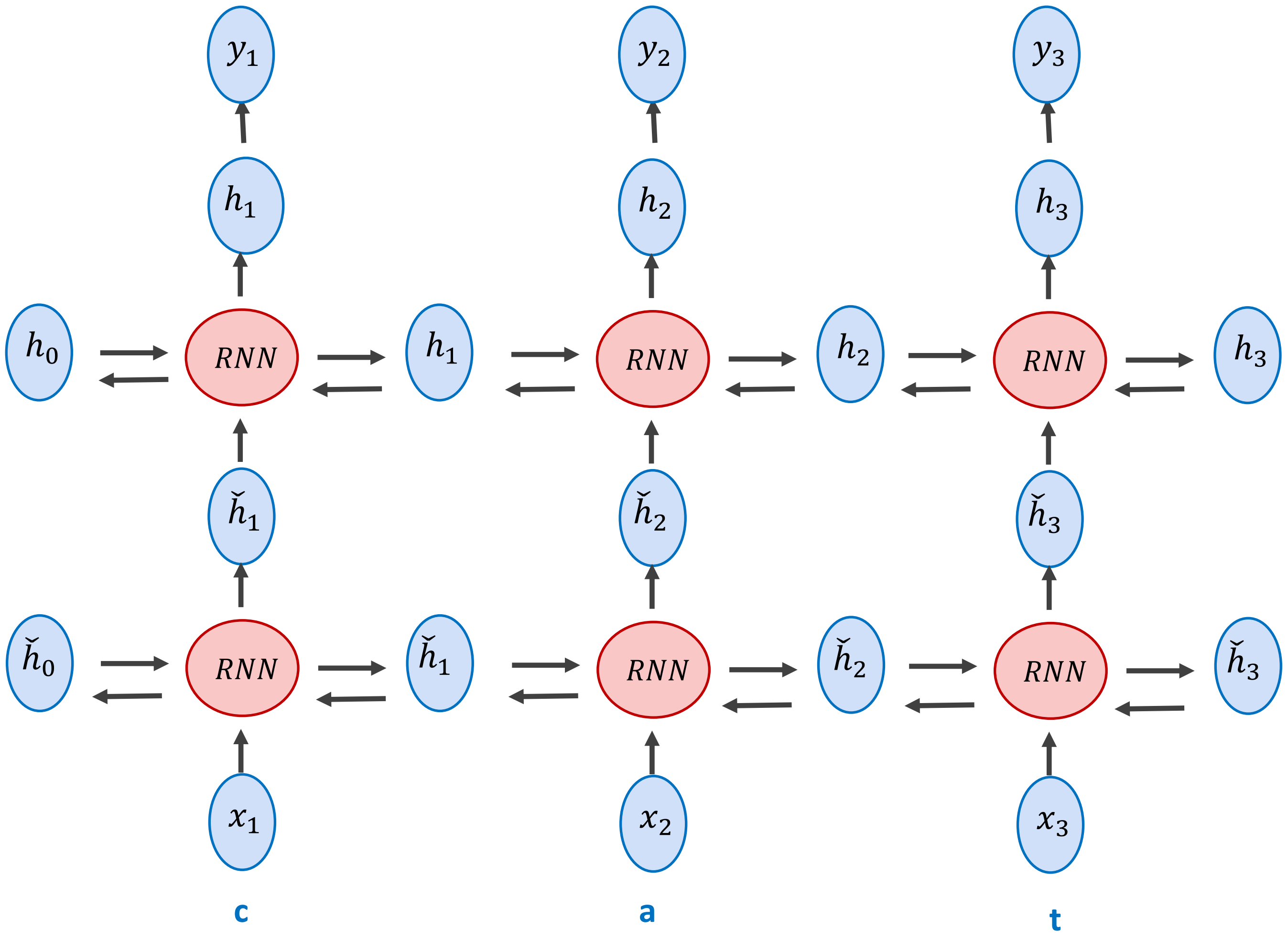
Bidirectional Recurrent Neural Network



Stacked Recurrent Neural Network



Stacked Bidirectional Recurrent Neural Network



RNN in Pytorch

Recurrent layers

class `torch.nn.RNN`(**args, **kwargs*) [source]

Applies a multi-layer Elman RNN with tanh or ReLU non-linearity to an input sequence.

For each element in the input sequence, each layer computes the following function:

$$h_t = \tanh(w_{ih} * x_t + b_{ih} + w_{hh} * h_{(t-1)} + b_{hh})$$

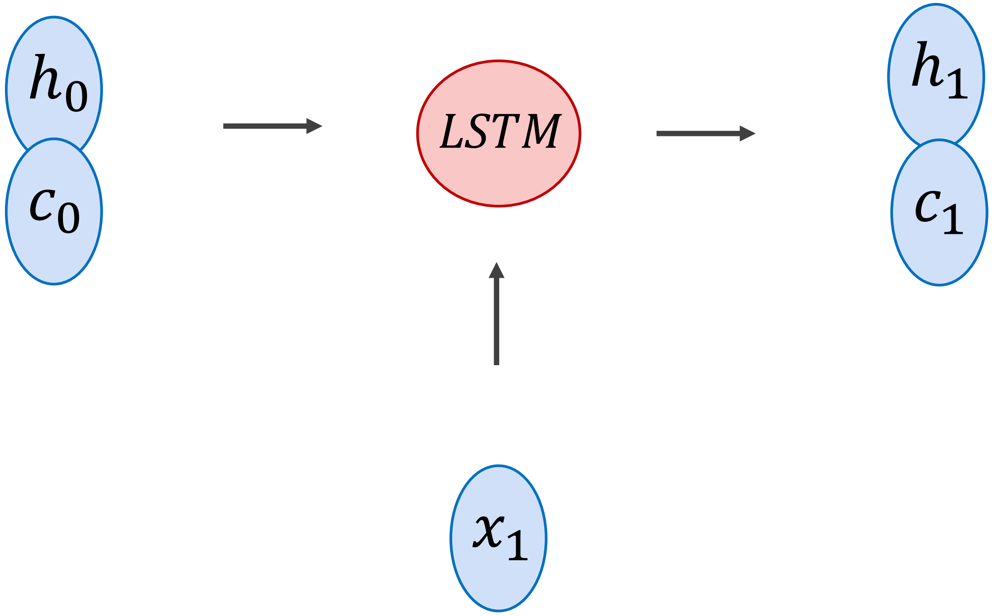
where h_t is the hidden state at time t, and x_t is the hidden state of the previous layer at time t or $input_t$ for the first layer. If nonlinearity='relu', then *ReLU* is used instead of *tanh*.

Parameters:

- **input_size** – The number of expected features in the input x
- **hidden_size** – The number of features in the hidden state h
- **num_layers** – Number of recurrent layers.
- **nonlinearity** – The non-linearity to use ['tanh'|'relu']. Default: 'tanh'
- **bias** – If False, then the layer does not use bias weights b_ih and b_hh. Default: True
- **batch_first** – If True, then the input and output tensors are provided as (batch, seq, feature)
- **dropout** – If non-zero, introduces a dropout layer on the outputs of each RNN layer except the last layer
- **bidirectional** – If True, becomes a bidirectional RNN. Default: False

LSTM Cell (Long Short-Term Memory)

$$i_t = \sigma\left(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i\right) \tag{7}$$
$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f\right) \tag{8}$$
$$c_t = f_t c_{t-1} + i_t \tanh\left(W_{xc}x_t + W_{hc}h_{t-1} + b_c\right) \tag{9}$$
$$o_t = \sigma\left(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o\right) \tag{10}$$
$$h_t = o_t \tanh(c_t) \tag{11}$$



LSTM in Pytorch

class `torch.nn.LSTM`(**args, **kwargs*) [source]

Applies a multi-layer long short-term memory (LSTM) RNN to an input sequence.

For each element in the input sequence, each layer computes the following function:

$$
\begin{aligned}
i_t &= \mathrm{sigmoid}(W_{ii}x_t + b_{ii} + W_{hi}h_{(t-1)} + b_{hi}) \\
f_t &= \mathrm{sigmoid}(W_{if}x_t + b_{if} + W_{hf}h_{(t-1)} + b_{hf}) \\
g_t &= \tanh(W_{ig}x_t + b_{ig} + W_{hc}h_{(t-1)} + b_{hg}) \\
o_t &= \mathrm{sigmoid}(W_{io}x_t + b_{io} + W_{ho}h_{(t-1)} + b_{ho}) \\
c_t &= f_t * c_{(t-1)} + i_t * g_t \\
h_t &= o_t * \tanh(c_t)
\end{aligned}
$$

where h_t is the hidden state at time t, c_t is the cell state at time t, x_t is the hidden state of the previous layer at time t or $input_t$ for the first layer, and i_t, f_t, g_t, o_t are the input, forget, cell, and out gates, respectively.

Parameters:

- **input_size** – The number of expected features in the input x
- **hidden_size** – The number of features in the hidden state h
- **num_layers** – Number of recurrent layers.
- **bias** – If False, then the layer does not use bias weights b_ih and b_hh. Default: True
- **batch_first** – If True, then the input and output tensors are provided as (batch, seq, feature)
- **dropout** – If non-zero, introduces a dropout layer on the outputs of each RNN layer except the last layer
- **bidirectional** – If True, becomes a bidirectional RNN. Default: False

GRU in Pytorch

class `torch.nn.GRU`(**args*, ***kwargs*) [source]

Applies a multi-layer gated recurrent unit (GRU) RNN to an input sequence.

For each element in the input sequence, each layer computes the following function:

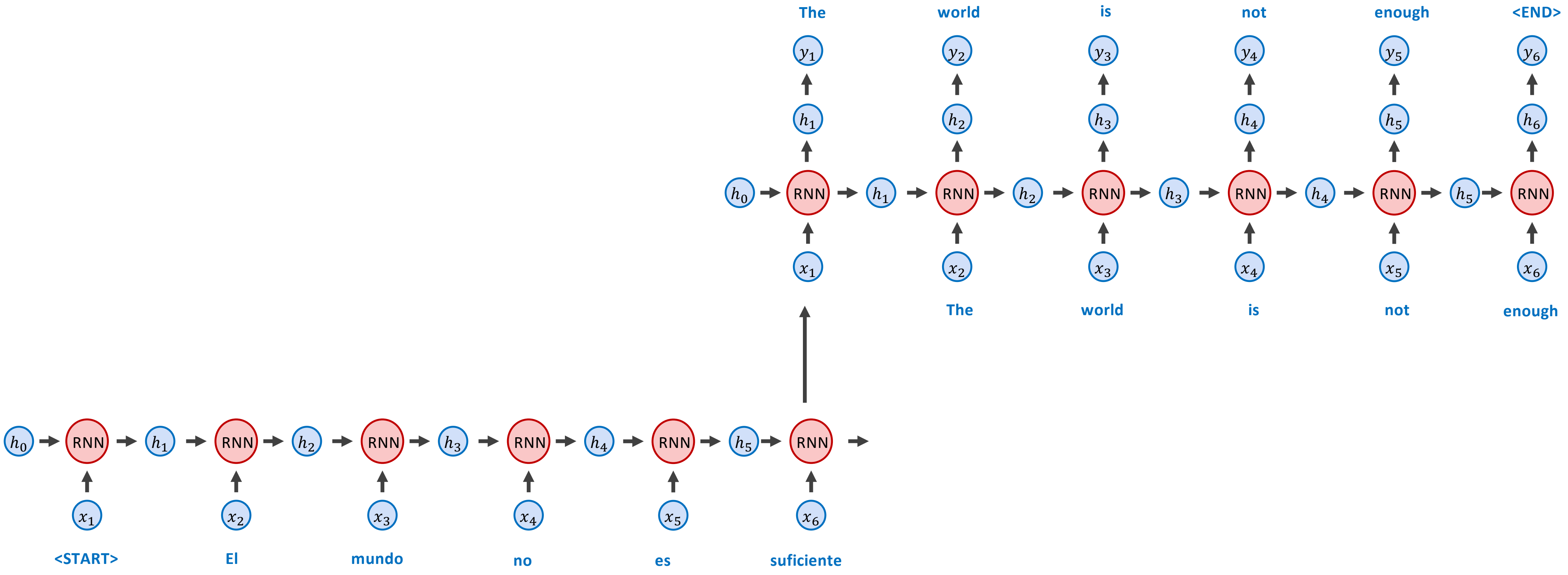
$$
\begin{aligned}
r_t &= \mathrm{sigmoid}(W_{ir}x_t + b_{ir} + W_{hr}h_{(t-1)} + b_{hr}) \\
z_t &= \mathrm{sigmoid}(W_{iz}x_t + b_{iz} + W_{hz}h_{(t-1)} + b_{hz}) \\
n_t &= \tanh(W_{in}x_t + b_{in} + r_t * (W_{hn}h_{(t-1)} + b_{hn})) \\
h_t &= (1 - z_t) * n_t + z_t * h_{(t-1)}
\end{aligned}
$$

where h_t is the hidden state at time t, x_t is the hidden state of the previous layer at time t or $input_t$ for the first layer, and r_t, z_t, n_t are the reset, input, and new gates, respectively.

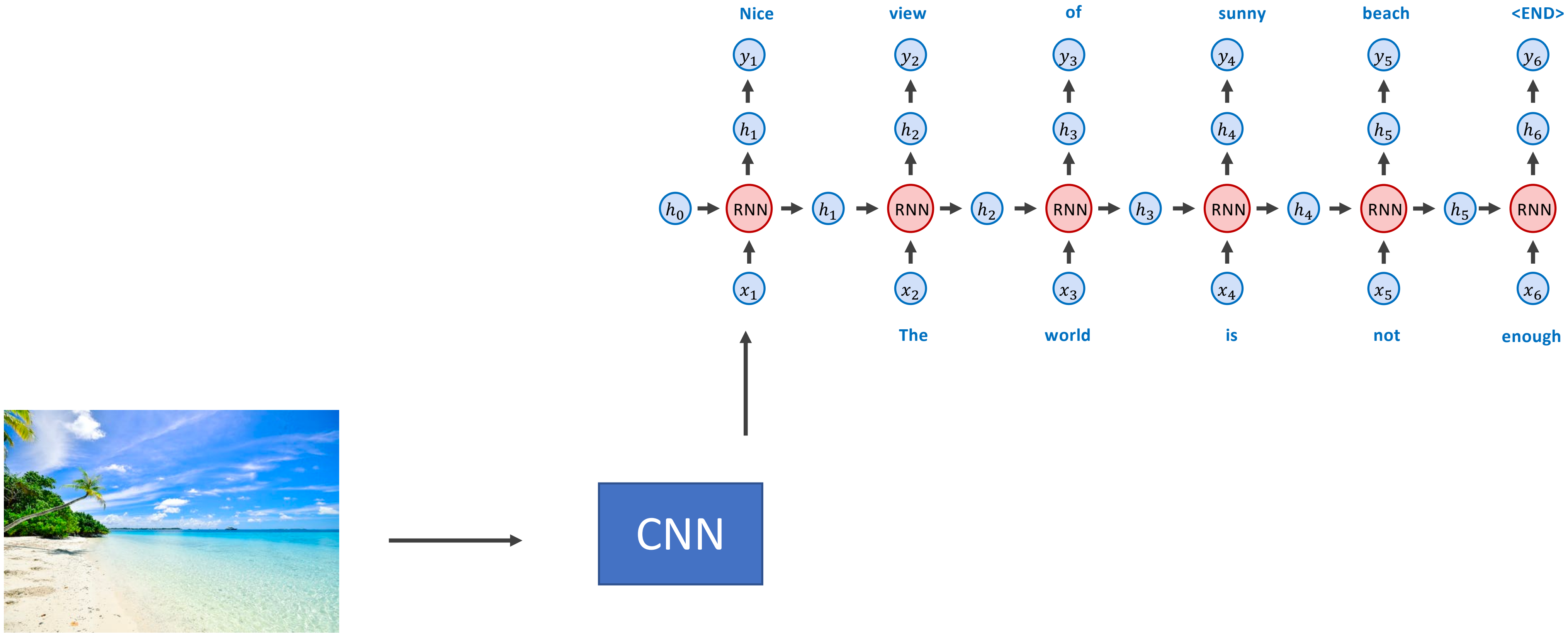
Parameters:

- **input_size** – The number of expected features in the input x
- **hidden_size** – The number of features in the hidden state h
- **num_layers** – Number of recurrent layers.
- **bias** – If False, then the layer does not use bias weights b_ih and b_hh. Default: True
- **batch_first** – If True, then the input and output tensors are provided as (batch, seq, feature)
- **dropout** – If non-zero, introduces a dropout layer on the outputs of each RNN layer except the last layer
- **bidirectional** – If True, becomes a bidirectional RNN. Default: False

RNNs for Image Caption Generation



RNNs for Image Caption Generation



References (a lot of them)

- Vinyals et al. Show and Tell: A Neural Image Caption Generator https://arxiv.org/abs/1411.4555
- Mao et al. Deep Captioning with Multimodal Recurrent Neural Networks (m-RNN). https://arxiv.org/abs/1412.6632
- Karpathy and Fei-Fei. Deep Visual-Semantic Alignments for Generating Image Descriptions. https://arxiv.org/abs/1412.2306
- Fang et al. From Captions to Visual Concepts and Back. https://arxiv.org/abs/1411.4952
- Yin and Ordonez. OBJ2TEXT: Generating Visually Descriptive Language from Object Layouts. https://arxiv.org/abs/1707.07102 (not exactly targeting image captioning specifically but locally grown paper so let me self-promote)

Questions?