Lecture 9

Tian Han

Outline

- Long Short Term Memory (LSTM)
- Several tricks
- RNNs: generation, translation

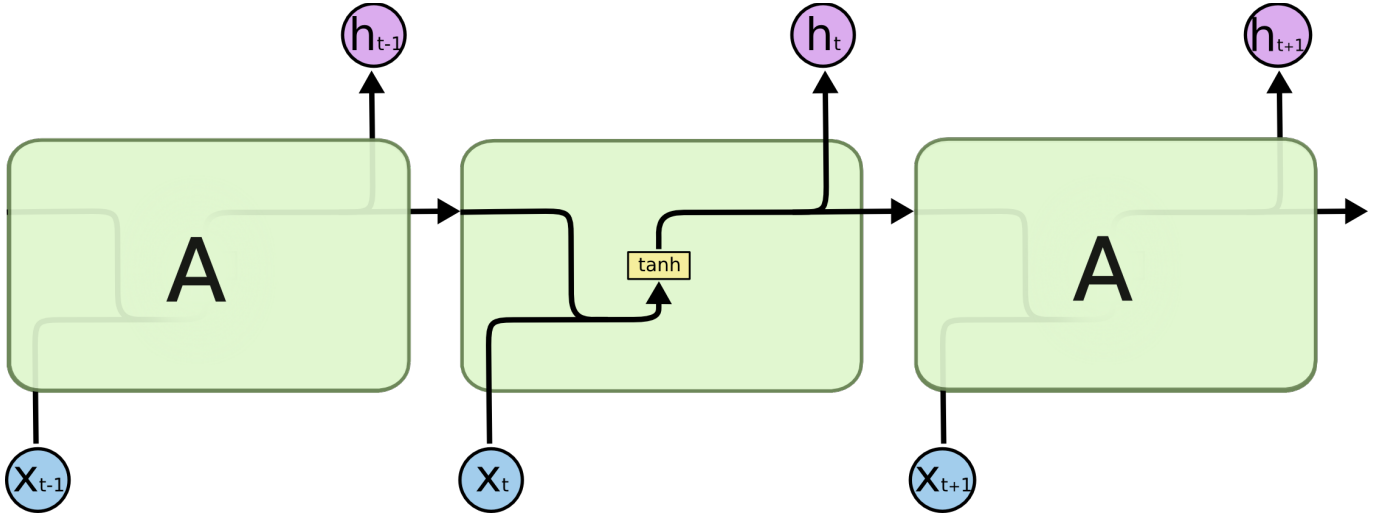
Long Short Term Memory (LSTM)

LSTM Model

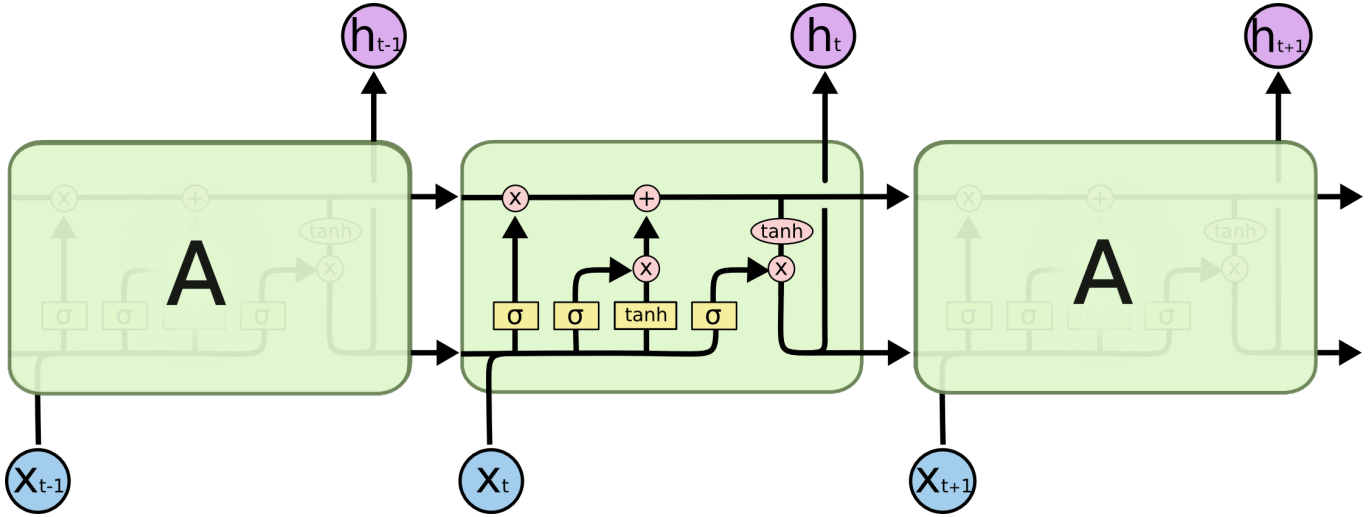
Reference

- Hochreiter and Schmidhuber. Long short-term memory. *Neural computation,* 1997.

LSTM Networks



Simple RNN

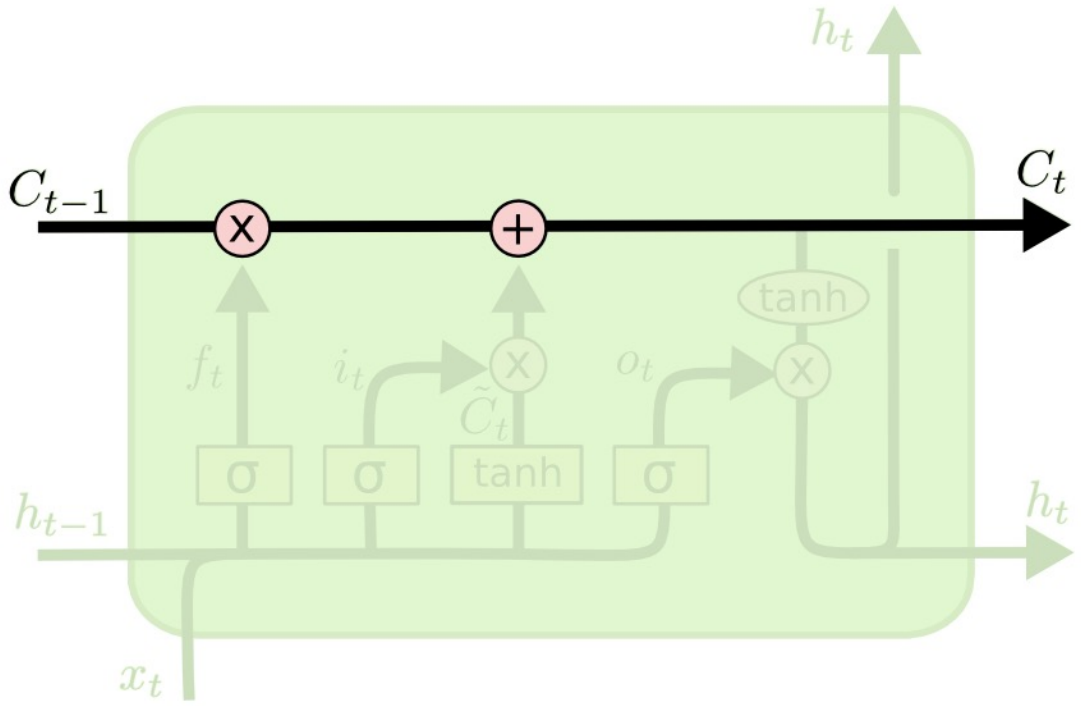


LSTM

Figures are from Christopher Olah's blog: Understanding LSTM Networks.

LSTM: Conveyor Belt

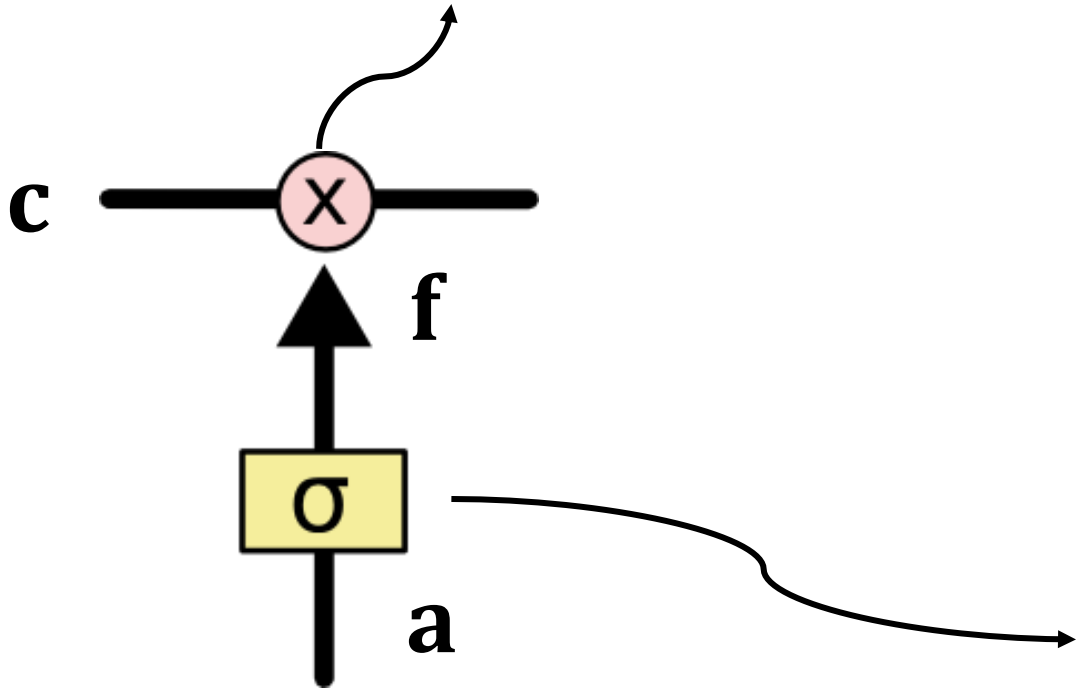
- Conveyor belt: allows the past information directly flows to the future.

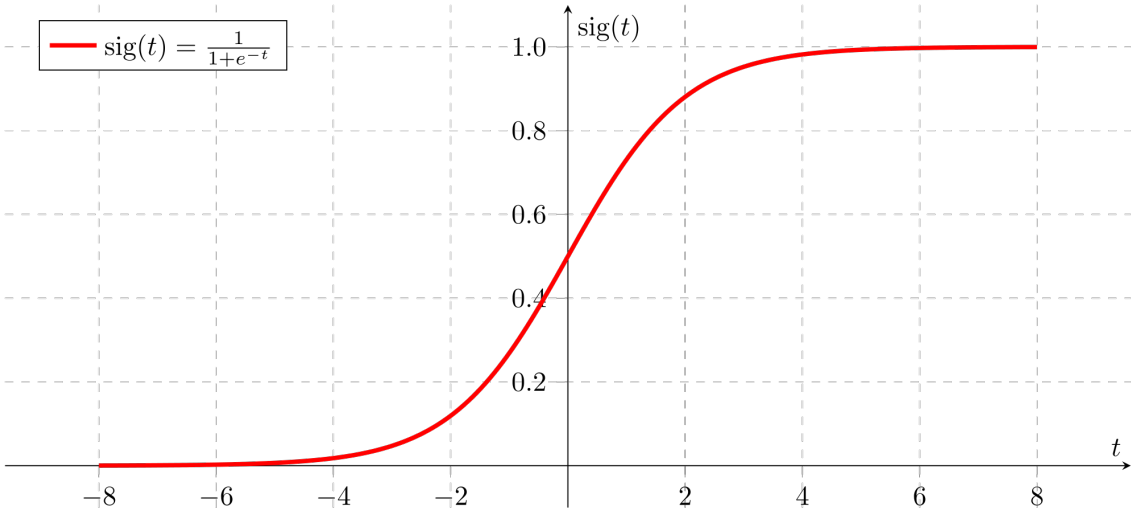


The Figure is from Christopher Olah's blog: Understanding LSTM Networks.

LSTM: Forget Gate

Elementwise multiplication of 2 vectors.

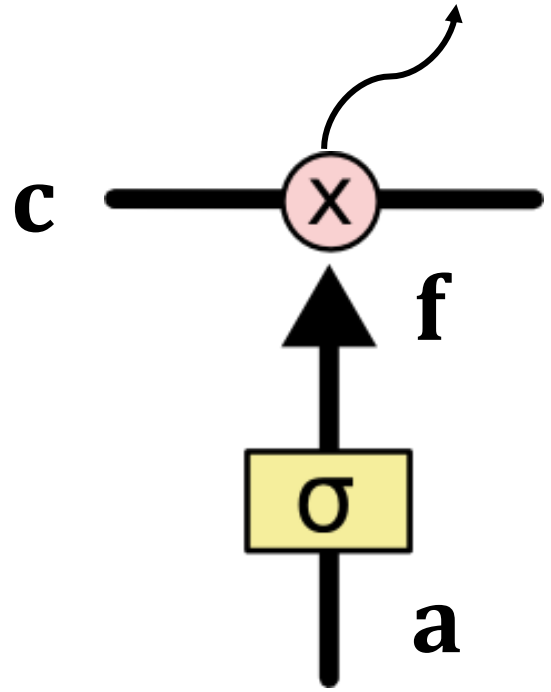




Sigmoid function: between 0 and 1.

LSTM: Forget Gate

Elementwise multiplication of 2 vectors.

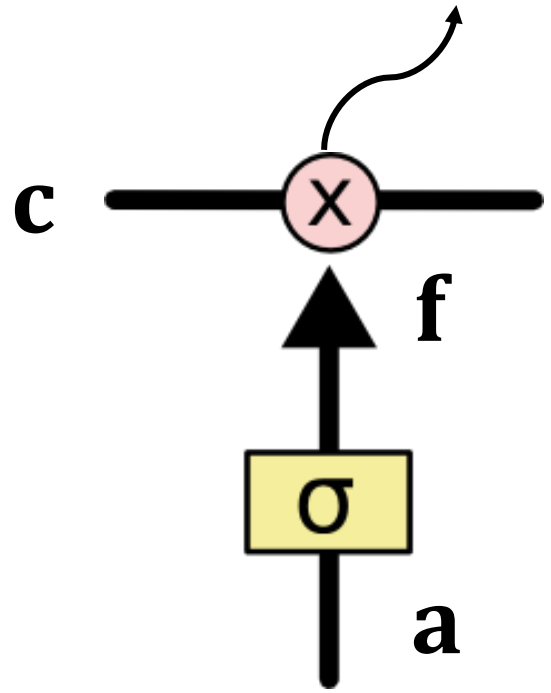


$$\sigma\left(\begin{bmatrix}1\\3\\0\\-2\end{bmatrix}\right) = \begin{bmatrix}0.73\\0.95\\0.5\\0.12\end{bmatrix}$$

a **f**

LSTM: Forget Gate

Elementwise multiplication of 2 vectors.



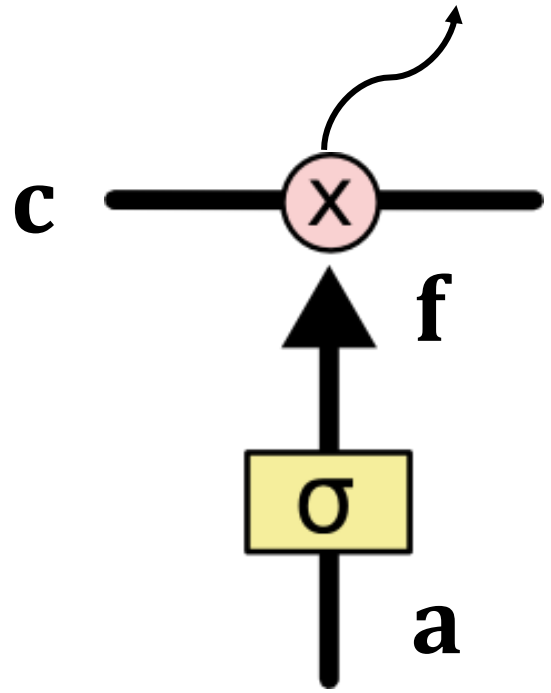
$$\begin{bmatrix} 0.9 \\ 0.2 \\ -0.5 \\ -0.1 \end{bmatrix} \circ \begin{bmatrix} 0.5 \\ 0 \\ 1 \\ 0.8 \end{bmatrix} = \begin{bmatrix} 0.45 \\ 0 \\ -0.5 \\ -0.08 \end{bmatrix}$$

c **f** **output**

LSTM: Forget Gate

- Forget gate ($\mathbf{f}$): a vector (the same shape as $\mathbf{c}$ and $\mathbf{h}$).
  - A value of zero means "let nothing through".
  - A value of one means "let everything through!"

Elementwise multiplication of 2 vectors.



$$\begin{bmatrix} 0.9 \\ 0.2 \\ -0.5 \\ -0.1 \end{bmatrix} \circ \begin{bmatrix} 0.5 \\ 0 \\ 1 \\ 0.8 \end{bmatrix} = \begin{bmatrix} 0.45 \\ 0 \\ -0.5 \\ -0.08 \end{bmatrix}$$

$\mathbf{c}$ $\mathbf{f}$ **output**

LSTM: Forget Gate

- Forget gate ($\mathbf{f}$): a vector (the same shape as $\mathbf{c}$ and $\mathbf{h}$).
  - A value of zero means "let nothing through".
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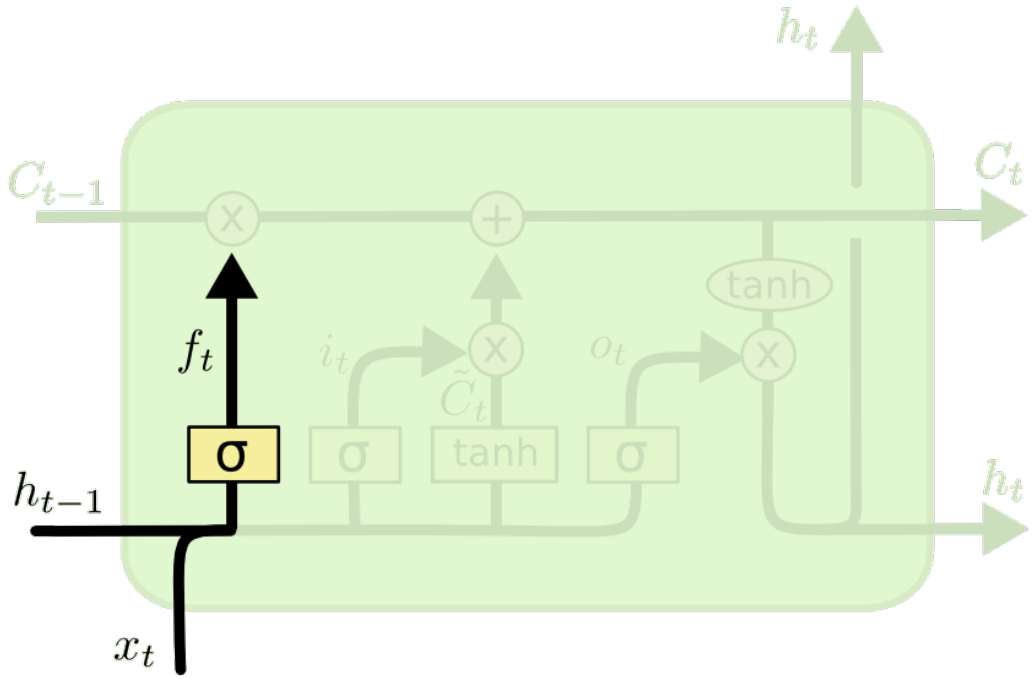
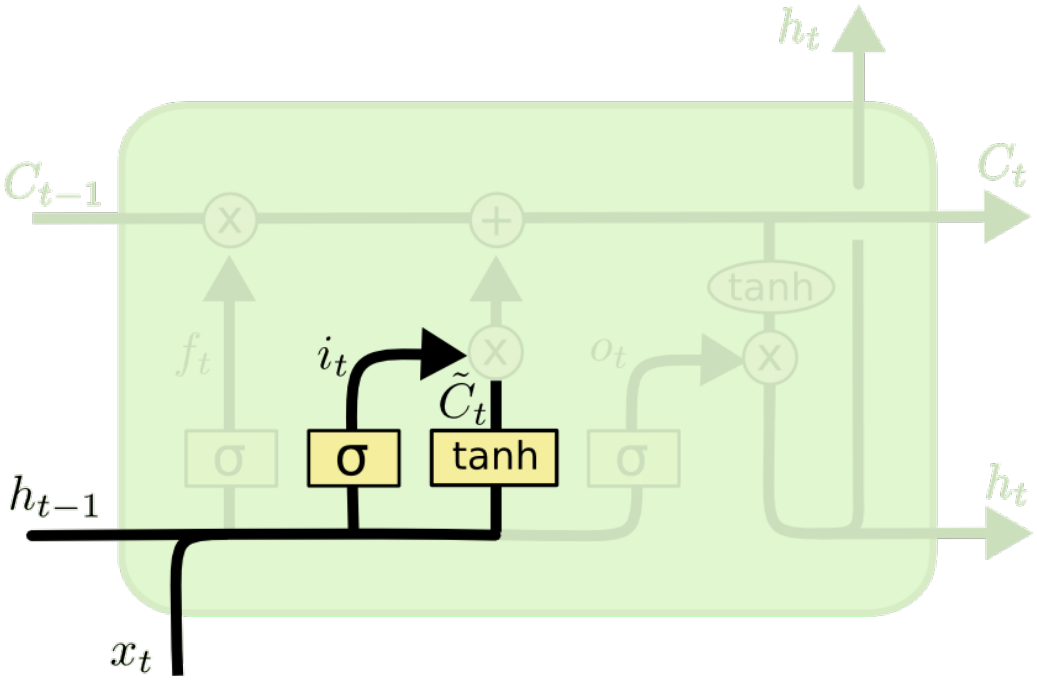


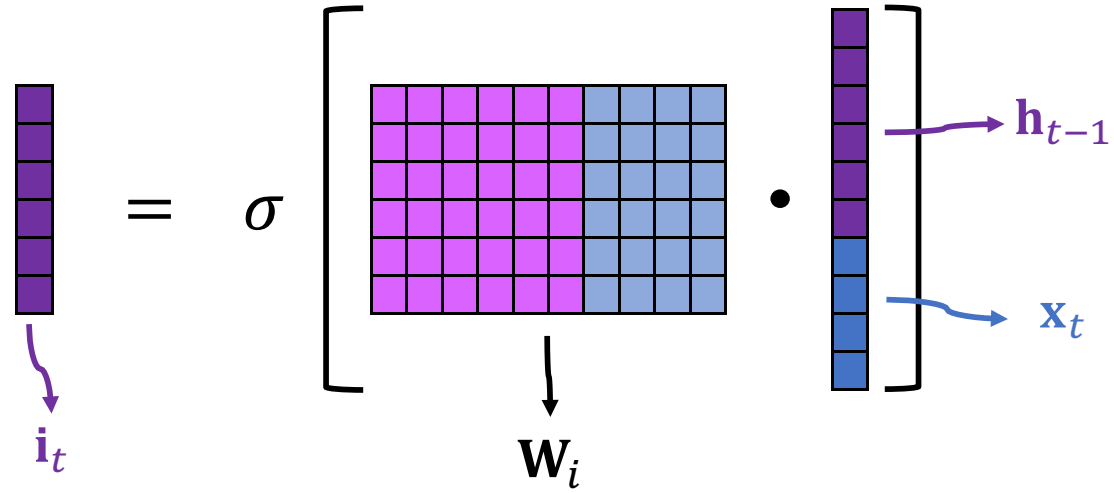
$$\mathbf{f}_t = \sigma\left(\mathbf{W}_f \cdot \begin{bmatrix} \mathbf{h}_{t-1} \\ \mathbf{x}_t \end{bmatrix}\right)$$

The left figure is from Christopher Olah's blog: Understanding LSTM Networks.

LSTM: Input Gate

- Input gate ($\mathbf{i}_t$): decides which values of the conveyor belt we'll update.

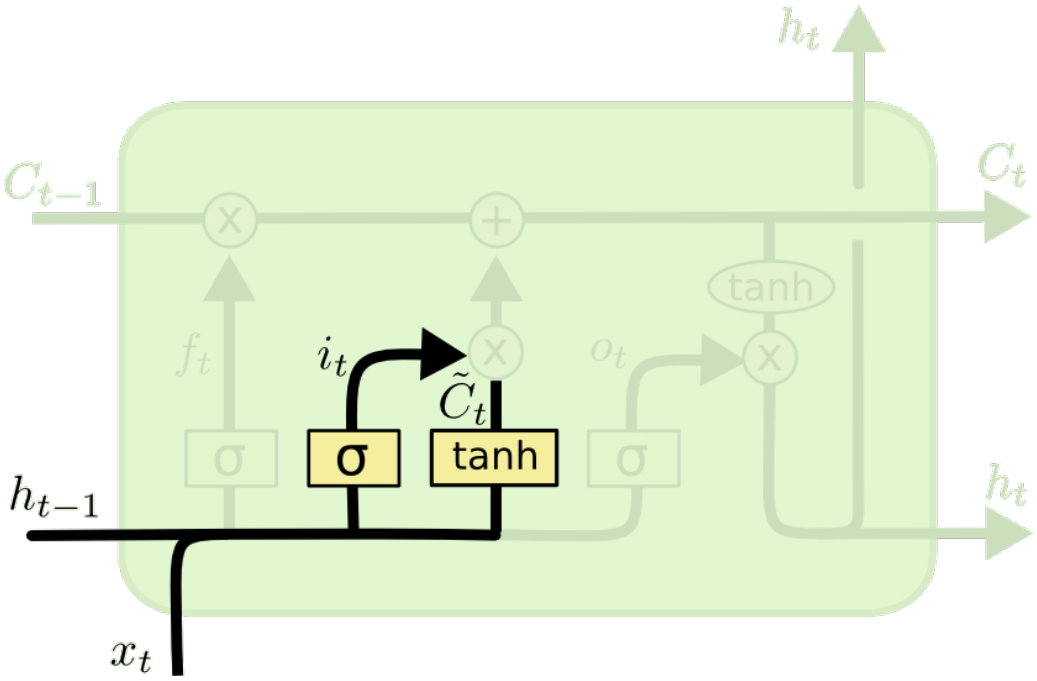




The left figure is from Christopher Olah's blog: Understanding LSTM Networks.

LSTM: New Value

- New value ($\tilde{\mathbf{c}}_t$): to be added to the conveyor belt.

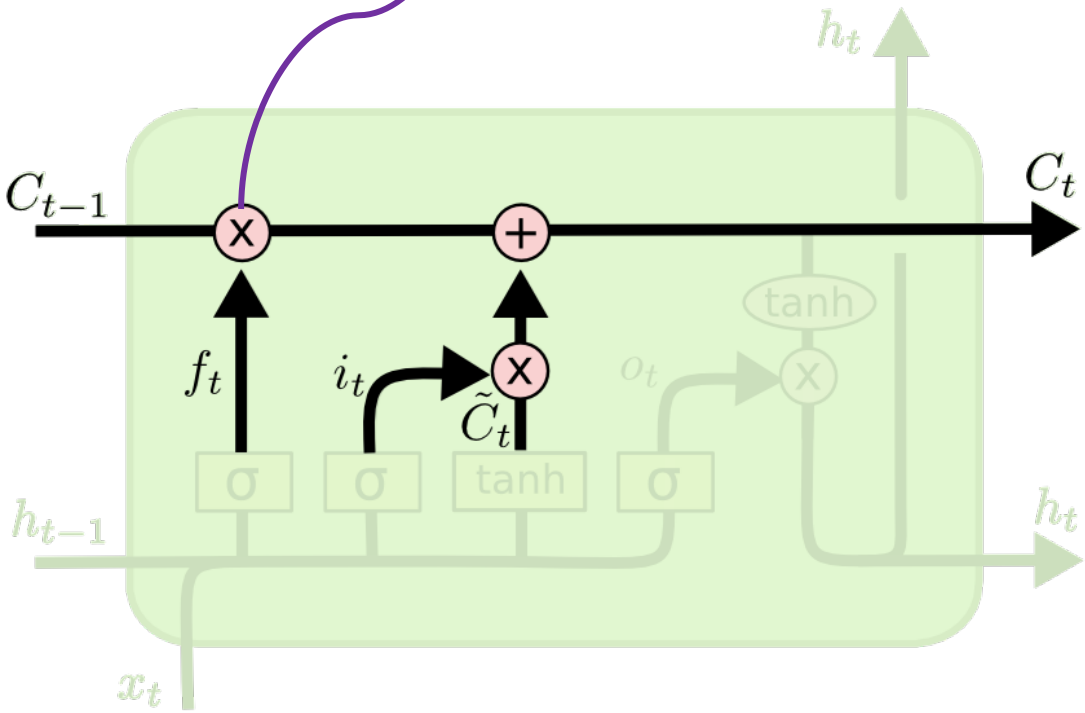


$$\tilde{\mathbf{c}}_t = \tanh\left(\mathbf{W}_c \cdot \begin{bmatrix} \mathbf{h}_{t-1} \\ \mathbf{x}_t \end{bmatrix}\right)$$

The left figure is from Christopher Olah's blog: Understanding LSTM Networks.

LSTM: Update the Conveyor Belt

optionally let information through

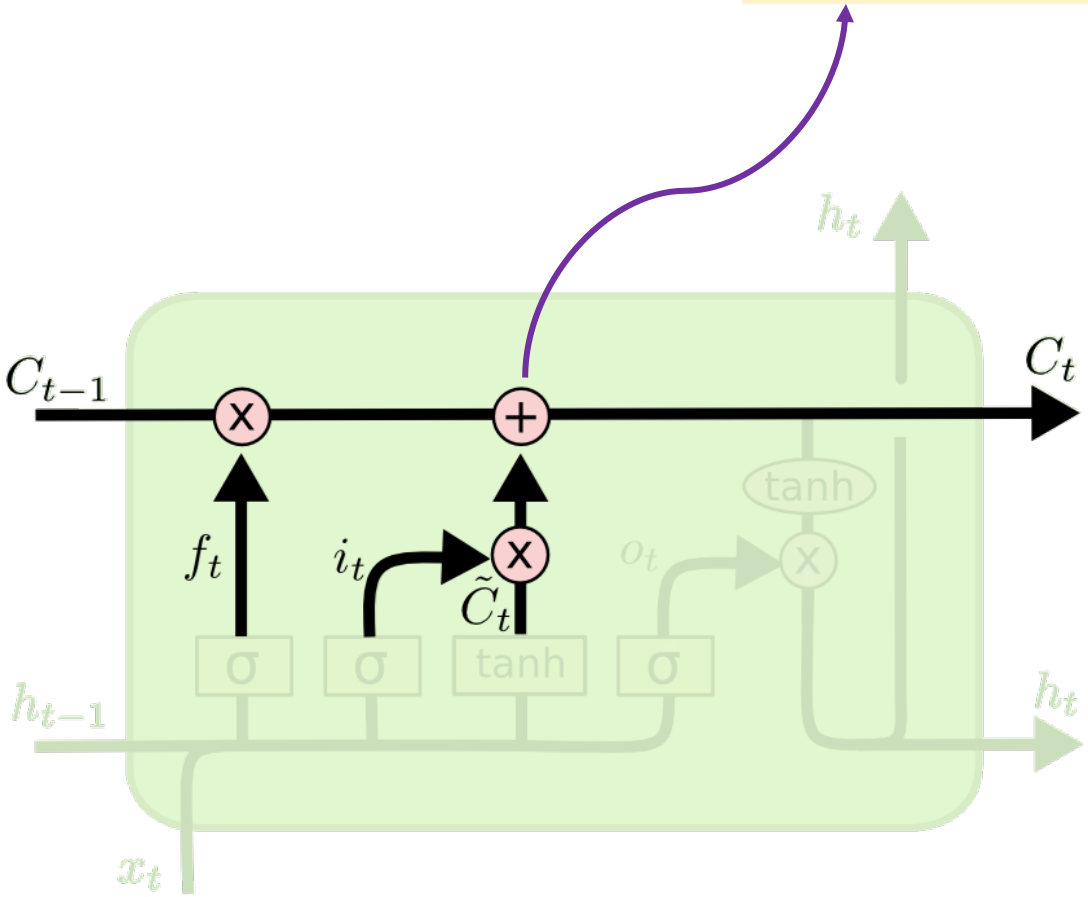


$$\mathbf{c}_t = \mathbf{f}_t \circ \mathbf{c}_{t-1} + \mathbf{i}_t \circ \tilde{\mathbf{c}}_t$$

The left figure is from Christopher Olah's blog: Understanding LSTM Networks.

LSTM: Update the Conveyor Belt

add new value

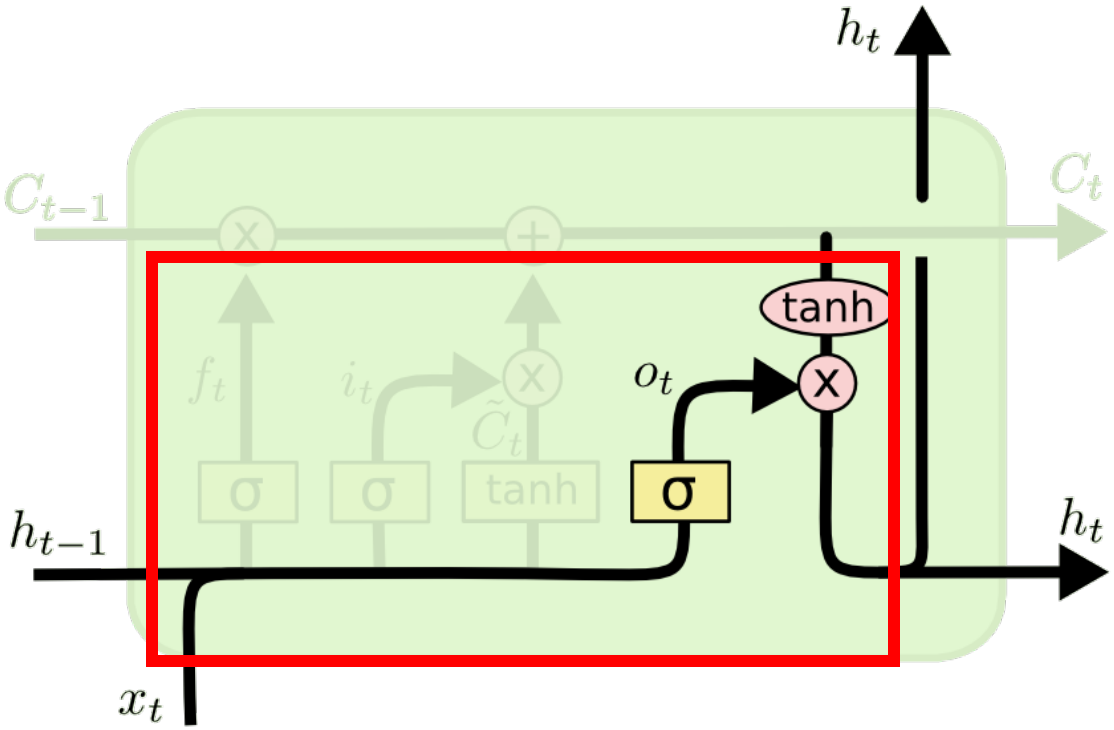


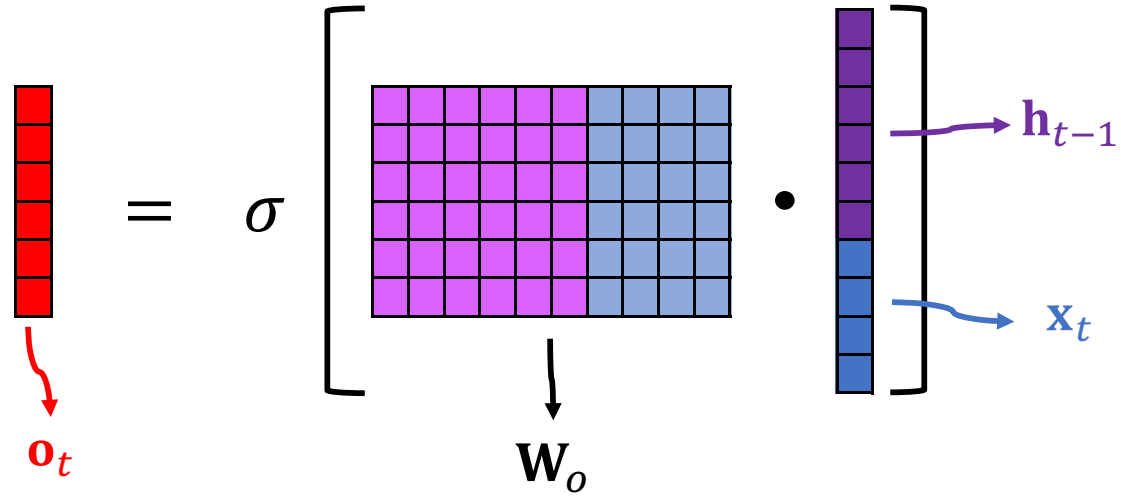
$$\mathbf{c}_t = \mathbf{f}_t \circ \mathbf{c}_{t-1} + \mathbf{i}_t \circ \tilde{\mathbf{c}}_t$$

The left figure is from Christopher Olah's blog: Understanding LSTM Networks.

LSTM: Output Gate

- Output gate ($\mathbf{o}_t$): decide what flows from the conveyor belt C_{t-1} to the state h_t.

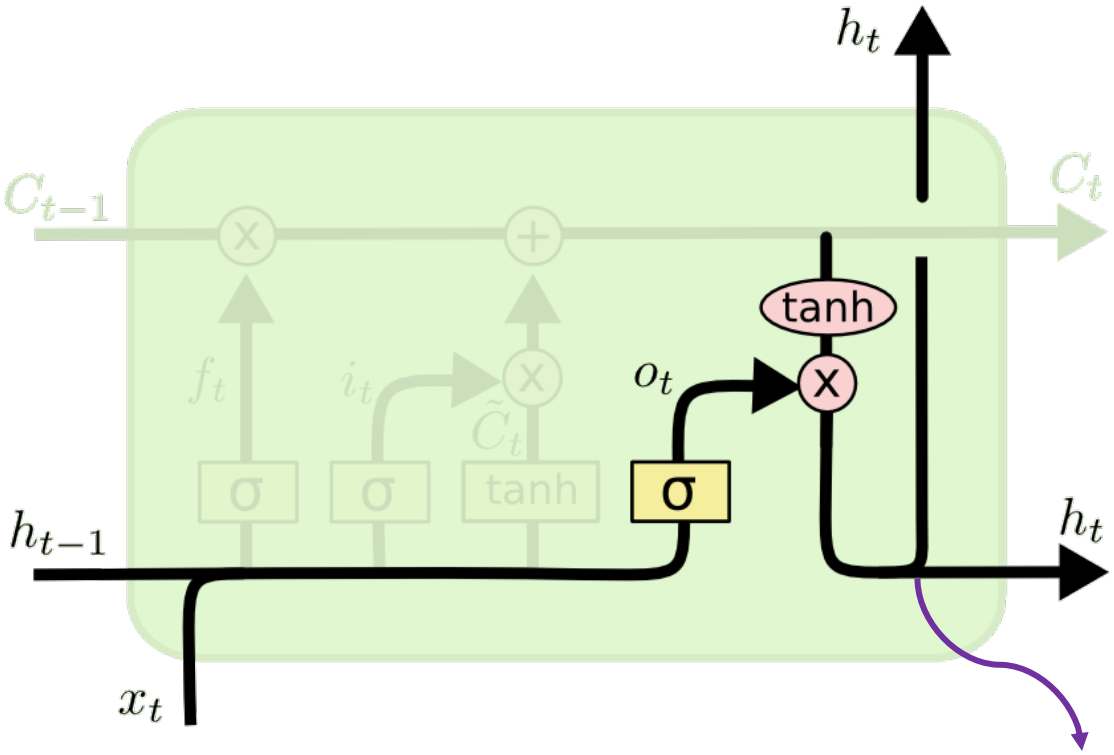




The left figure is from Christopher Olah's blog: Understanding LSTM Networks.

LSTM: Update State

- State ($\mathbf{h}_t$): the output of LSTM.

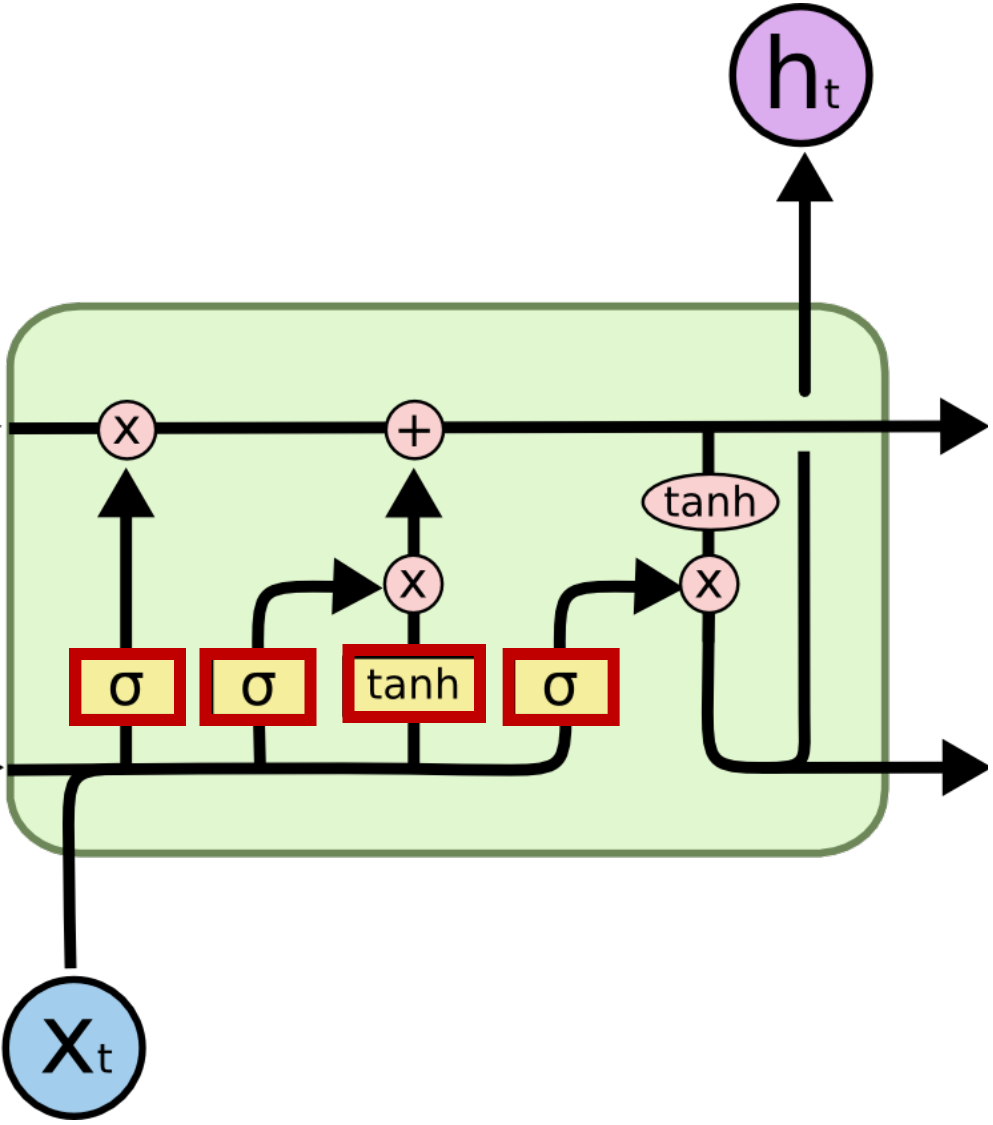


Two copies of h_t

$$\mathbf{h}_t = \mathbf{o}_t \circ \tanh\left[\mathbf{c}_t\right]$$

The left figure is from Christopher Olah's blog: Understanding LSTM Networks.

LSTM: Number of Parameters



#parameters: 4 times as many as SimpleRNN

- 4 parameter matrices, each of which has
  - `#rows: shape(h)`
  - `#cols: shape(h)+shape(x)`

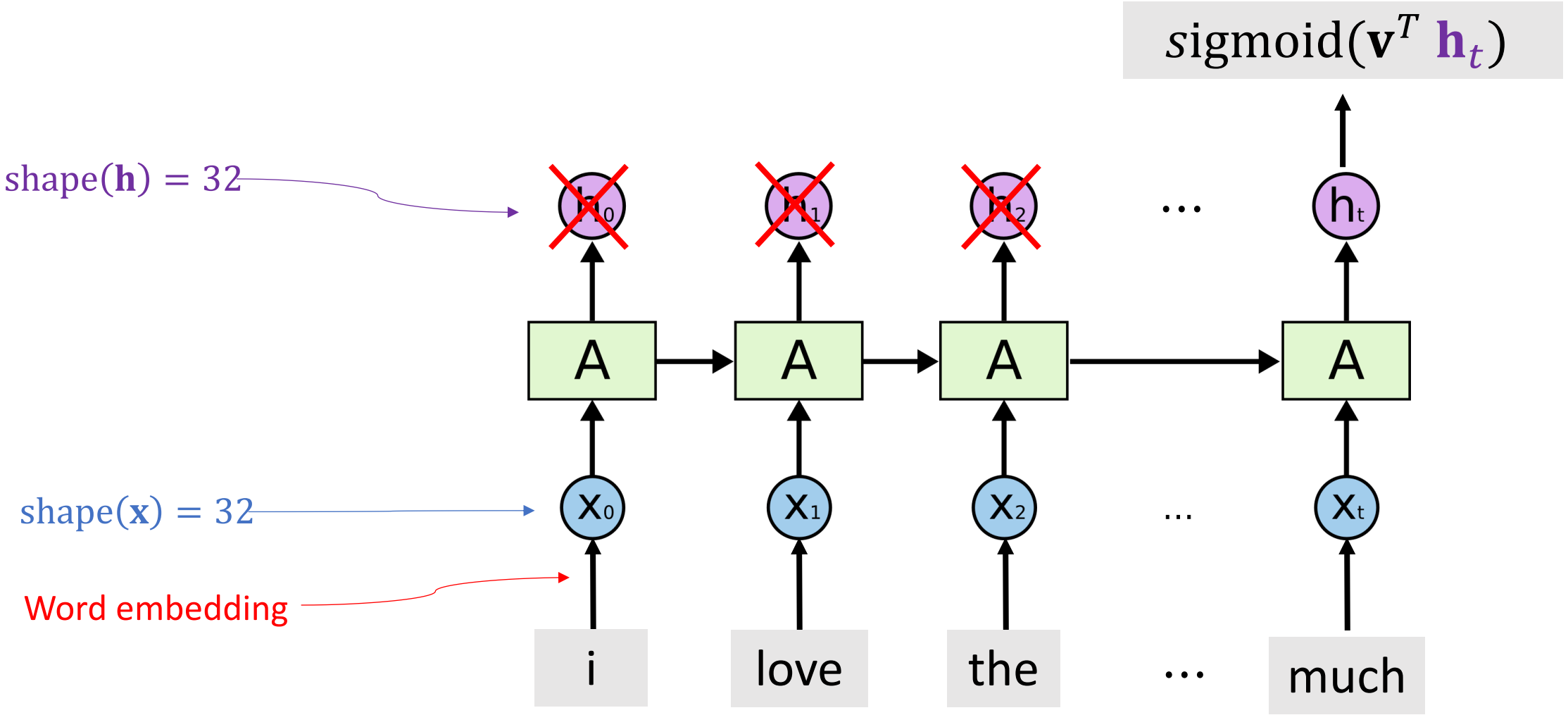
- #parameter (do not count intercept):

`4 × shape(h) × [shape(h)+shape(x)]`

The left figure is from Christopher Olah's blog: Understanding LSTM Networks.

LSTM Using Keras

LSTM for IMDB Review



LSTM for IMDB Review

```
from keras.models import Sequential
from keras.layers import LSTM, Embedding, Dense, Flatten

vocabulary = 10000
embedding_dim = 32
word_num = 500
state_dim = 32

model = Sequential()
model.add(Embedding(vocabulary, embedding_dim, input_length=word_num))
model.add(LSTM(state_dim, return_sequences=False))
model.add(Dense(1, activation='sigmoid'))
```

Replace “SimpleRNN” by “LSTM”.

```
model.summary()
```

LSTM for IMDB Review

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, 500, 32)	320000
lstm_1 (LSTM)	(None, 32)	8320
dense_1 (Dense)	(None, 1)	33

Total params: 328,353
Trainable params: 328,353
Non-trainable params: 0

LSTM for IMDB Review

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, 500, 32)	320000
lstm_1 (LSTM)	(None, 32)	8320
dense_1 (Dense)	(None, 1)	33

Total params: 328,353
Trainable params: 328,353
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#parameters in LSTM:

- $8320 = 2080 \times 4$
- $2080 = 32 \times (32 + 32) + 32$

$\text{shape}(\mathbf{h}) = 32$

$\text{shape}(\mathbf{x})$

LSTM for IMDB Review

- Training Accuracy: 91.8%
- Validation Accuracy: 88.7%
- Test Accuracy: 88.6%

Substantial improvement over SimpleRNN (whose test accuracy is 84%).

LSTM Dropout

```
from keras.models import Sequential
from keras.layers import LSTM, Embedding, Dense, Flatten

vocabulary = 10000
embedding_dim = 32
word_num = 500
state_dim = 32

model = Sequential()
model.add(Embedding(vocabulary, embedding_dim, input_length=word_num))
model.add(LSTM(state_dim, return_sequences=False, dropout=0.2))
model.add(Dense(1, activation='sigmoid'))

model.summary()
```

Summary

- LSTM uses a “conveyor belt” to get longer memory than SimpleRNN.

Summary

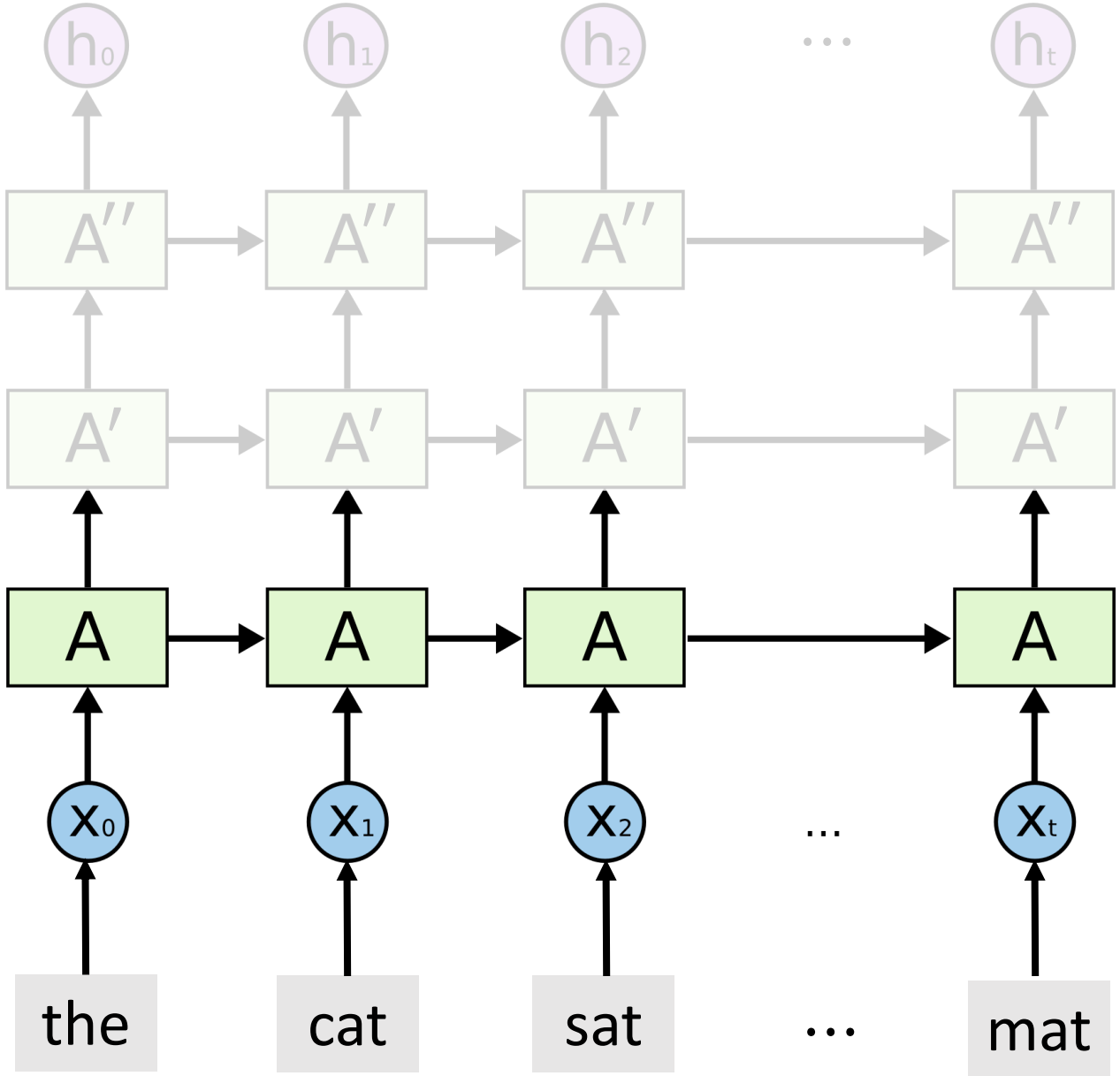
- LSTM uses a "conveyor belt" to get longer memory than SimpleRNN.
- Each of the following blocks has a parameter matrix:
  - Forget gate.
  - Input gate.
  - New values.
  - Output gate.
- Number of parameters:

$$4 \times \text{shape}(\mathbf{h}) \times [\text{shape}(\mathbf{h}) + \text{shape}(\mathbf{x})].$$

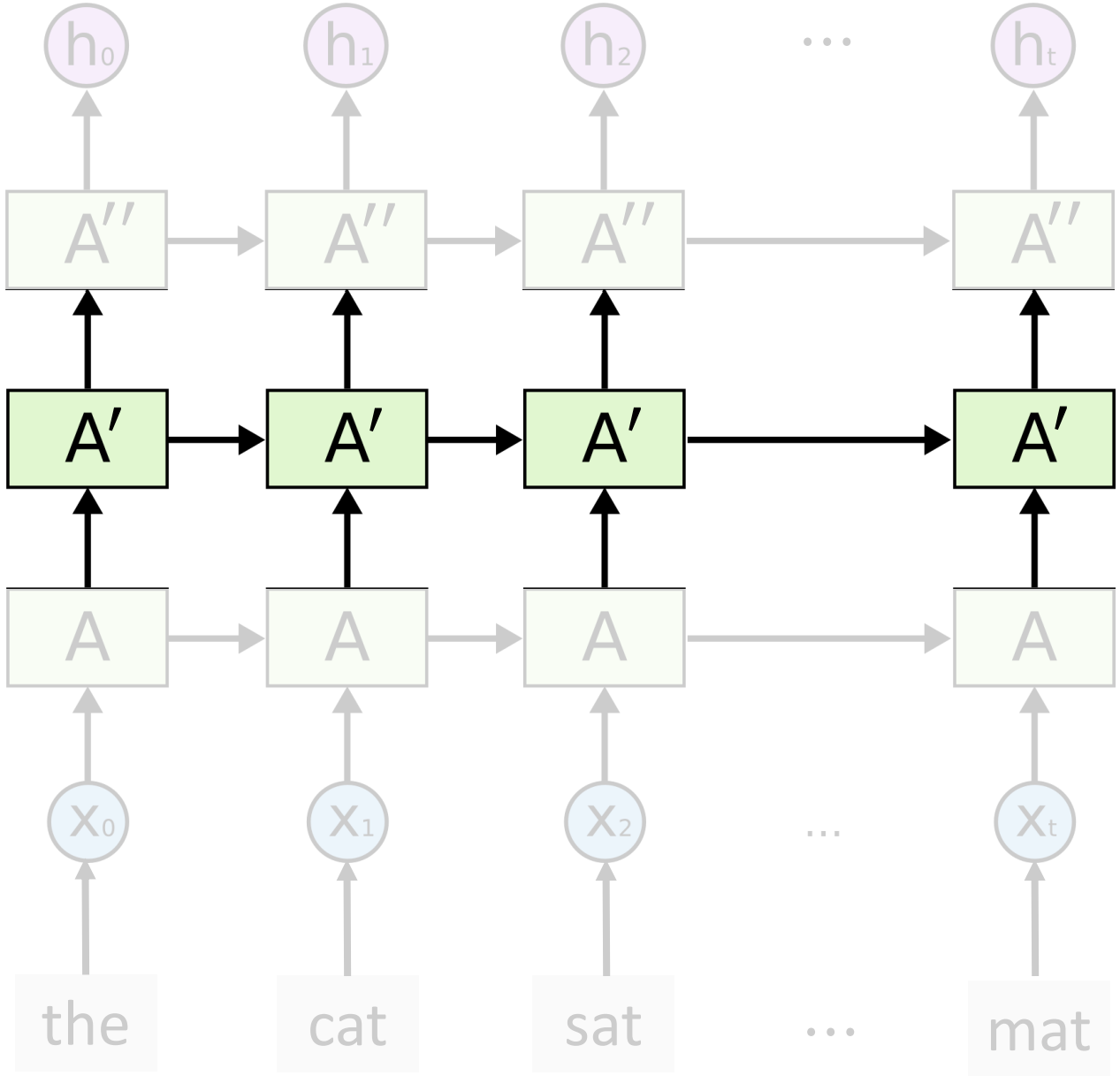
Making RNNs More Effective

Stacked RNN

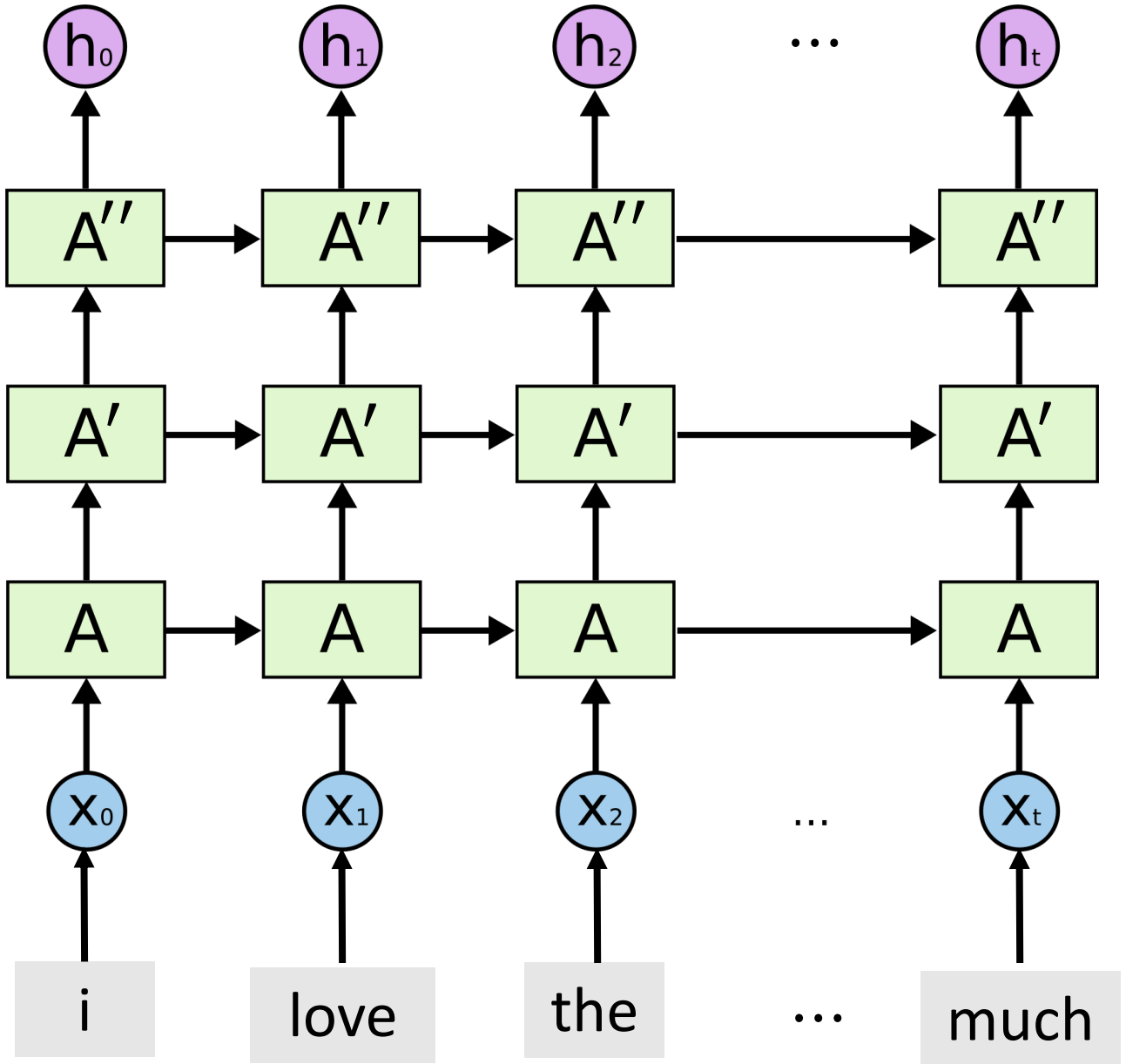
Stacked RNN



Stacked RNN



Stacked RNN



Stacked LSTM

```
from keras.models import Sequential
from keras.layers import LSTM, Embedding, Dense

vocabulary = 10000
embedding_dim = 32
word_num = 500
state_dim = 32

model = Sequential()
model.add(Embedding(vocabulary, embedding_dim, input_length=word_num))
model.add(LSTM(state_dim, return_sequences=True, dropout=0.2))
model.add(LSTM(state_dim, return_sequences=True, dropout=0.2))
model.add(LSTM(state_dim, return_sequences=False, dropout=0.2))
model.add(Dense(1, activation='sigmoid'))
```

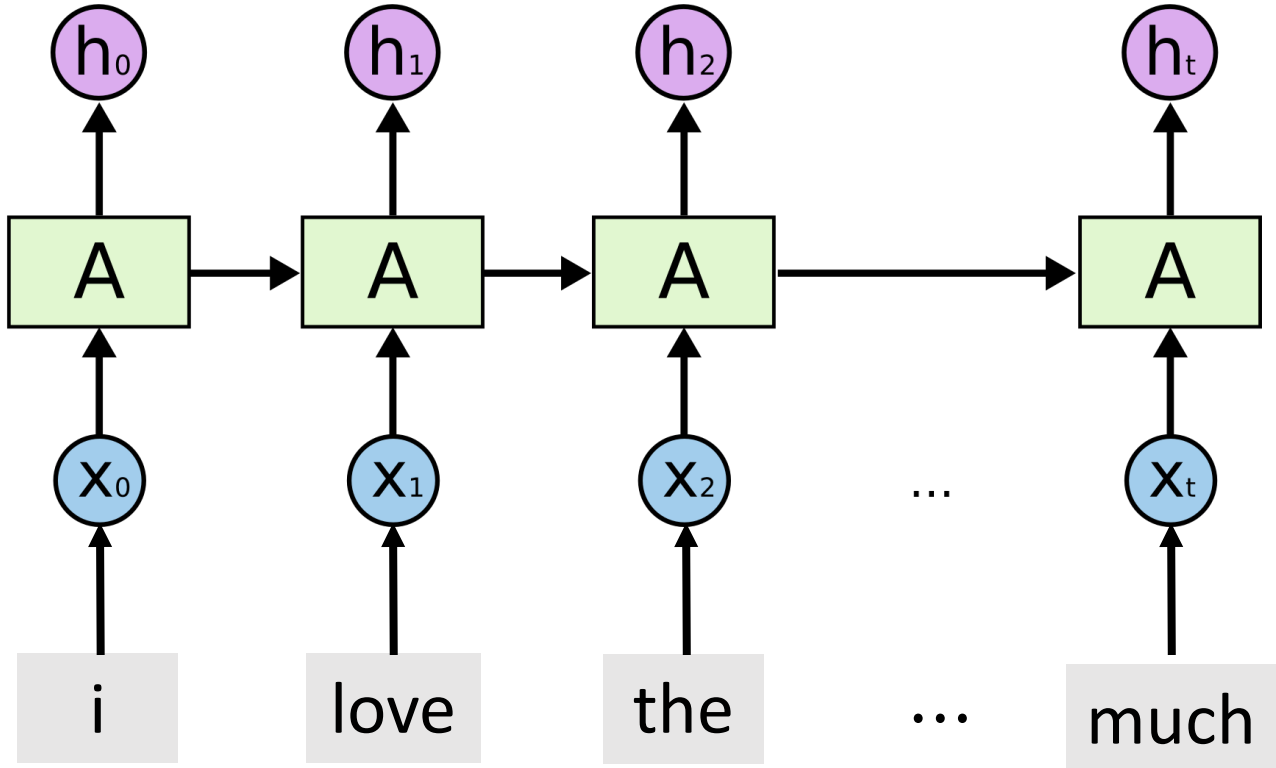
Stacked LSTM

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, 500, 32)	320000
lstm_1 (LSTM)	(None, 500, 32)	8320
lstm_2 (LSTM)	(None, 500, 32)	8320
lstm_3 (LSTM)	(None, 32)	8320
dense_1 (Dense)	(None, 1)	33

Total params: 344,993
Trainable params: 344,993
Non-trainable params: 0

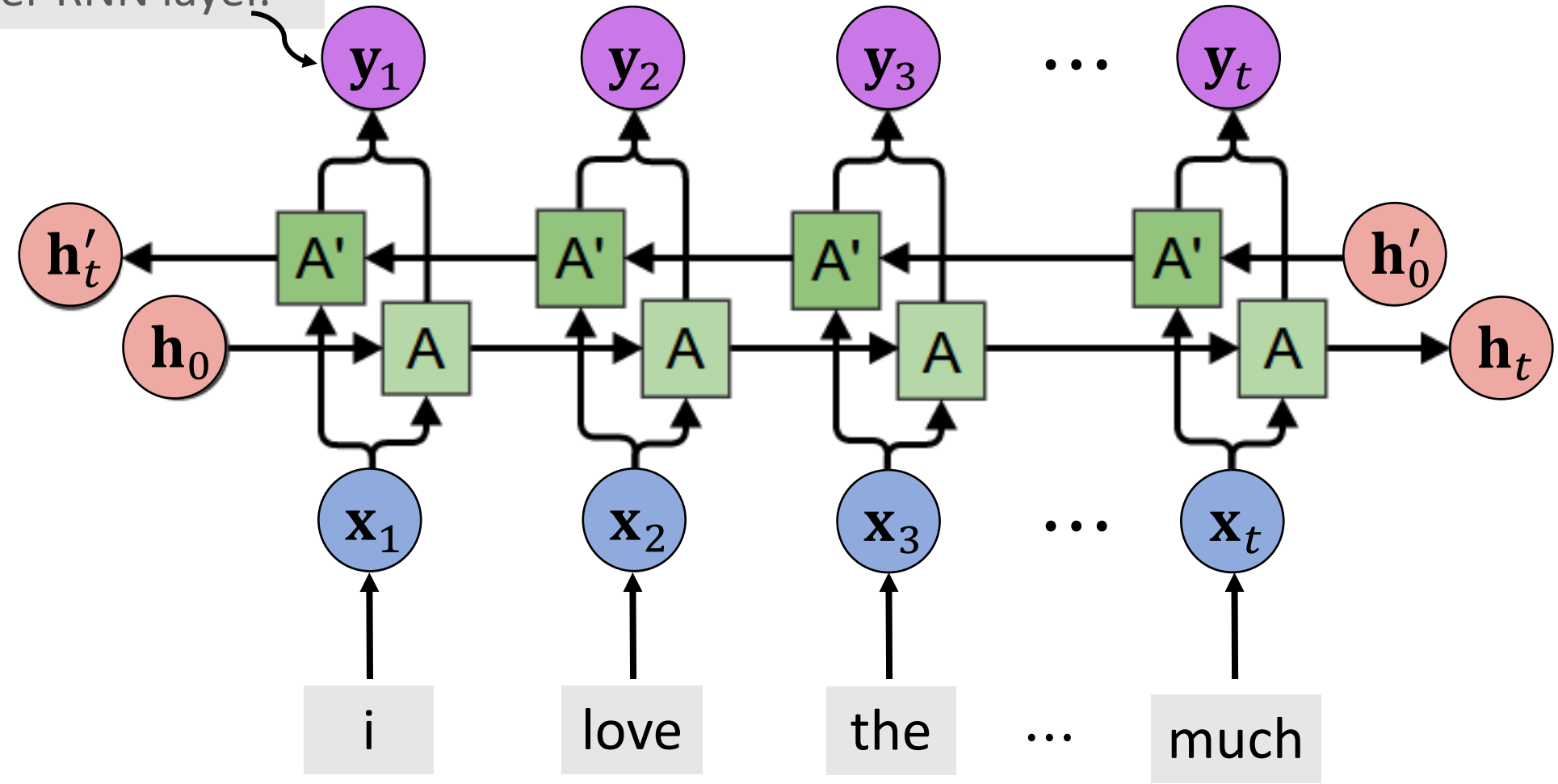
Bidirectional RNN

Standard RNN



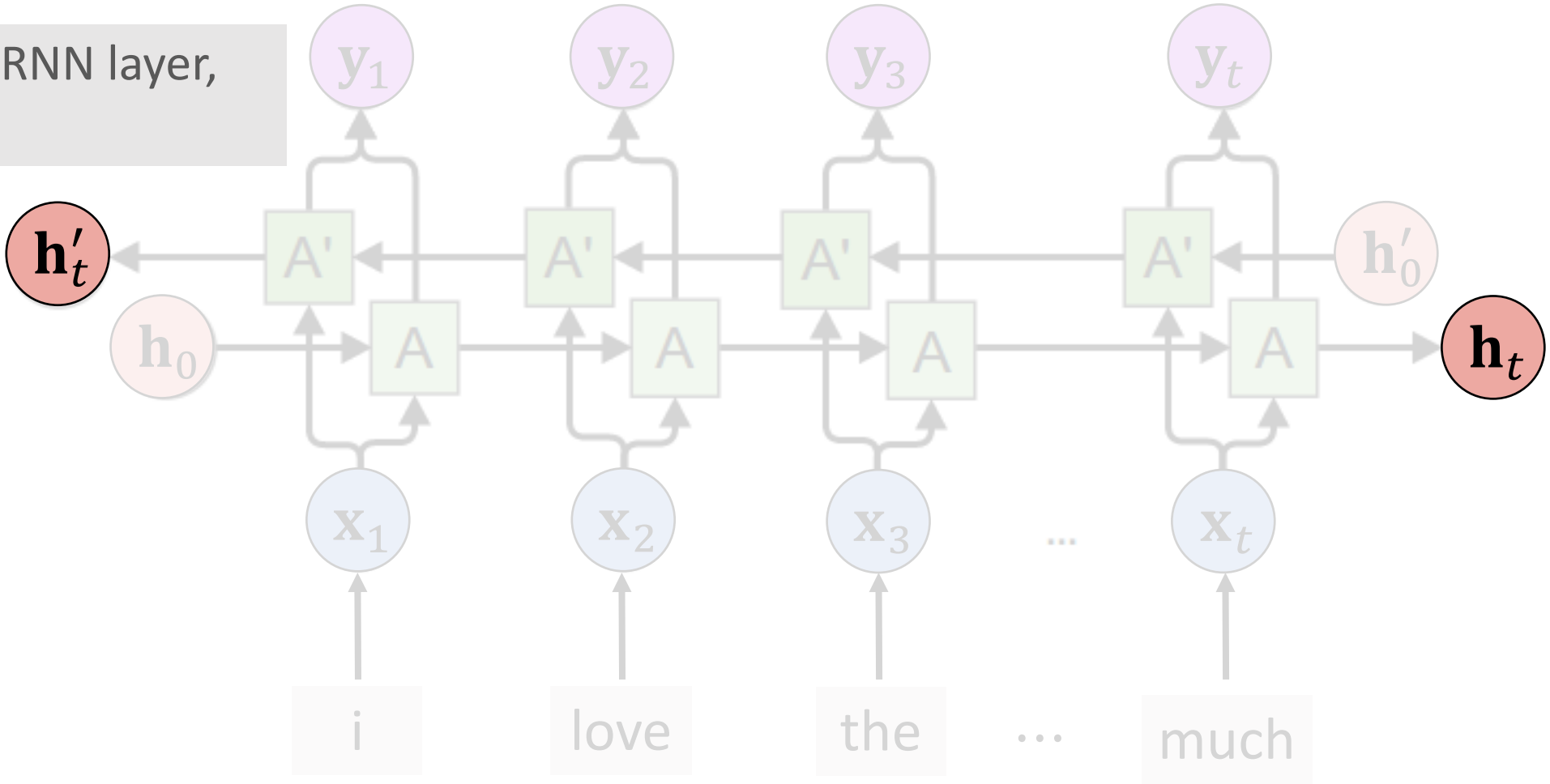
Bidirectional RNN

- Stack of 2 states.
- Passed to the upper RNN layer.



Bidirectional RNN

If there is no upper RNN layer, then return $[\mathbf{h}_t, \mathbf{h}'_t]$



Bi-LSTM

```
from keras.models import Sequential
from keras.layers import LSTM, Embedding, Dense, Bidirectional

vocabulary = 10000
embedding_dim = 32
word_num = 500
state_dim = 32

model = Sequential()
model.add(Embedding(vocabulary, embedding_dim, input_length=word_num))
model.add(Bidirectional(LSTM(state_dim, return_sequences=False, dropout=0.2)))
model.add(Dense(1, activation='sigmoid'))

model.summary()
```

Bi-LSTM

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, 500, 32)	320000
bidirectional_1 (Bidirection	(None, 64)	16640
dense_1 (Dense)	(None, 1)	65

Total params: 336,705
Trainable params: 336,705
Non-trainable params: 0

Pretrain

Why pretraining?

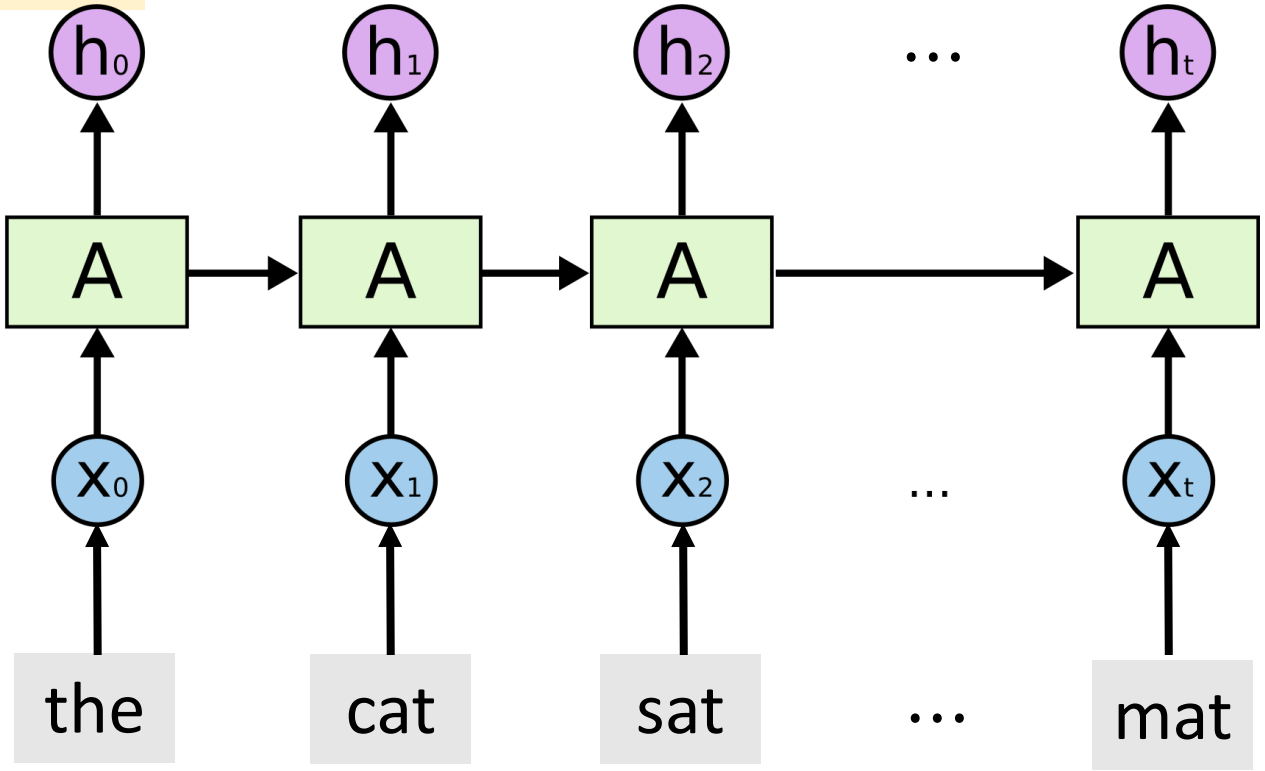
Observation: The embedding layer contributes most of the parameters!

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, 500, 32)           320000
_________________________________________________________________
bidirectional_1 (Bidirection (None, 64)                16640
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 65
=================================================================
Total params: 336,705
Trainable params: 336,705
Non-trainable params: 0
```

Pretrain the Embedding Layer

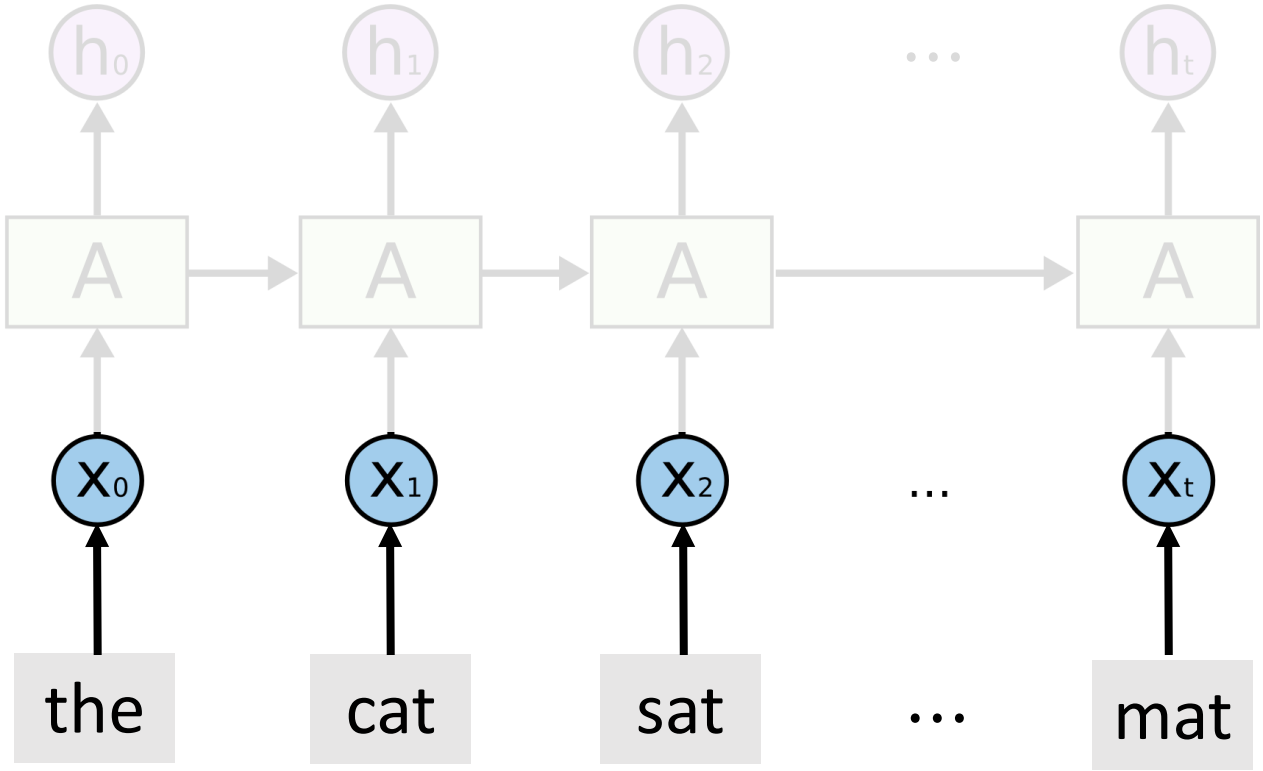
Step 1: Train a model on large dataset.

- Perhaps different problem.
- Perhaps different model.



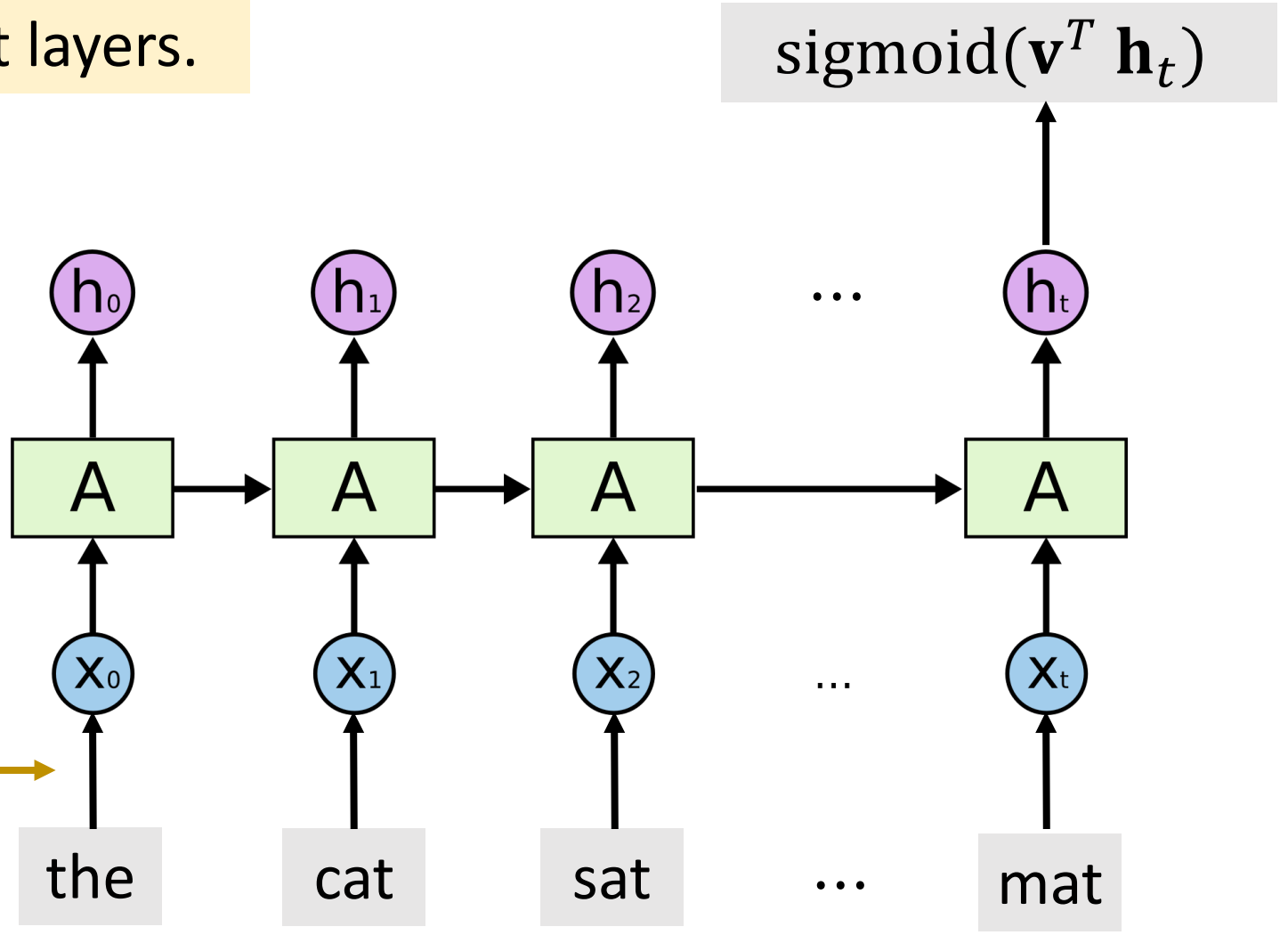
Pretrain the Embedding Layer

Step 2: Keep only the embedding layer.



Pretrain the Embedding Layer

Step 3: Train new LSTM and output layers.



Set the embedding layer non-trainable.

Summary

Summary

- SimpleRNN and LSTM are two kinds of RNNs; always use LSTM instead of SimpleRNN.
- Use Bi-RNN instead of RNN whenever possible.
- Stacked RNN may be better than a single RNN layer (if n is big).
- Pretrain the embedding layer (if n is small).

Text Generation

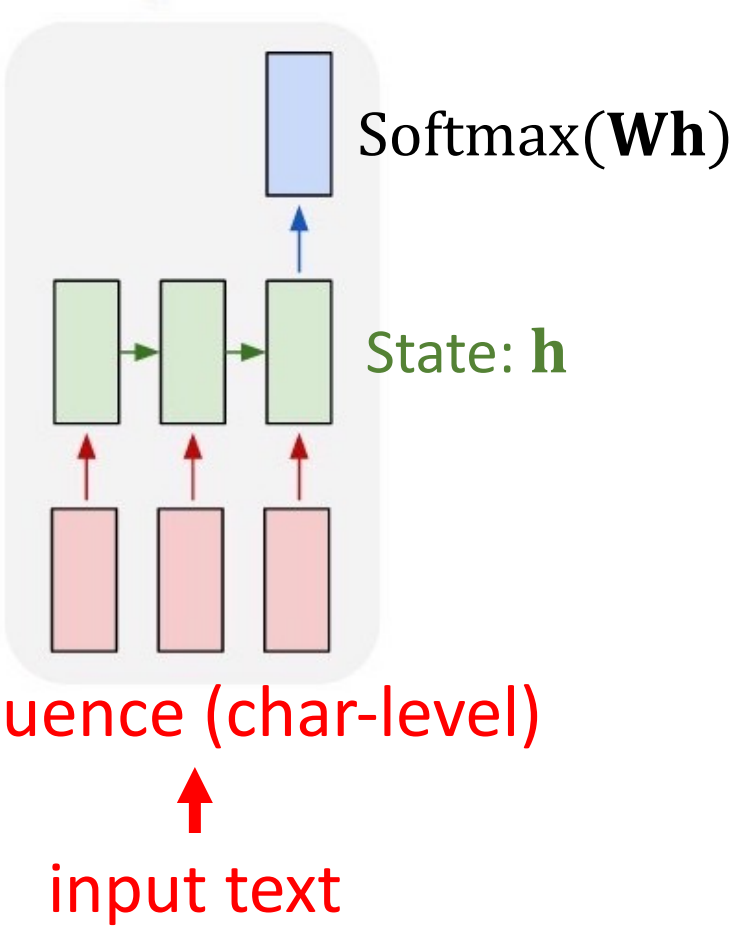
Main Idea

RNN for Text Prediction

Example

- Input text: “`the cat sat on the ma`”
- Question: what is the next char?

RNN for Text Prediction

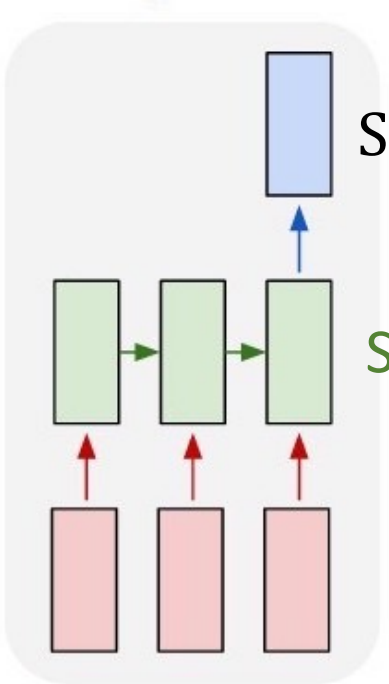


Example

- Input text: "the cat sat on the ma"
- Question: what is the next char?

RNN for Text Prediction

predict the next char



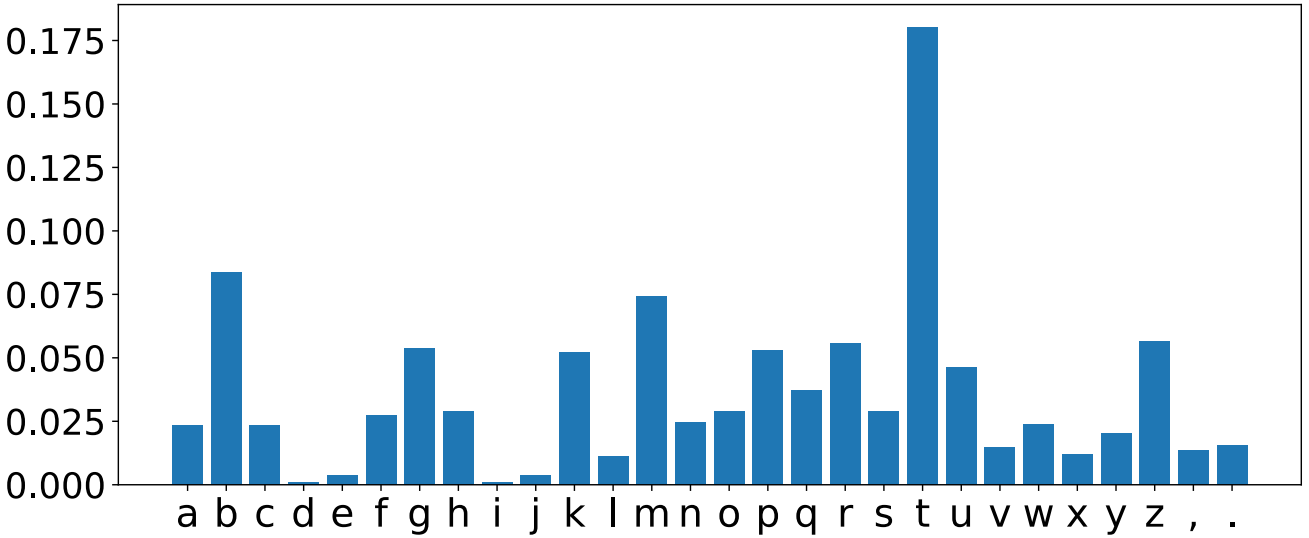
sequence (char-level)

input text

Example

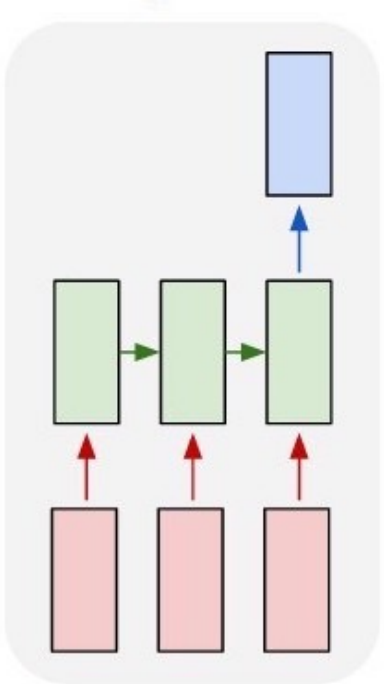
- Input text: "the cat sat on the ma"
- Question: what is the next char?

- RNN outputs a distribution over the chars.



RNN for Text Prediction

predict the next char



sequence (char-level)

input text

Example

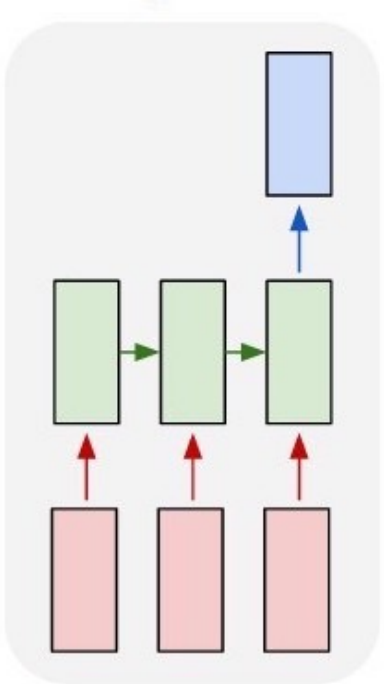
- Input text: "`the cat sat on the ma`"
- Question: what is the next char?

- RNN outputs a distribution over the chars.

- Sample a char from it; we may get '`t`'.
- Take "`the cat sat on the mat`" as input.
- Maybe the next char is period '`.`'.

Train an RNN for Text Prediction

predict the next char



sequence (char-level)

input text

How do we train such an RNN?

- Cut text to segments (with overlap).
  - E.g., `seg_len=40` and `stride=3`.

Machine learning is a subset of artificial intelligence in the field of computer science that often uses statistical techniques to give computers the ability to "learn" (i.e., progressively improve performance on a specific task) with data, without being explicitly programmed. The name machine learning was coined in 1959 by Arthur Samuel.

…

…

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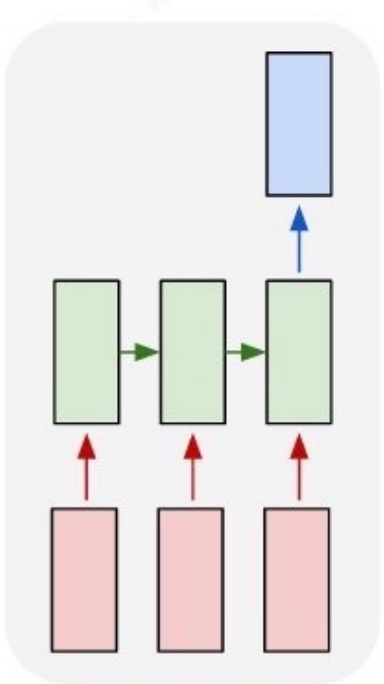

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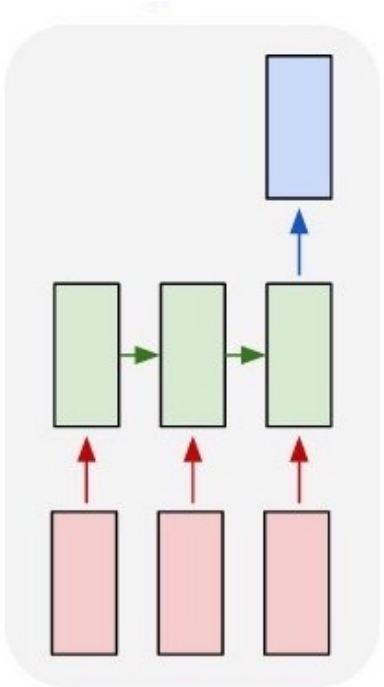

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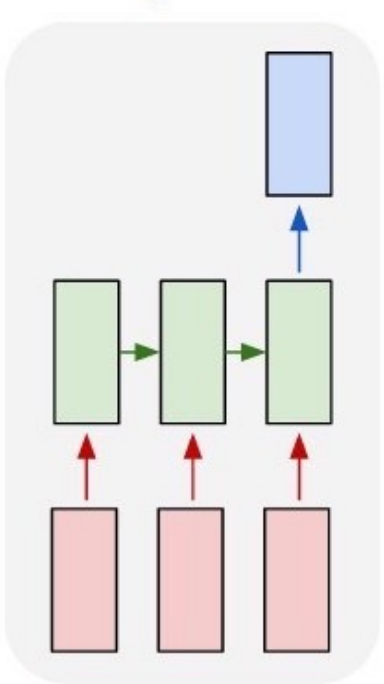

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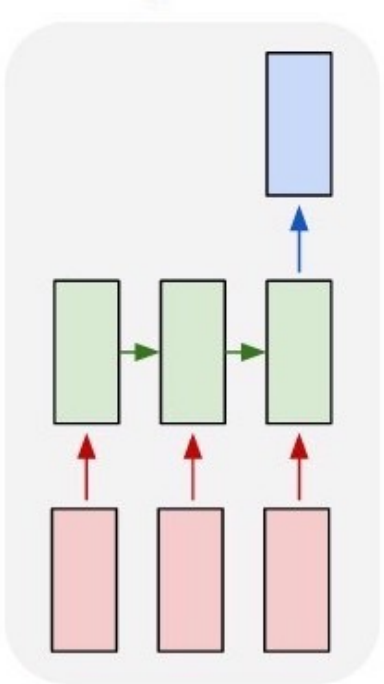

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- Training data: `(segment, next_char)` pairs

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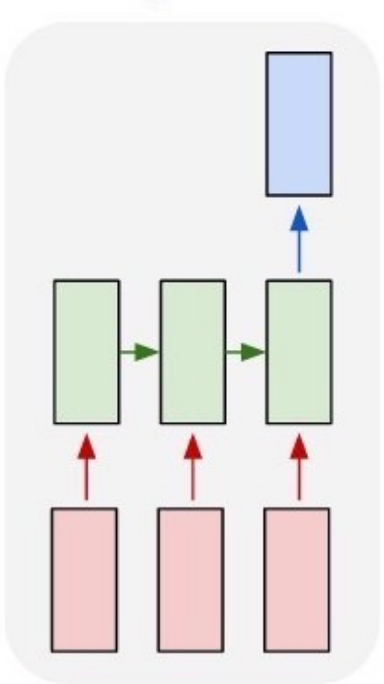

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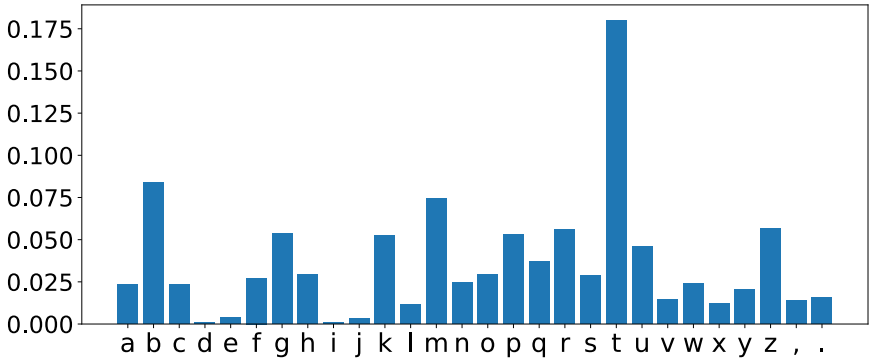
- It is a multi-class classification problem.
  - #class = #unique chars.



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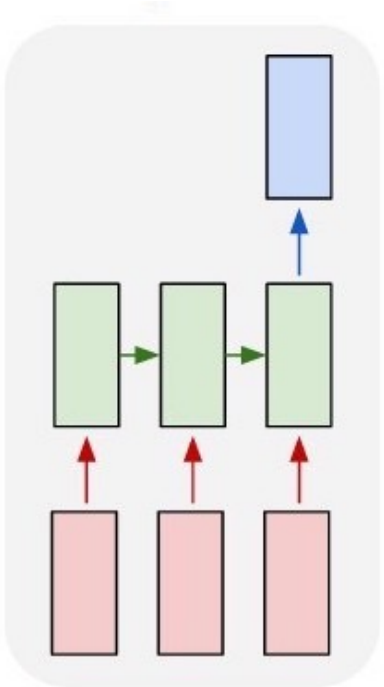
predict the next char



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- Training data: `(segment, next_char)` pairs
- It is a multi-class classification problem.
  - #class = #unique chars.

If the RNN is trained on Shakespeare's books, then the generated text is Shakespeare's style.

Fun with Text Generation

Generate baby names (trained on 8000 baby names).

Rudi Levette Berice Lussa Hany Mareanne Chrestina Carissy Marylen Hammine Janye Marlise Jacacrie Hendred Romand Charienna Nenotto Ette Dorane Wallen Marly Darine Salina Elvyn Ersia Maralena Minoria Ellia Charmin Antley Nerille Chelon Walmor Evena Jeryly Stachon Charisa Allisa Anatha Cathanie Geetra Alexie Jerin Cassen Herbett Cossie Velen Daurenge Robester Shermond Terisa Licia Roselen Ferine Jayn Lusine Charyanne Sales Sanny Resa Wallon Martine Merus Jelen Candica Wallin Tel Rachene Tarine Ozila Ketia Shanne Arnande Karella Roselina Alessia Chasty Deland Berther Geamar Jackein Mellisand Sagdy Nenc Lessie Rasemy Guen Gavi Milea Anneda Margoris Janin Rodelin Zeanna Elyne Janah Ferzina Susta Pey Castina

Fun with Text Generation

Generate C code (trained on Linux source code).

```
/*
 * Increment the size file of the new incorrect UI_FILTER group information
 * of the size generatively.
 */
static int indicate_policy(void)
{
  int error;
  if (fd == MARN_EPT) {
    /*
     * The kernel blank will coeld it to userspace.
     */
    if (ss->segment < mem_total)
      unblock_graph_and_set_blocked();
    else
      ret = 1;
    goto bail;
  }
  segaddr = in_SB(in.addr);
  selector = seg / 16;
  setup_works = true;
  for (i = 0; i < blocks; i++) {
    seq = buf[i++];
    bpf = bd->bd.next + i * search;
    if (fd) {
      current = blocked;
    }
  }
  rw->name = "Getjbbregs";
  bprm_self_clearl(&iv->version);
  regs->new = blocks[(BPF_STATS << info->historidac)] | PFMR_CLOBATHINC_SECONDS << 12;
  return segtable;
}
```

Fun with Text Generation

Generate academic articles (LaTeX source files).

For $\bigoplus_{n=1,\ldots,m}$ where $\mathcal{L}_{m_\bullet} = 0$, hence we can find a closed subset $\mathcal{H}$ in $\mathcal{H}$ and any sets $\mathcal{F}$ on X, U is a closed immersion of S, then $U \to T$ is a separated algebraic space.

Proof. Proof of (1). It also start we get

$$S = \mathrm{Spec}(R) = U \times_X U \times_X U$$

and the compariciely in the fibre product covering we have to prove the lemma generated by $\coprod Z \times_U U \to V$. Consider the maps M along the set of points Sch_{fppf} and $U \to U$ is the fibre category of S in U in Section, **??** and the fact that any U affine, see Morphisms, Lemma **??**. Hence we obtain a scheme S and any open subset $W \subset U$ in $Sh(G)$ such that $\mathrm{Spec}(R') \to S$ is smooth or an

$$U = \bigcup U_i \times_{S_i} U_i$$

which has a nonzero morphism we may assume that f_i is of finite presentation over S. We claim that $\mathcal{O}_{X,x}$ is a scheme where $x, x', s'' \in S'$ such that $\mathcal{O}_{X,x'} \to \mathcal{O}'_{X',x'}$ is separated. By Algebra, Lemma **??** we can define a map of complexes $\mathrm{GL}_{S'}(x'/S'')$ and we win. □

To prove study we see that $\mathcal{F}|_U$ is a covering of $\mathcal{X}'$, and $\mathcal{T}_i$ is an object of $\mathcal{F}_{X/S}$ for $i > 0$ and $\mathcal{F}_p$ exists and let $\mathcal{F}_i$ be a presheaf of $\mathcal{O}_X$-modules on $\mathcal{C}$ as a $\mathcal{F}$-module. In particular $\mathcal{F} = U/\mathcal{F}$ we have to show that

$$\widetilde{M}^\bullet = \mathcal{I}^\bullet \otimes_{\mathrm{Spec}(k)} \mathcal{O}_{S,s} - i_X^{-1}\mathcal{F})$$

is a unique morphism of algebraic stacks. Note that

$$\mathrm{Arrows} = (Sch/S)^{opp}_{fppf}, (Sch/S)_{fppf}$$

and

$$V = \Gamma(S, \mathcal{O}) \longmapsto (U, \mathrm{Spec}(A))$$

is an open subset of X. Thus U is affine. This is a continuous map of X is the inverse, the groupoid scheme S.

Proof. See discussion of sheaves of sets. □

The result for prove any open covering follows from the less of Example **??**. It may replace S by $X_{spaces,étale}$ which gives an open subspace of X and T equal to S_{Zar}, see Descent, Lemma **??**. Namely, by Lemma **??** we see that R is geometrically regular over S.

Lemma 0.1. *Assume (3) and (3) by the construction in the description.*

Suppose $X = \lim |X|$ *(by the formal open covering* X *and a single map* $\underline{Proj}_X(\mathcal{A}) = \mathrm{Spec}(B)$ *over* U *compatible with the complex*

$$Set(\mathcal{A}) = \Gamma(X, \mathcal{O}_{X,\mathcal{O}_X}).$$

When in this case of to show that $\mathcal{Q} \to \mathcal{C}_{Z/X}$ *is stable under the following result in the second conditions of (1), and (3). This finishes the proof. By Definition* **??** *(without element is when the closed subschemes are catenary. If* T *is surjective we may assume that* T *is connected with residue fields of* S*. Moreover there exists a closed subspace* $Z \subset X$ *of* X *where* U *in* X' *is proper (some defining as a closed subset of the uniqueness it suffices to check the fact that the following theorem*

(1) f *is locally of finite type. Since* $S = \mathrm{Spec}(R)$ *and* $Y = \mathrm{Spec}(R)$.

Proof. This is form all sheaves of sheaves on X. But given a scheme U and a surjective étale morphism $U \to X$. Let $U \cap U = \coprod_{i=1,\ldots,n} U_i$ be the scheme X over S at the schemes $X_i \to X$ and $U = \lim_i X_i$. □

The following lemma surjective restrocomposes of this implies that $\mathcal{F}_{x_0} = \mathcal{F}_{x_0} = \mathcal{F}_{\mathcal{X},\ldots,0}$.

Lemma 0.2. *Let* X *be a locally Noetherian scheme over* S, $E = \mathcal{F}_{X/S}$. *Set* $\mathcal{I} = \mathcal{J}_1 \subset \mathcal{I}'_n$. *Since* $\mathcal{I}^n \subset \mathcal{I}^n$ *are nonzero over* $i_0 \leq \mathfrak{p}$ *is a subset of* $\mathcal{J}_{n,0} \circ \overline{A}_2$ *works.*

Lemma 0.3. *In Situation* **??**. *Hence we may assume* $\mathfrak{q}' = 0$.

Proof. We will use the property we see that $\mathfrak{p}$ is the mext functor (**??**). On the other hand, by Lemma **??** we see that

$$D(\mathcal{O}_{X'}) = \mathcal{O}_X(D)$$

where K is an F-algebra where δ_{n+1} is a scheme over S. □

Training a Text Generator

1. Prepare Training Data

```
print('Text length:', len(text))
```

```
Text length: 600893
```

```
text[0:1000]
```

```
'preface\n\n\nsupposing that truth is a woman--what then? is there
not ground\nfor suspecting that all philosophers, in so far as they
have been\ndogmatists, have failed to understand women--that the te
rrible\nseriousness and clumsy importunity with which they have usu
ally paid\ntheir addresses to truth, have been unskilled and unseem
ly methods for\nwinning a woman? certainly she has never allowed he
rself to be won; and\nat present every kind of dogma stands with sa
d and discouraged mien--if,\nindeed, it stands at all! for there ar
e scoffers who maintain that it\nhas fallen, that all dogma lies on
the ground--nay more, that it is at\nits last gasp. but to speak se
riously, there are good grounds for hoping\nthat all dogmatizing in
philosophy, whatever solemn, whatever conclusive\nand decided airs
it has assumed, may have been only a noble puerilism\nand tyronism;
and probably the time is at hand when it will be once\nand again un
```

1. Prepare Training Data

segment:

preface\n\n\nsupposing that truth is a woman--what then? is there not ground\nfor suspecting that all philosophers, in so far as they have been\ndogmatists, have failed to understand women--that the terrible\nseriousness and clumsy importunity with which they have usually paid\ntheir addresses to truth, have been unskilled and unseem

segments[0]: preface\n\n\nsupposing that truth **next_chars[0]:** i

1. Prepare Training Data

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'preface\n\n\nsupposing that truth is a woman--what then? is there not ground\nfor suspecting that all philosophers, in so far as they have been\ndogmatists, have failed to understand women--that the terrible\nseriousness and clumsy importunity with which they have usually paid\ntheir addresses to truth, have been unskilled and unseem

segments[0]: preface\n\n\nsupposing that truth **next_chars[0]:** i

segments[1]: face\n\n\nsupposing that truth is **next_chars[1]:** a

1. Prepare Training Data

segment:

```
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ally paid\ntheir addresses to truth, have been unskilled and unseem
```

segments[0]:	preface\n\n\nsupposing that truth	**next_chars[0]:**	**i**
segments[1]:	face\n\n\nsupposing that truth is	**next_chars[1]:**	**a**
segments[2]:	e\n\n\nsupposing that truth is a w	**next_chars[2]:**	**o**

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segment:

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```

segments[0]:	preface\n\n\nsupposing that truth	next_chars[0]:	i
segments[1]:	face\n\n\nsupposing that truth is	next_chars[1]:	a
segments[2]:	e\n\n\nsupposing that truth is a w	next_chars[2]:	o
segments[3]:	\nsupposing that truth is a woma	next_chars[3]:	n
⋮		⋮	

2. Character to Vector

Dictionary

Token	Index
a	1
b	2
c	3
d	4
e	5

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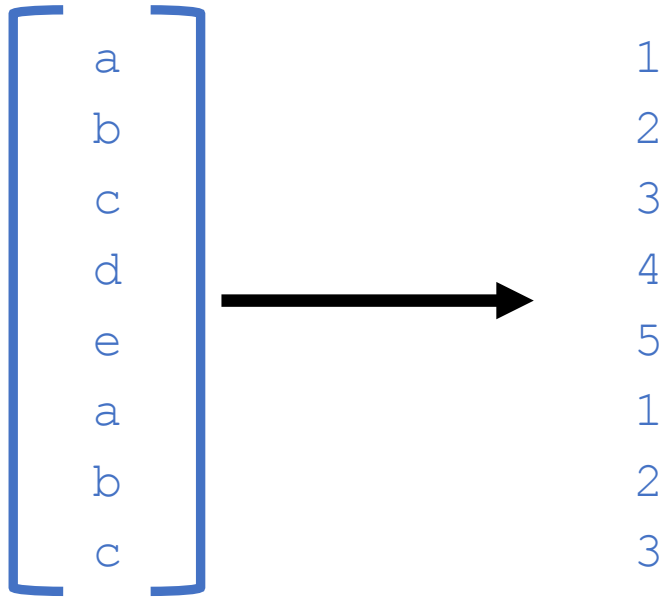
One-hot encoding (token to vector)



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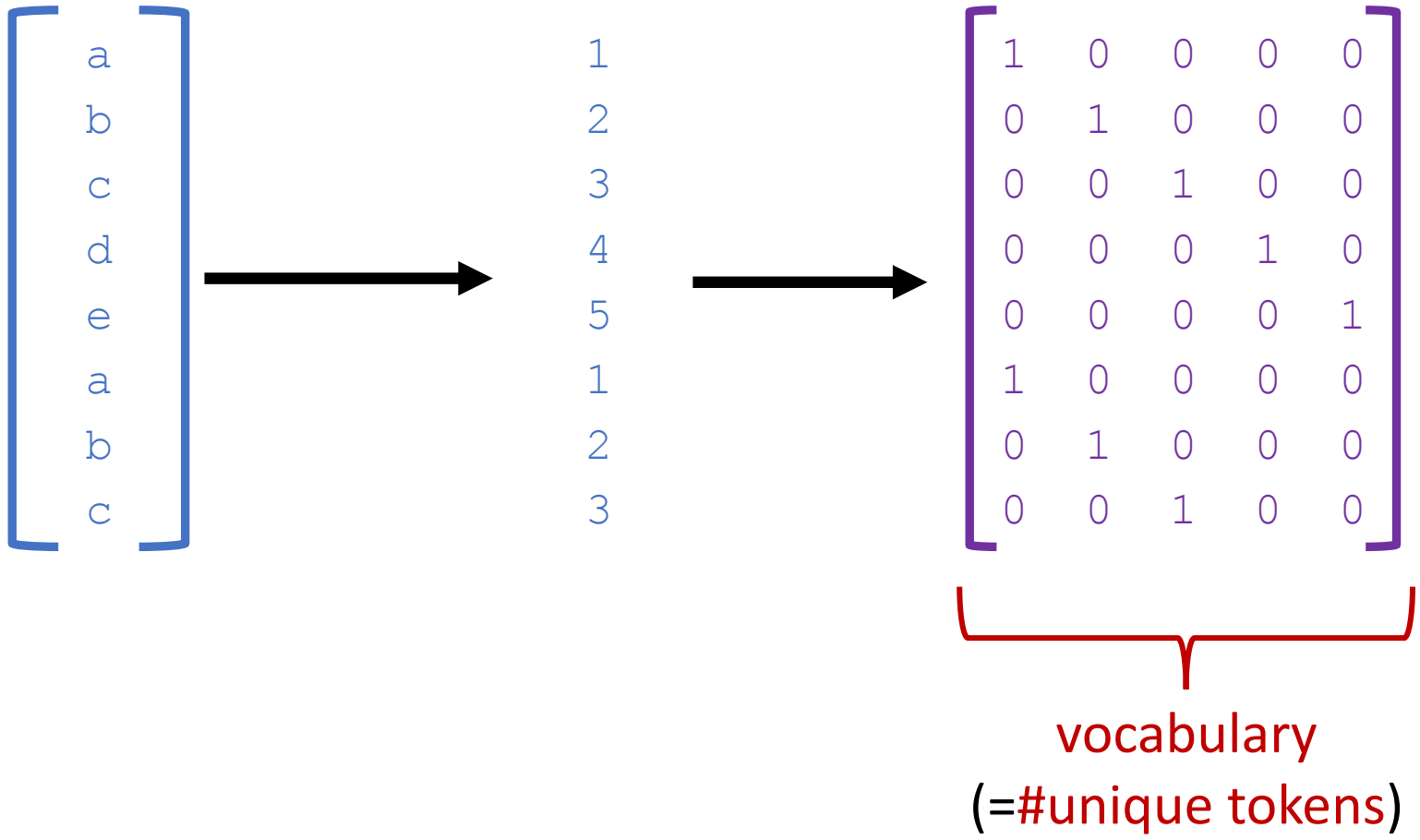

2. Character to Vector

- Vocabulary is $v = 57$ (including letter, blank, punctuation, etc.)
- Segment length is $l = 60$. (A segment has 60 chars.)

`segments[i]:` `\nsupposing that truth is a woma`

$\mathbf{X}$: 60×57 matrix

`next_chars[i]:` `n`

$\mathbf{y}$: 57×1 vector

2. Character to Vector

- Vocabulary is $v = 57$ (including letter, blank, punctuation, etc.)
- Segment length is $l = 60$. (A segment has 60 chars.)
- Number of segments is $n = 200{,}278$. (Number of training samples.)

`segments[i]:` `\nsupposing that truth is a woma` `next_chars[i]:` `n`

$\mathbf{X}$: 60×57 matrix

$\mathbf{y}$: 57×1 vector

There are $n = 200{,}278$ such pairs.

3. Build a Neural Network

```
from keras import layers

model = keras.models.Sequential()
model.add(layers.LSTM(128, input_shape=(seg_len, vocabulary)))
model.add(layers.Dense(vocabulary, activation='softmax'))
model.summary()
```

$l = 60$ $v = 57$ $v = 57$

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, 128)               95232
_________________________________________________________________
dense_1 (Dense)              (None, 57)                7353
=================================================================
Total params: 102,585
Trainable params: 102,585
Non-trainable params: 0
```

4. Train the Neural Network

```
optimizer = keras.optimizers.RMSprop(lr=0.01)
model.compile(loss='categorical_crossentropy', optimizer=optimizer)
```

4. Train the Neural Network

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optimizer = keras.optimizers.RMSprop(lr=0.01)
model.compile(loss='categorical_crossentropy', optimizer=optimizer)
```

```
model.fit(x, y, batch_size=128, epochs=1)
```

```
Epoch 1/1
200278/200278 [==============================] - 117s 586us/step -
loss: 1.6746
```

- **`x[i,:,:]`** is a segment of 60 chars represented by a 60×57 matrix.
- **`y[i,:]`** is the next char represented by a 57-dim vector.

Text Generation

Predict the Next Char

```
pred = model.predict(x_input, verbose=0)[0]
```

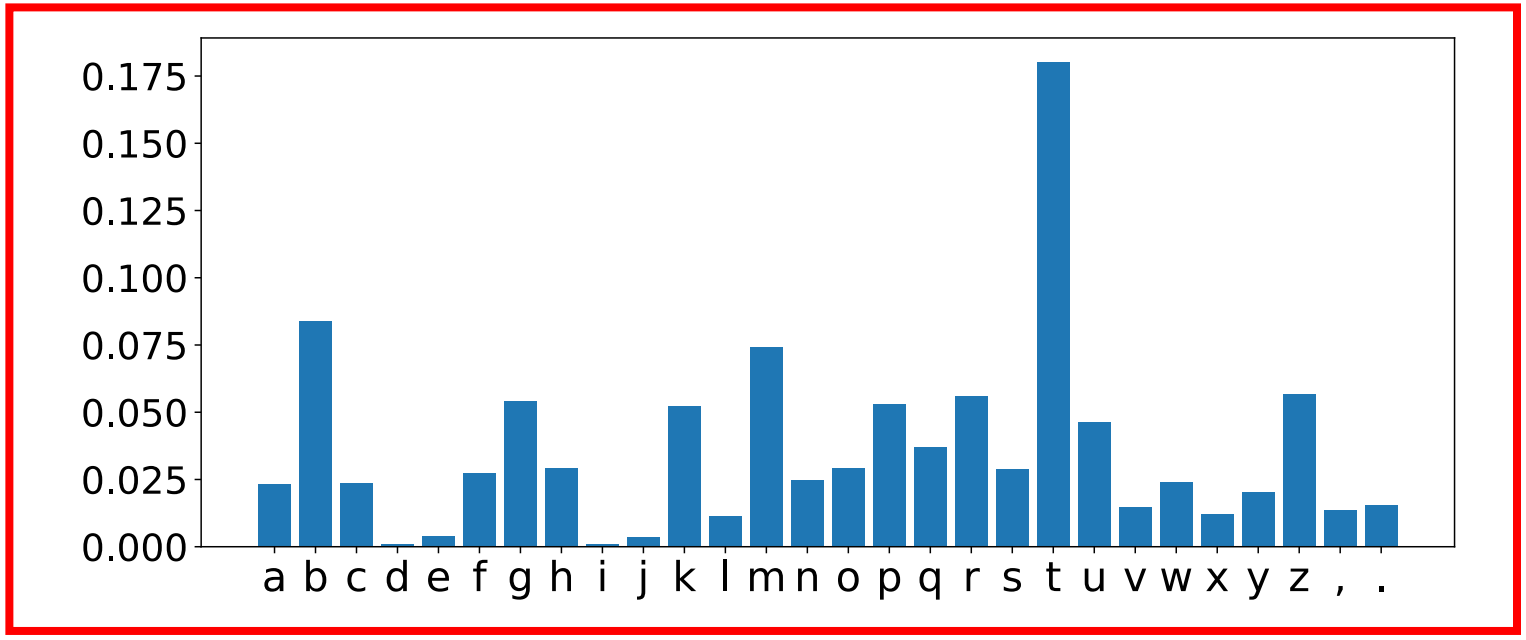
- A segment of 60 chars (represented by a 60×57 matrix).

The probability distribution over the 57 unique chars.

Predict the Next Char

```
pred = model.predict(x_input, verbose=0)[0]
```

Question: Given the distribution, what will be the next char?



Predict the Next Char

```
pred = model.predict(x_input, verbose=0)[0]
```

Question: Given the distribution, what will be the next char?

- Option 1: greedy selection.
  - `next_index = np.argmax(pred)`
  - It is deterministic.
  - Empirically not good.

Predict the Next Char

```
pred = model.predict(x_input, verbose=0)[0]
```

Question: Given the distribution, what will be the next char?

- Option 1: greedy selection.
- Option 2: sampling from the multinomial distribution.
  - `next_onehot = np.random.multinomial(1, pred, 1)`
  - `next_index = np.argmax(next_onehot)`
  - Maybe too random.

Predict the Next Char

```
pred = model.predict(x_input, verbose=0)[0]
```

Question: Given the distribution, what will be the next char?

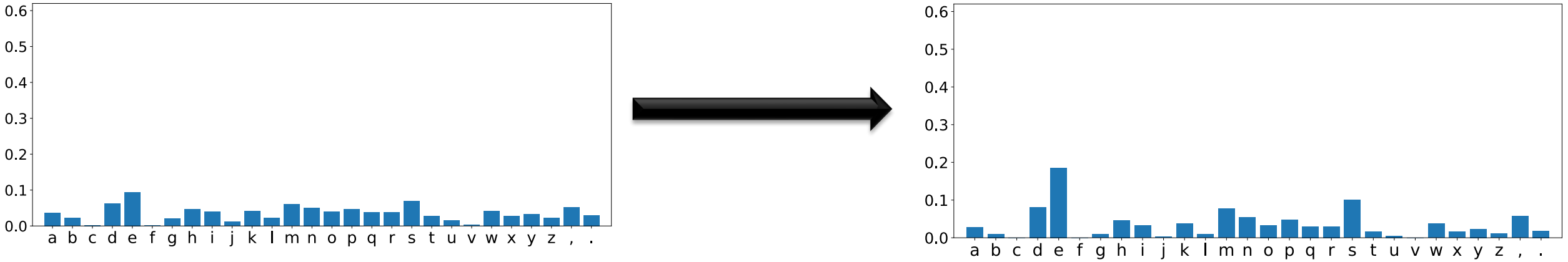
- Option 1: greedy selection.
- Option 2: sampling from the multinomial distribution.
- Option 3: adjusting the multinomial distribution.
  - `pred = pred ** (1 / temperature)`
  - `pred = pred / np.sum(pred)`
  - Sample according to `pred`.
  - Between greedy and multinomial (controlled `temperature`).

Predict the Next Char

Option 3: adjusting the multinomial distribution.

- `pred = pred ** (1 / temperature)`
- `pred = pred / np.sum(pred)`
- Between greedy and multinomial (controlled `temperature`).

`temperature=0.5`

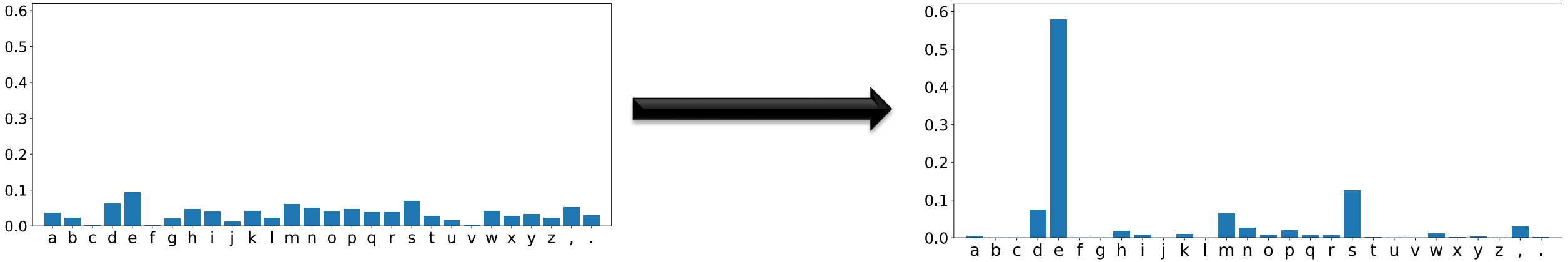


Predict the Next Char

Option 3: adjusting the multinomial distribution.

- `pred = pred ** (1 / temperature)`
- `pred = pred / np.sum(pred)`
- Between greedy and multinomial (controlled `temperature`).

`temperature=0.2`



Text Generation: An Example

Example: `seg_len=18`

`initial_input (seed):` `“the cat sat on the”`

`next_char:` `'_'` (blank)

Text Generation: An Example

Example: `seg_len=18`

`initial_input (seed):` “the cat sat on the”

`next_char:` `'_'` (blank)

`input:` “he cat sat on the_”

`next_char:` `'m'`

Text Generation: An Example

Example: seg_len=18

initial_input (seed): “the cat sat on the”

next_char: '_' (blank)

input: “he cat sat on the ”

next_char: 'm'

input: “e cat sat on the m”

next_char: 'a'

Generate Text Using the Trained LSTM

Initial input (seed)

"immediately disclose what it really is--namely, a will to the"

Generated text after 1 epoch

"immediately disclose what it really is--namely, a will to the the believest constive the art of the persision the says of a gan himself need not religion a consting be naturing and suld the pretendents as the constion. the are the good teach that the most and find of endent and the self it of instinct a mean constition of can the constive in this sour from the bad and all the philosophy to condividuation men and the goence the condines the all as most strat"

Generate Text Using the Trained LSTM

Initial input (seed)

"immediately disclose what it really is--namely, a will to the"

Generated text after 1 epoch (another sample)

"immediately disclose what it really is--namely, a will to thes and in the world the mist a dest reality and lading the been in the most as and fanition as the reaption of the stenles a prease and be and disting and regard the goven the most and distentive to the from stinct forms and instinct the believes the need itself the feess and virtue this says of the gone consting to man instinctian the become and discative of the present the free the consine of pas"

Generate Text Using the Trained LSTM

Initial input (seed)

"immediately disclose what it really is--namely, a will to the"

Generated text after 5 epochs

"immediately disclose what it really is--namely, a will to the oll and power and that the complises the fundamental and emotions of the developation of the propest and sympathy of the far the long standard, and the most present--under the personally man hard and every stands have been hat the soul and conscience, the intellection of germans of should for the religious profoundly in this included and naturally as we progres and "will of the most same same and"

Generate Text Using the Trained LSTM

Initial input (seed)

"immediately disclose what it really is--namely, a will to the"

Generated text after 20 epochs

"immediately disclose what it really is--namely, a will to the self-religious superitial self-partial religion himself of the superstition of the contrast in the accomant in the person of the assertion, at the valuations and consequences and things has no longer and how only an man of the soul and manifest of the disciplides and an whom all to the constance of its own power, in the constraining in the truth of the strength of life of the see to remain in the"

Summary

Train a Neural Network

1. Partition text to (segment, next_char) pairs.
2. One-hot encode the characters.
   - Character → $v \times 1$ vector.
   - Segment → $l \times v$ matrix.
3. Build and train a neural network.
   - $l \times v$ matrix ==> LSTM ==> Dense ==> $v \times 1$ vector.

Text Generation

1. Propose a seed segment.
2. Repeat the followings:
    a) Feed the segment (with one-hot) to the neural network.
    b) The neural network outputs probabilities.
    c) next_char ← Sample from the probabilities.
    d) Append next_char to the segment.

RNNs for Machine Translation

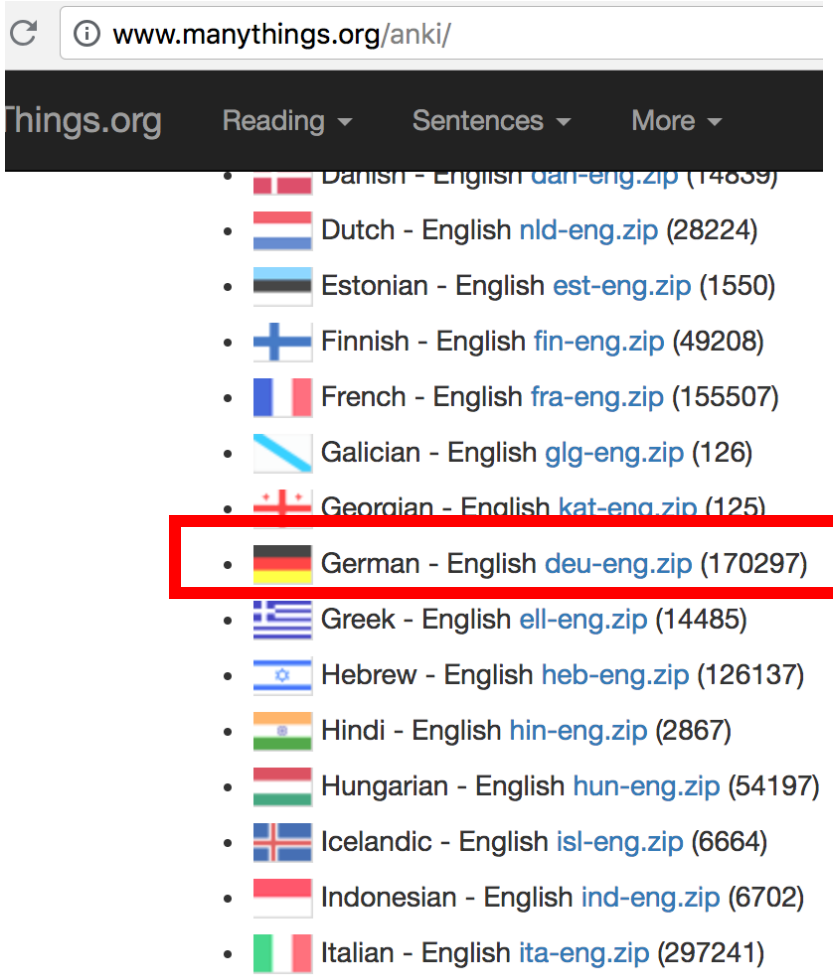
Sequence-to-Sequence Model (Seq2Seq)

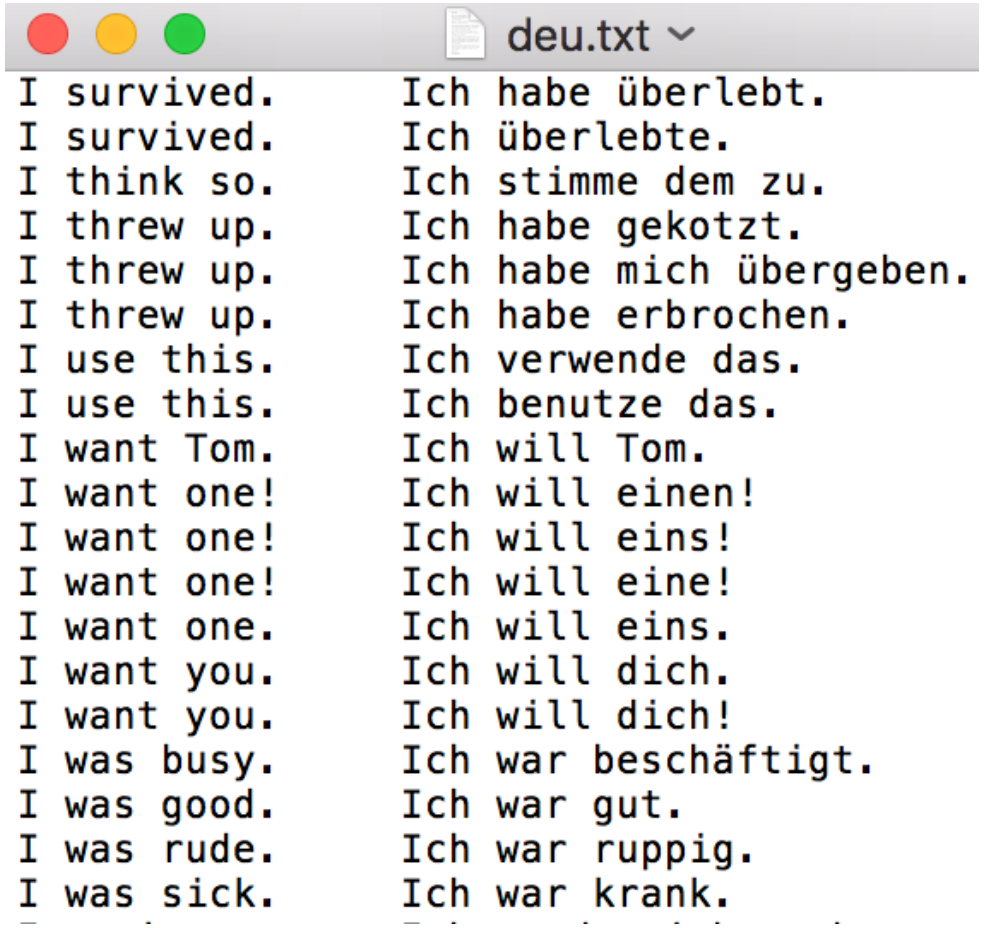
English		German
“do you agree”	=> **[Seq2Seq]** =>	“bist du einverstanden”
“go to sleep”	=> **[Seq2Seq]** =>	“gehen Sie schlafen”
“We will fight”	=> **[Seq2Seq]** =>	“Wir werden kämpfen”

Machine Translation Data

Datasets

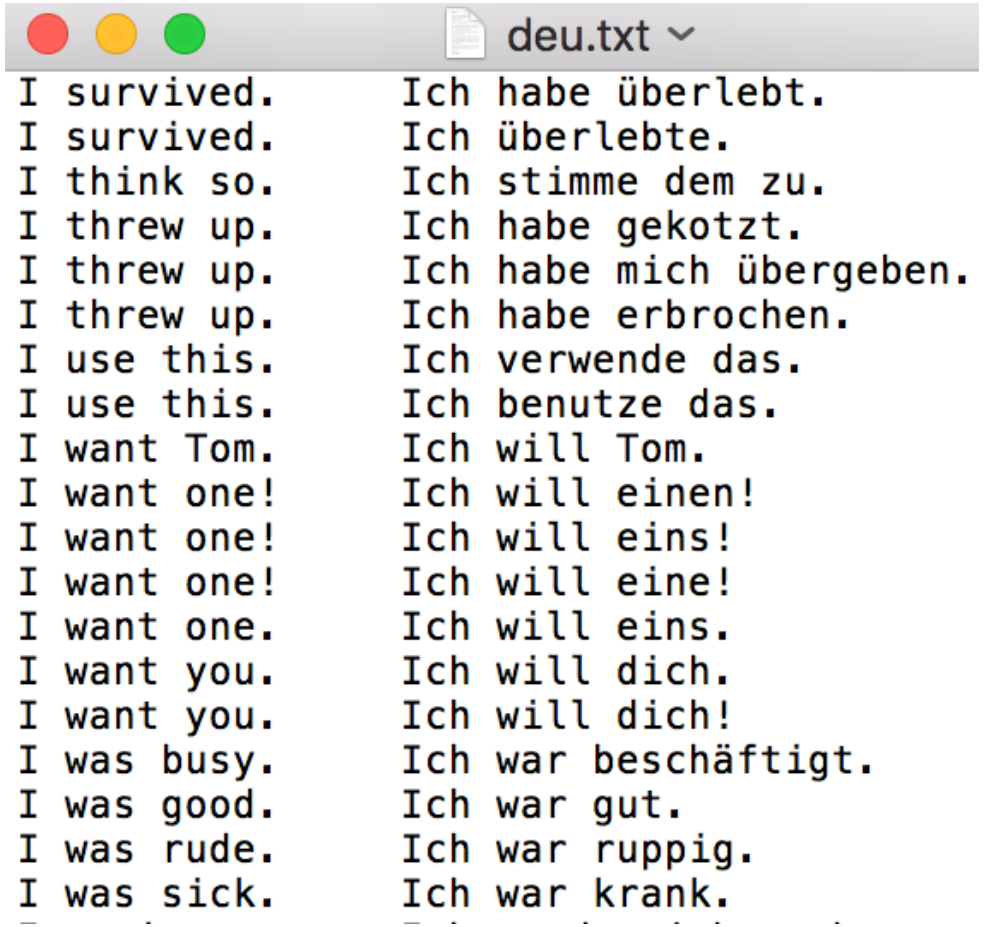
- Tab-delimited Bilingual Sentence Pairs: http://www.manythings.org/anki/





Datasets

- **Preprocessing**: to lower case, remove punctuation, etc.



1. Tokenization & Build Dictionary

- `input_texts  => [Eng_Tokenizer] => input_tokens`
- `target_texts => [Deu_Tokenizer] => target_tokens`

- Use 2 different tokenizers for the 2 languages.
- Then build 2 different dictionaries.

1. Tokenization & Build Dictionary

- `input_texts  => [Eng_Tokenizer] => input_tokens`
- `target_texts => [Deu_Tokenizer] => target_tokens`

Tokenization in the char-level.

Tokenization in the word-level.

1. Tokenization & Build Dictionary

- `input_texts  => [Eng_Tokenizer] => input_tokens`
- `target_texts => [Deu_Tokenizer] => target_tokens`

Tokenization in the char-level.

Eng_Tokenizer

- **"I_am_okay." => ['i', '_', 'a', 'm', ..., 'a', 'y']**

Deu_Tokenizer

- **"Es geht mir gut" => ['e', 's', '_', ..., 'u', 't']**

1. Tokenization & Build Dictionary

Question: Why 2 different tokenizers and dictionaries?

Answer: In the char-level, languages have different alphabets/chars.

- English: A a, B b, C c …, Z z. (26 letters ×2).
- German: 26 letters, 3 umlauts (Ä,Ö,Ü), and one ligature (ß).
- Greek: Α α, Β β, Γ γ, Δ δ, …, Ω ω. (24 letters ×2).
- Chinese: 金 木 水 火 土 … 赵 钱 孙 李 (a few thousands characters).
- Japanese: あ い う え お … (46 Hiragana, 46 Karagana, hundreds 漢字).

1. Tokenization & Build Dictionary

Question: Why 2 different tokenizers and dictionaries?

Answer: In the word-level, languages have different vocabulary.

- English:

```
Machine learning is a generic term for the artificial generation of
knowledge from experience: An artificial system learns from examples
and can generalize these after completion of the learning phase.
```

- Deutsche:

```
Maschinelles Lernen ist ein Oberbegriff für die künstliche
Generierung von Wissen aus Erfahrung: Ein künstliches System lernt
aus Beispielen und kann diese nach Beendigung der Lernphase
verallgemeinern.
```

1. Tokenization & Build Dictionary

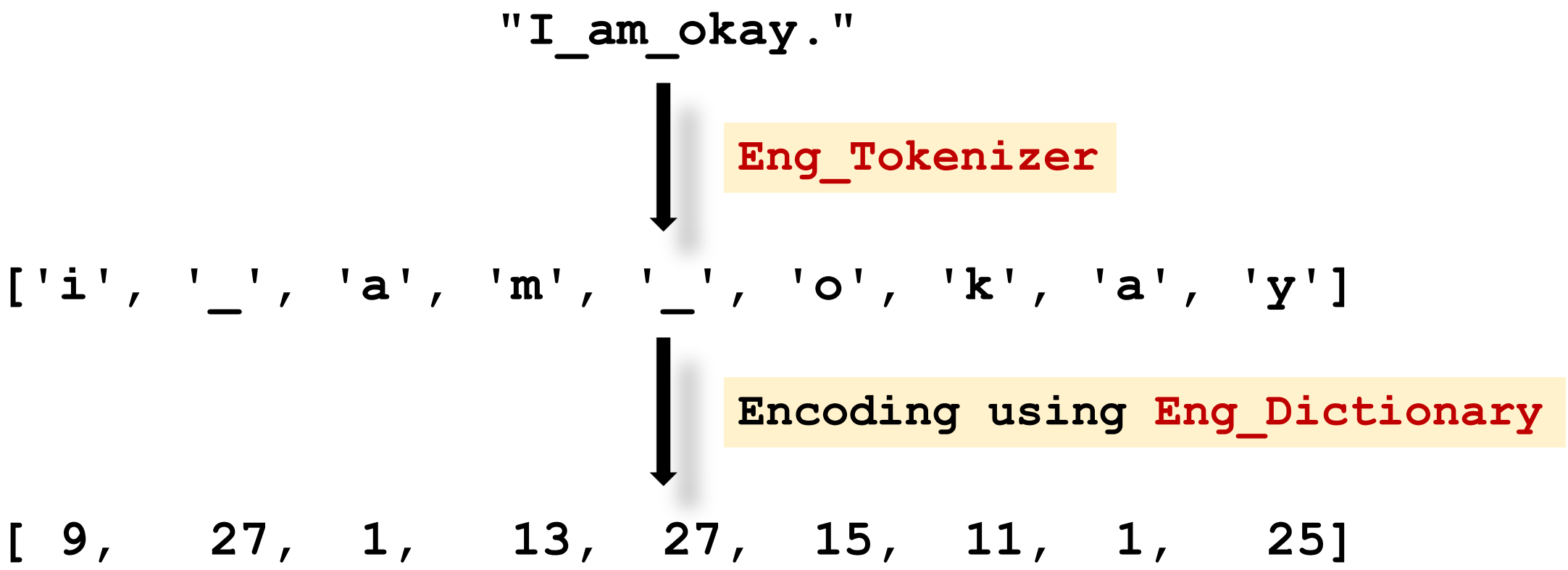
Eng_Dictionary

- 'a' => 1
- 'b' => 2
- 'c' => 3
- 'd' => 4
- …
- 'z' => 26
- '_' => 27

Deu_Dictionary

- '\t' => 1 ← start sign
- '\n' => 2 ← stop sign
- 'a' => 3
- 'b' => 4
- 'c' => 5
- 'd' => 6
- …
- 'z' => 28
- '_' => 29

2. One-Hot Encoding



2. One-Hot Encoding

"Es geht mir gut"

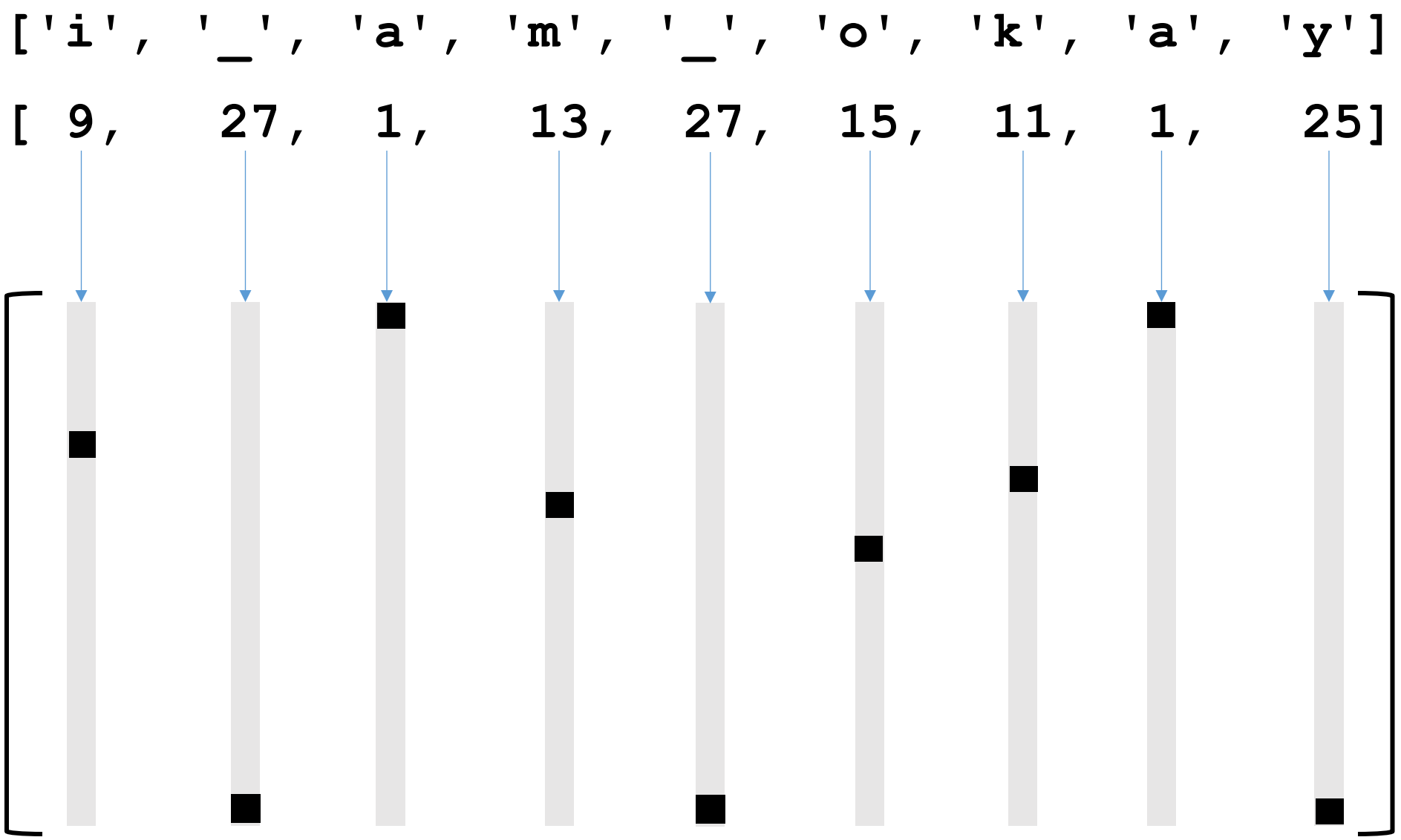
Deu_Tokenizer

['e', 's', '_', 'g', 'e', ..., 'g', 'u', 't']

Encoding using Deu_Dictionary

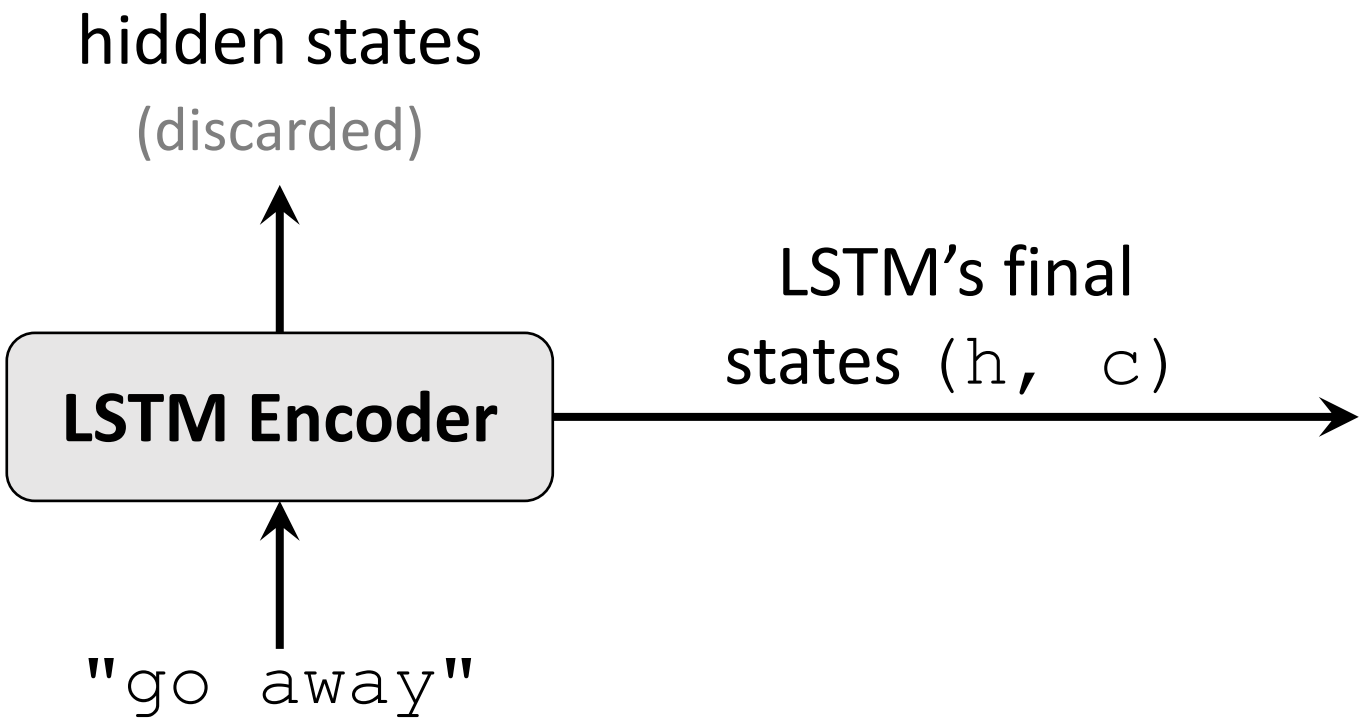
[7, 21, 29, 9, 7, ..., 9, 23, 22]

2. One-Hot Encoding

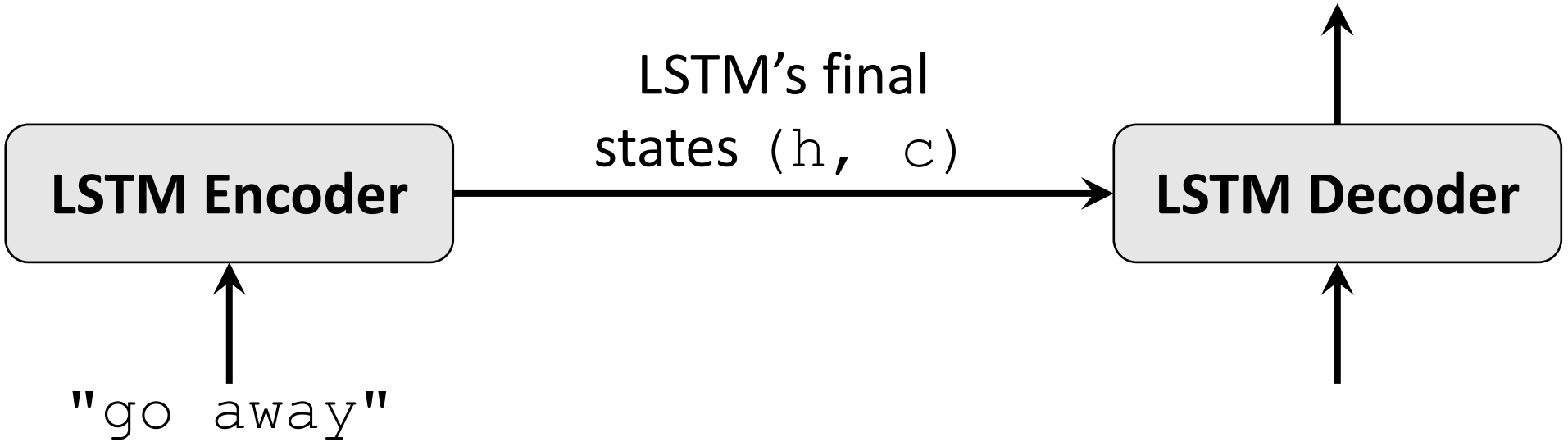


Training Seq2Seq Model

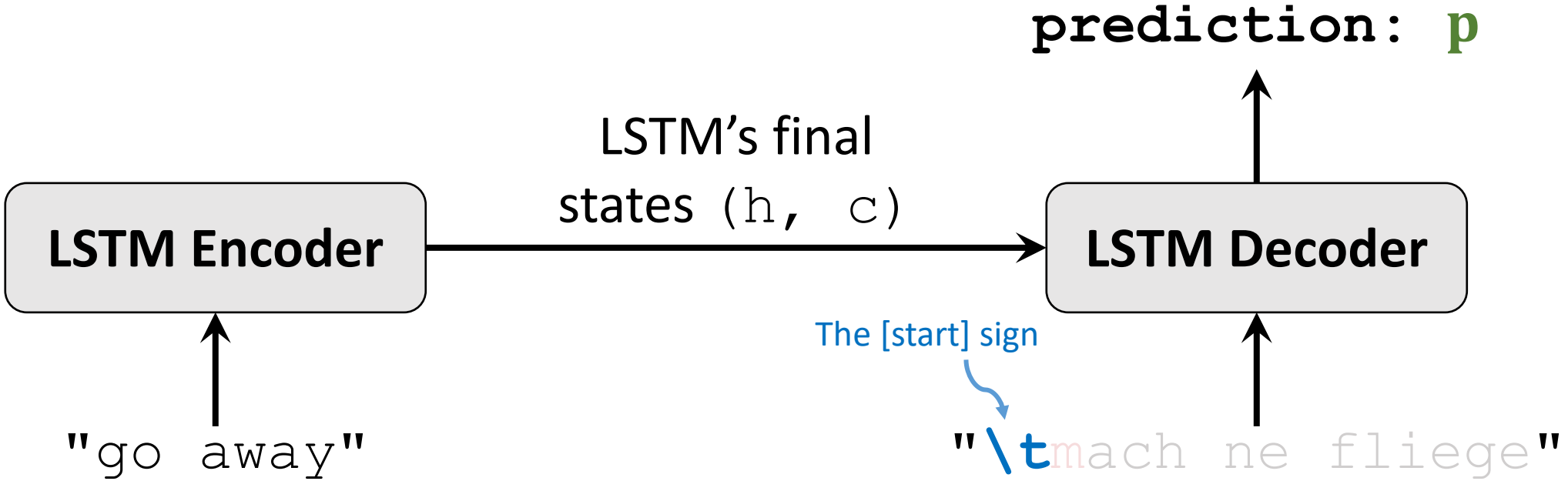
Seq2Seq Model



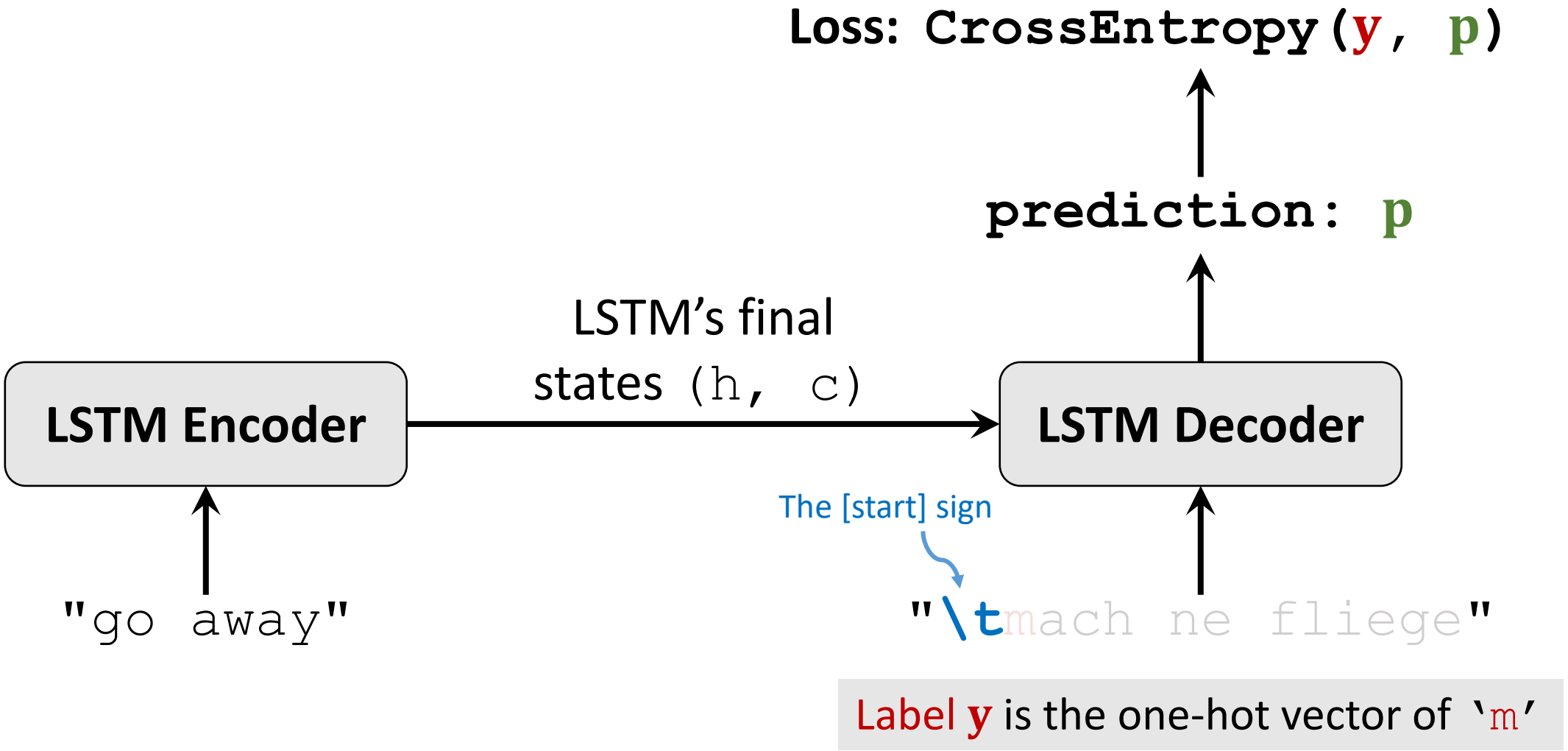
Seq2Seq Model



Training Seq2Seq Model

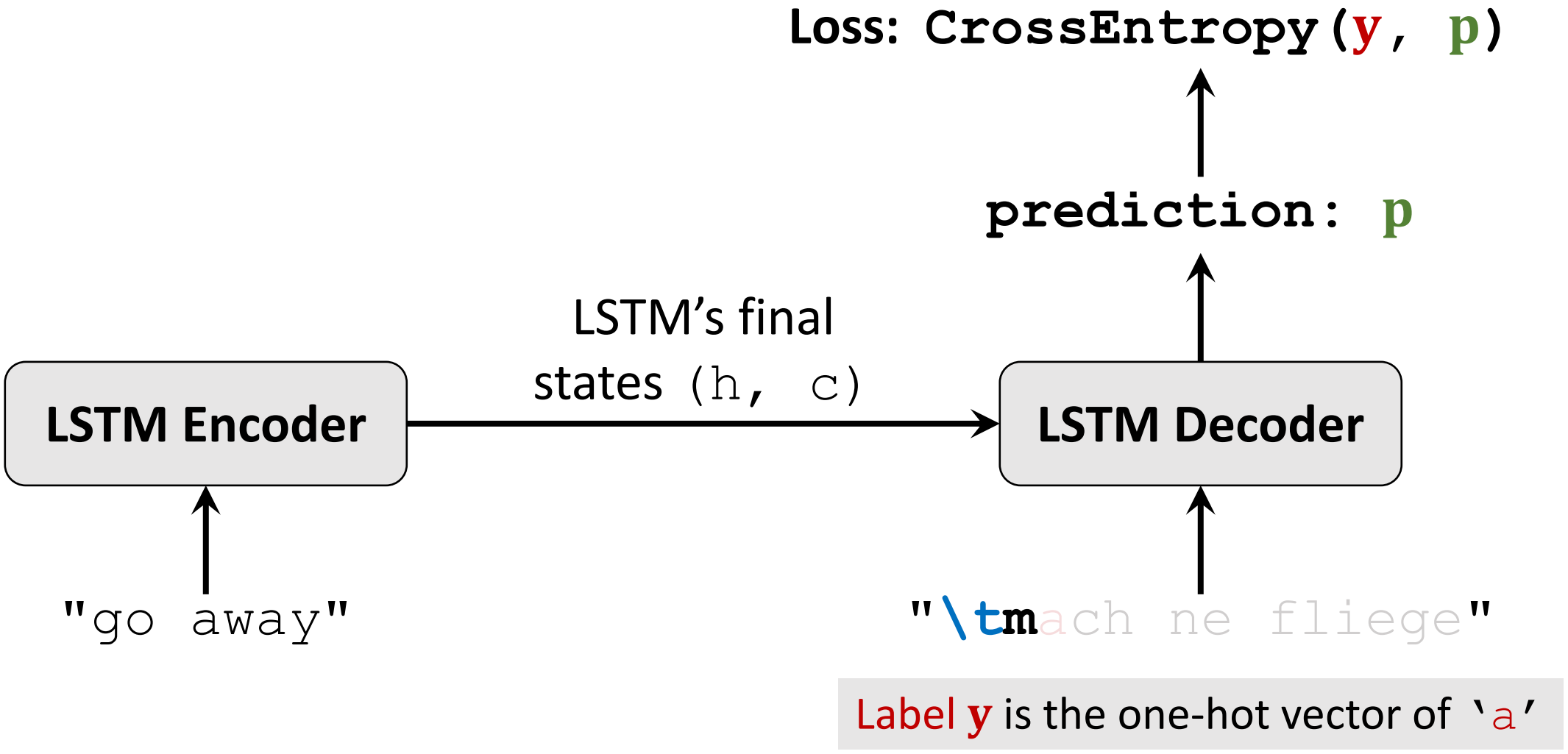


Training Seq2Seq Model



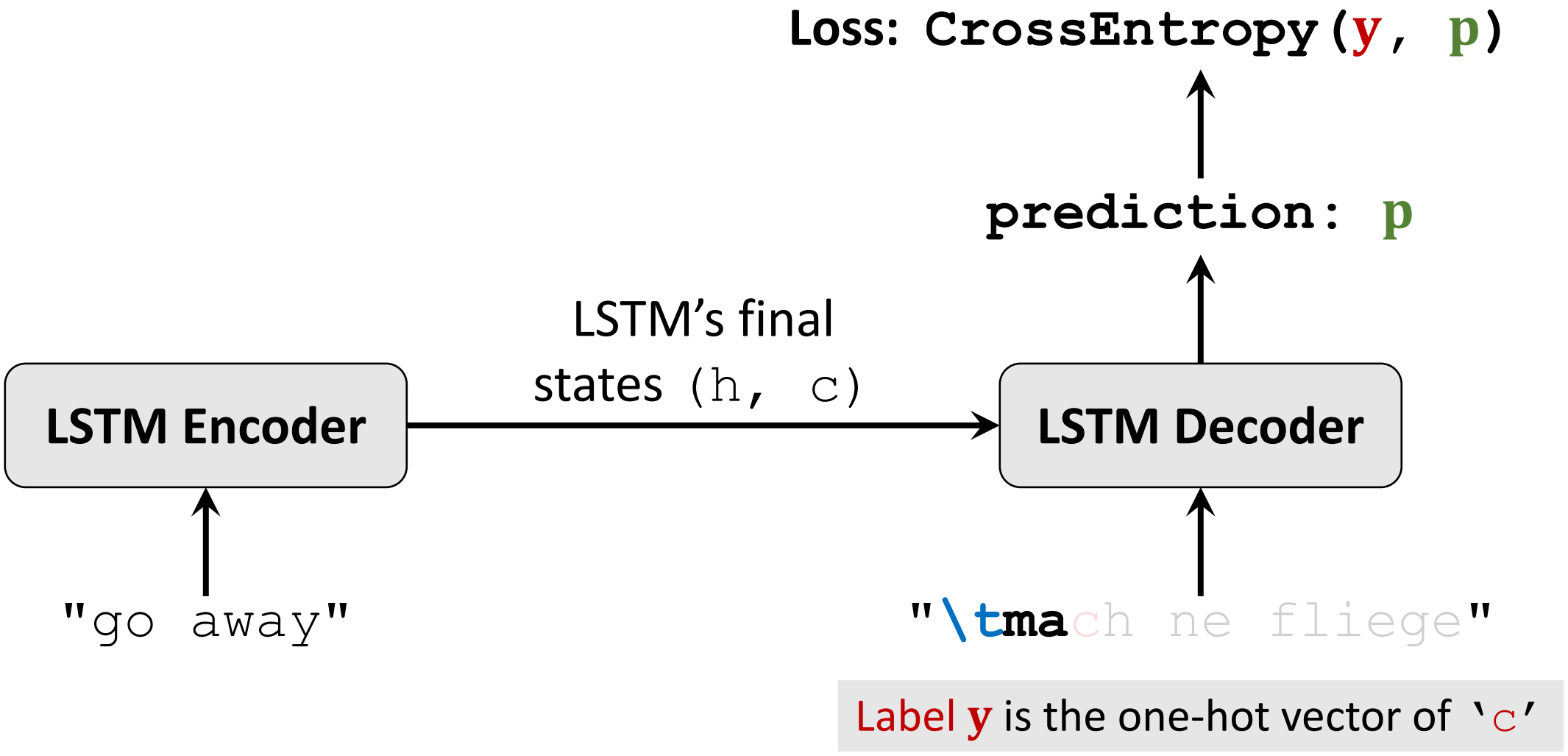
Label **y** is the one-hot vector of 'm'

Training Seq2Seq Model



Label **y** is the one-hot vector of 'a'

Training Seq2Seq Model

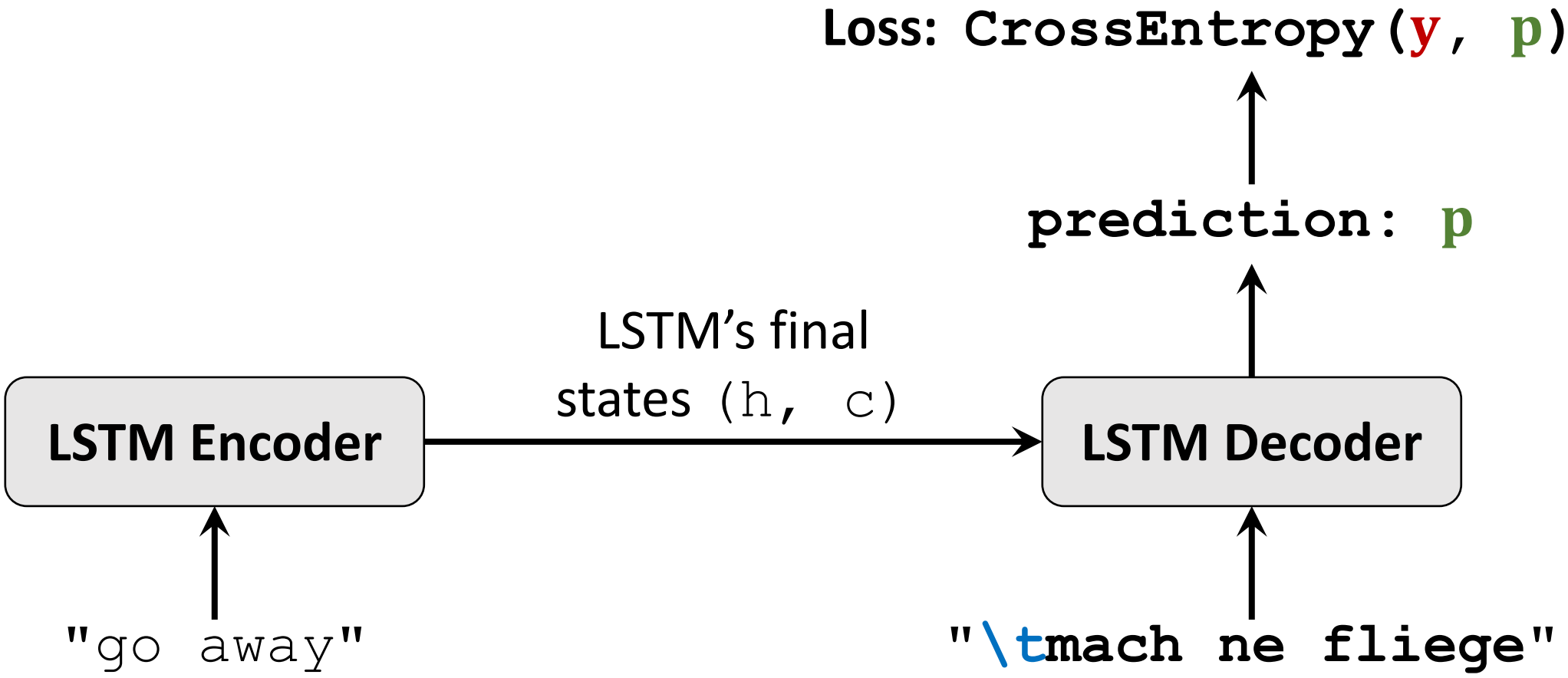


Label **y** is the one-hot vector of `'c'`

Training Seq2Seq Model

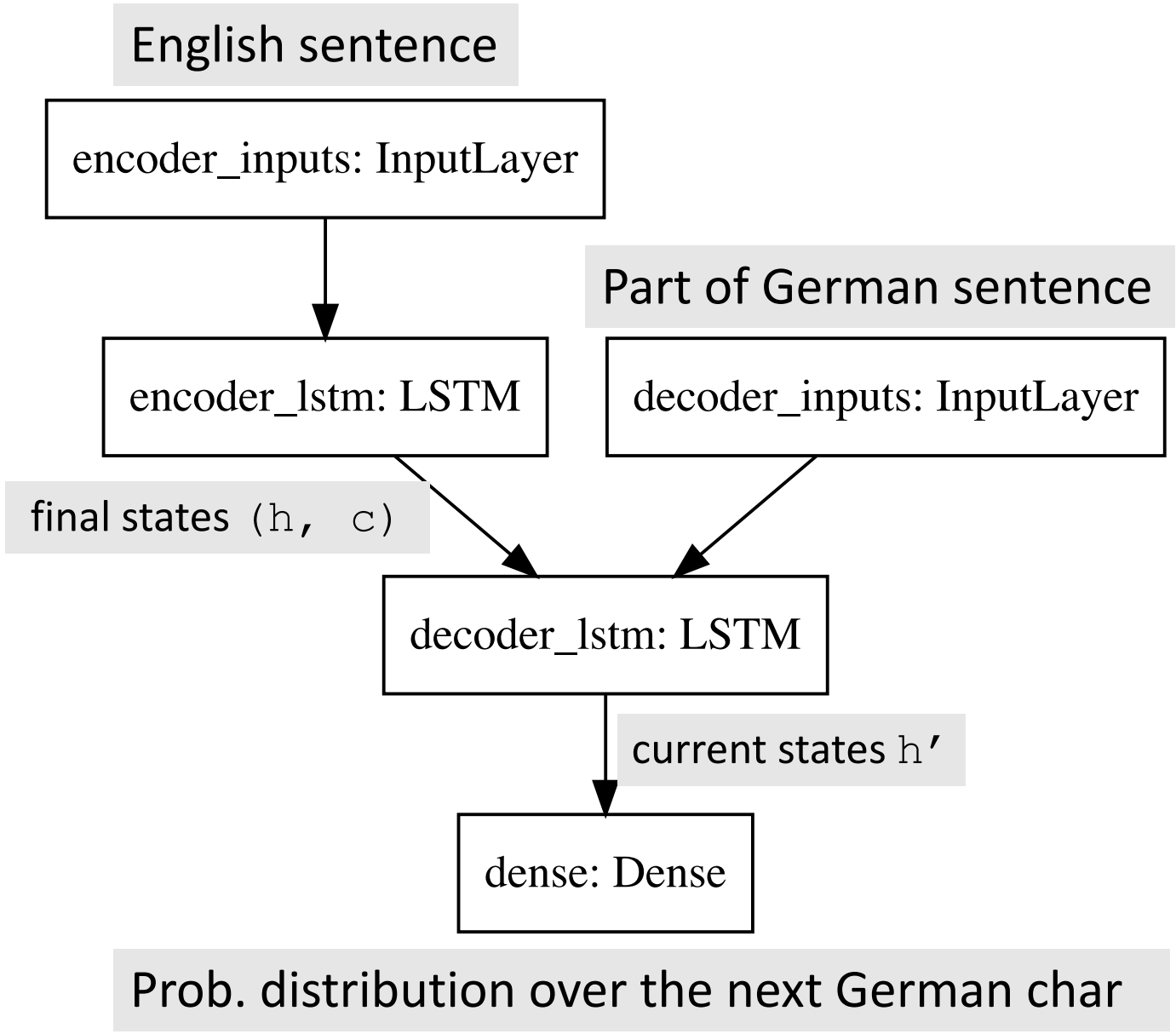
Repeat this process

Training Seq2Seq Model



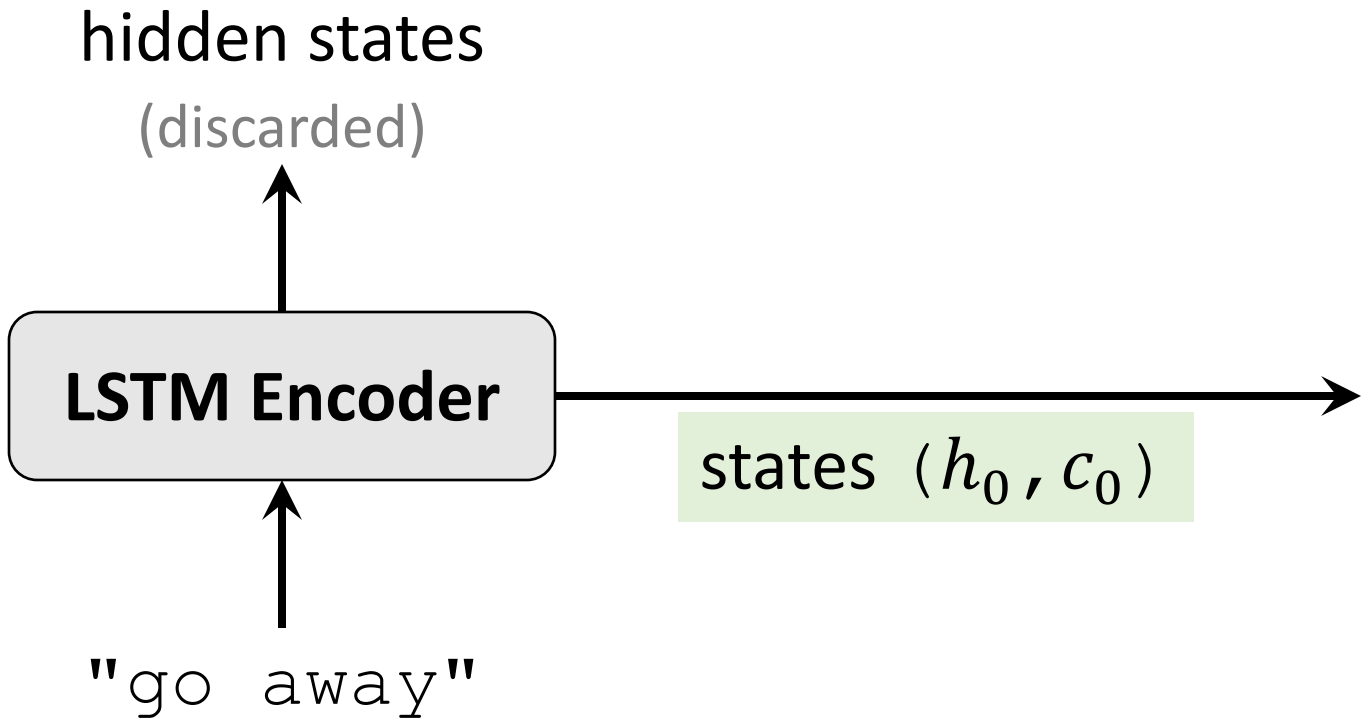
Label **y** is the one-hot vector of the [stop] sign.

Seq2Seq Model in Keras

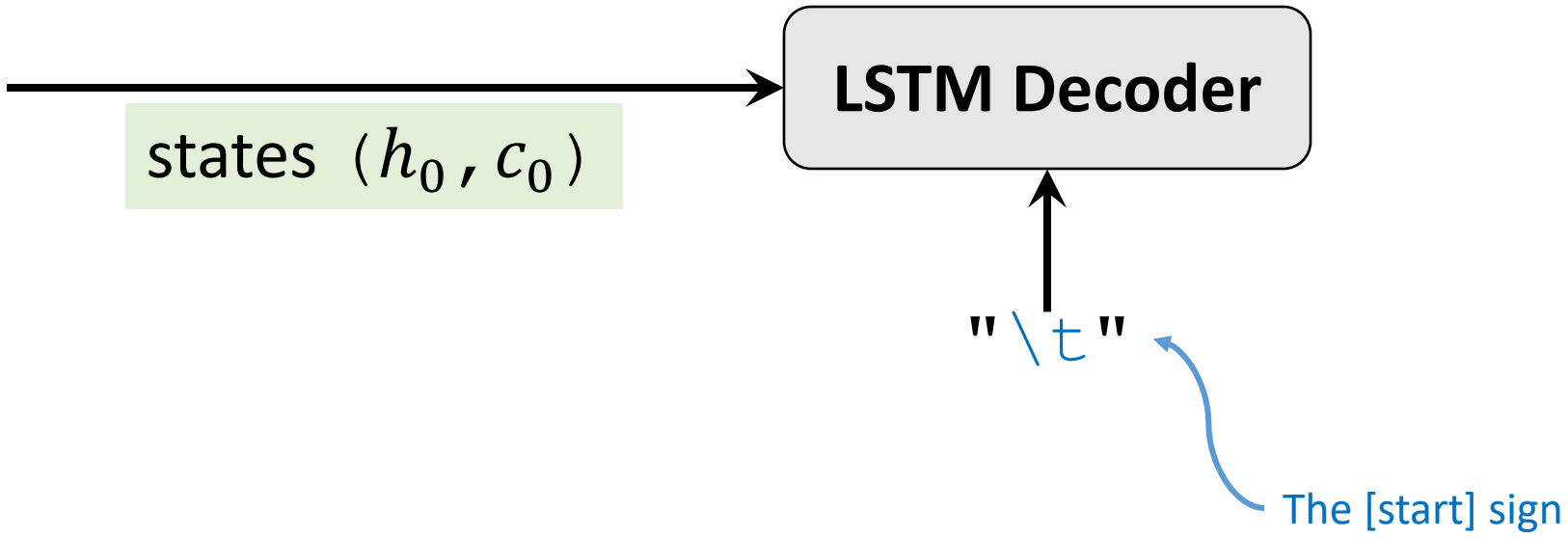


Inference Using the Seq2Seq Model

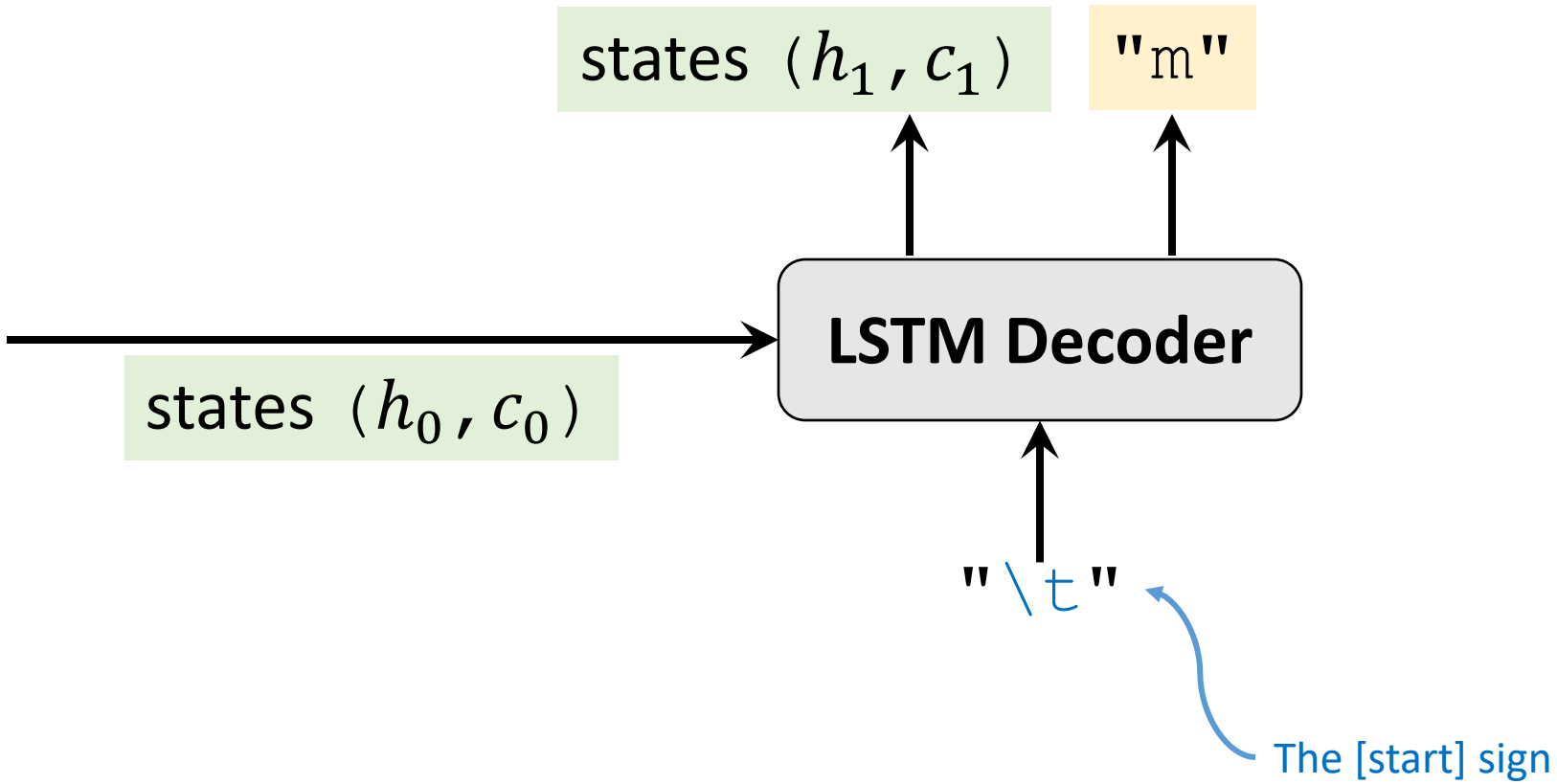
Inference



Inference

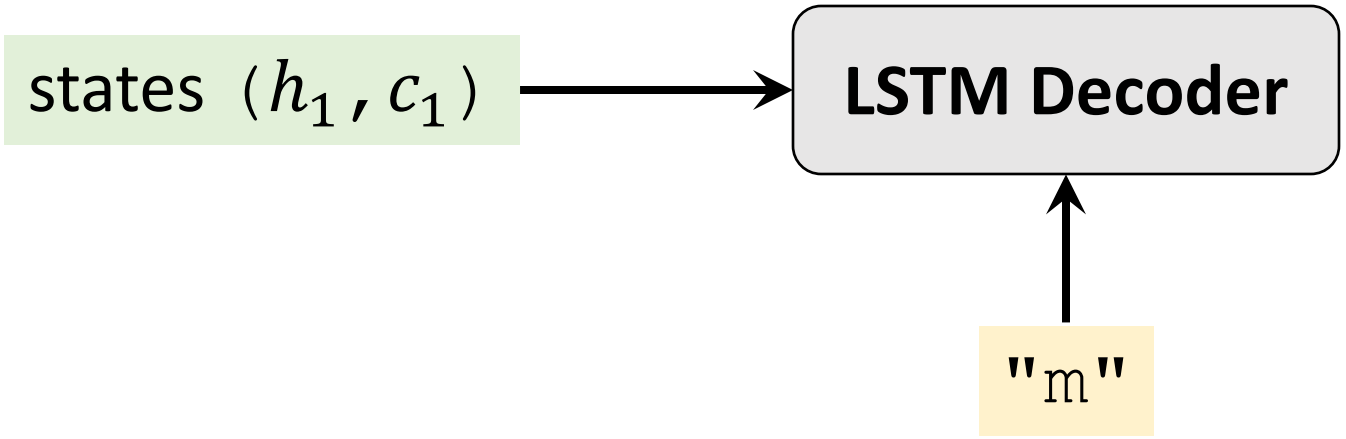


Inference



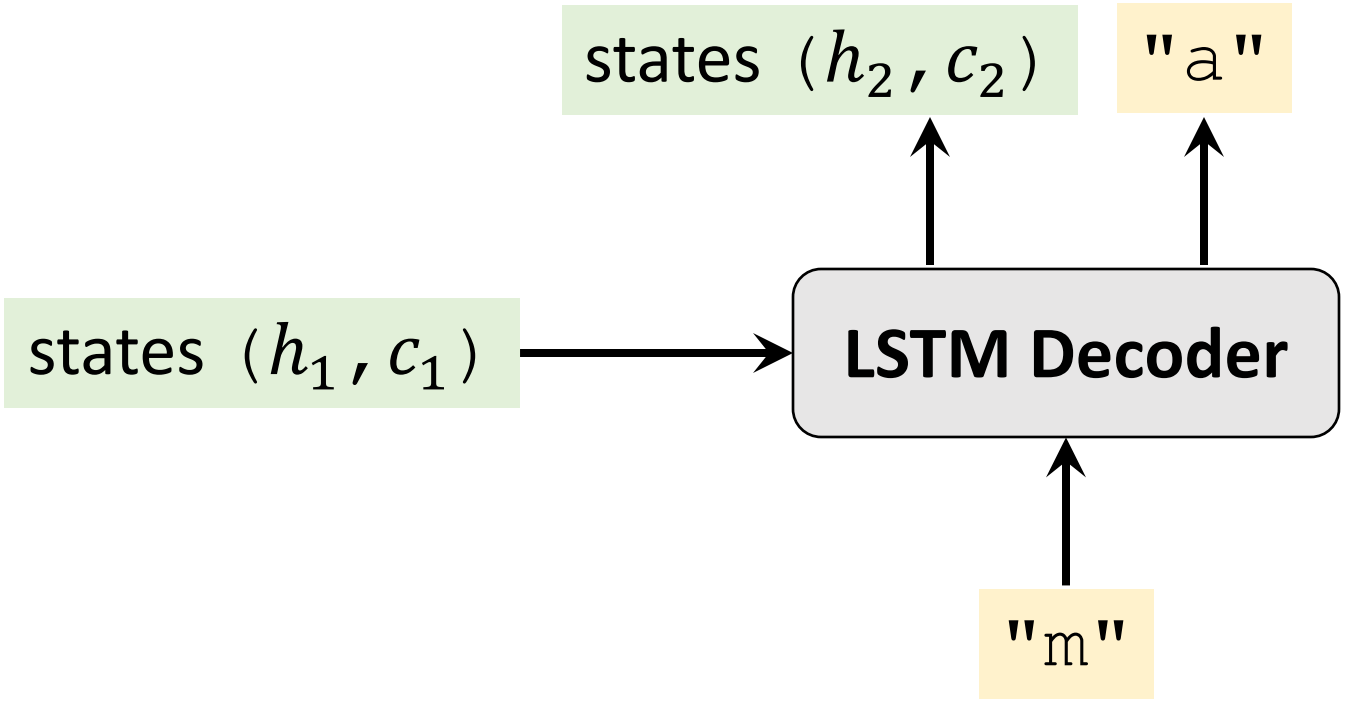
Record: "m"

Inference



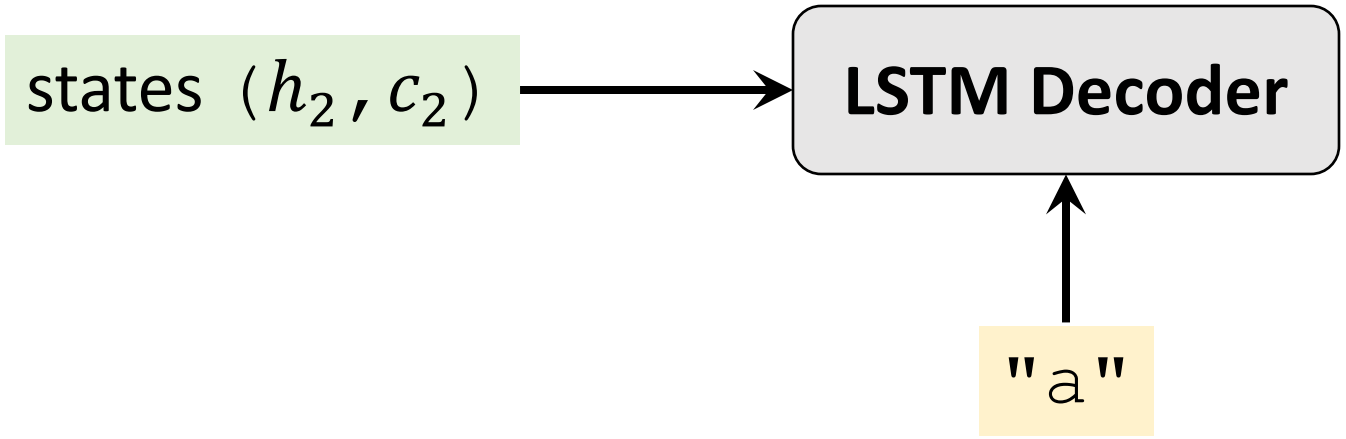
Record: "m"

Inference



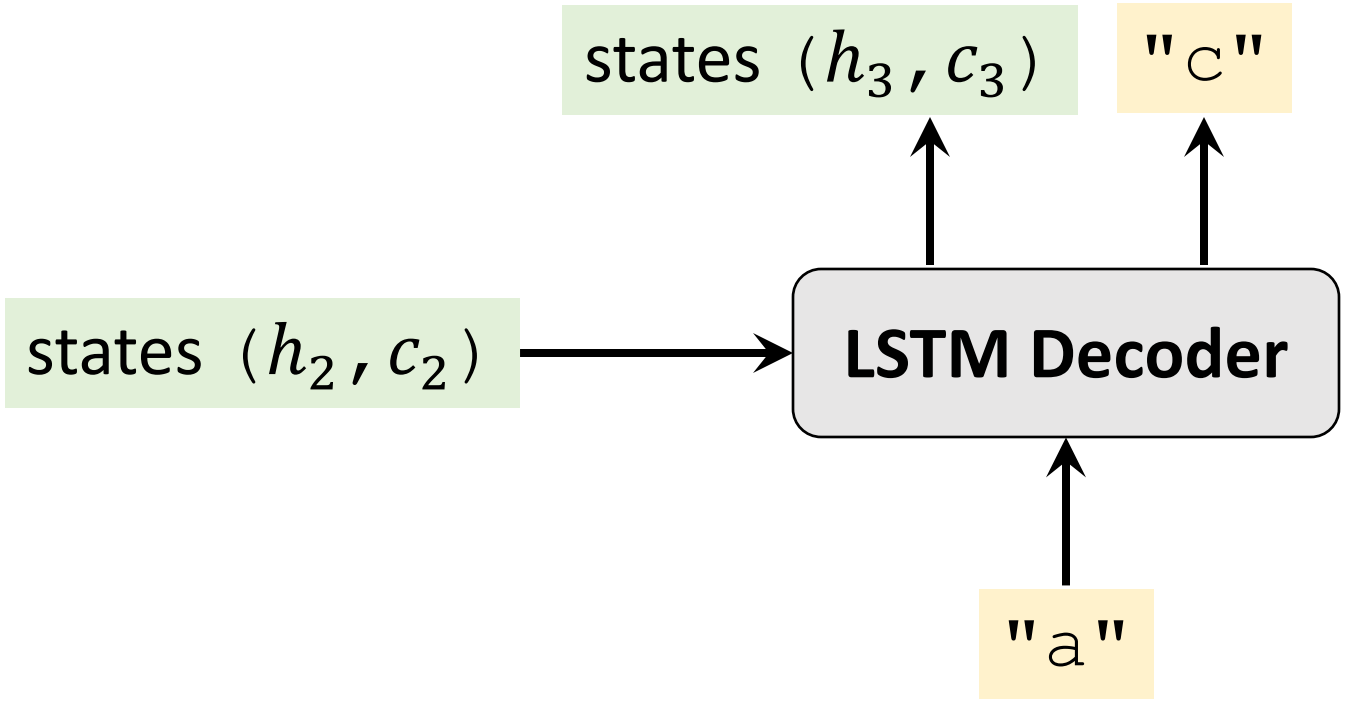
Record: "ma"

Inference



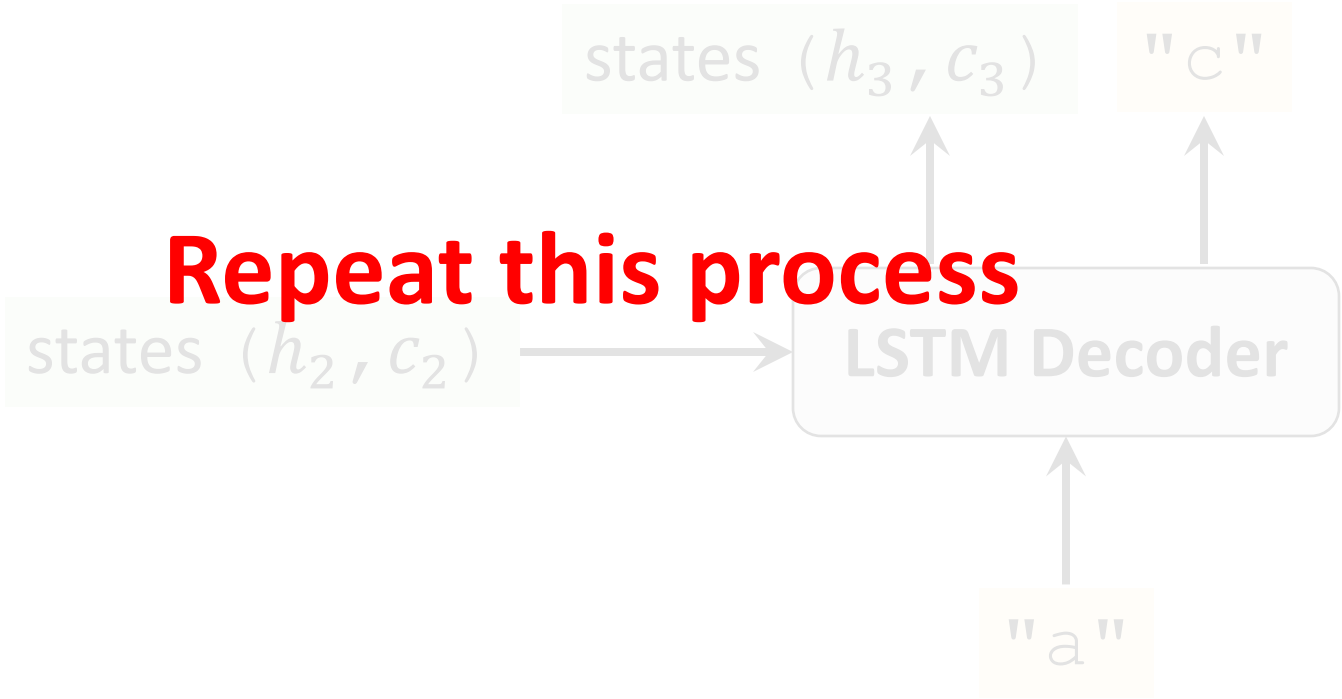
Record: "ma"

Inference



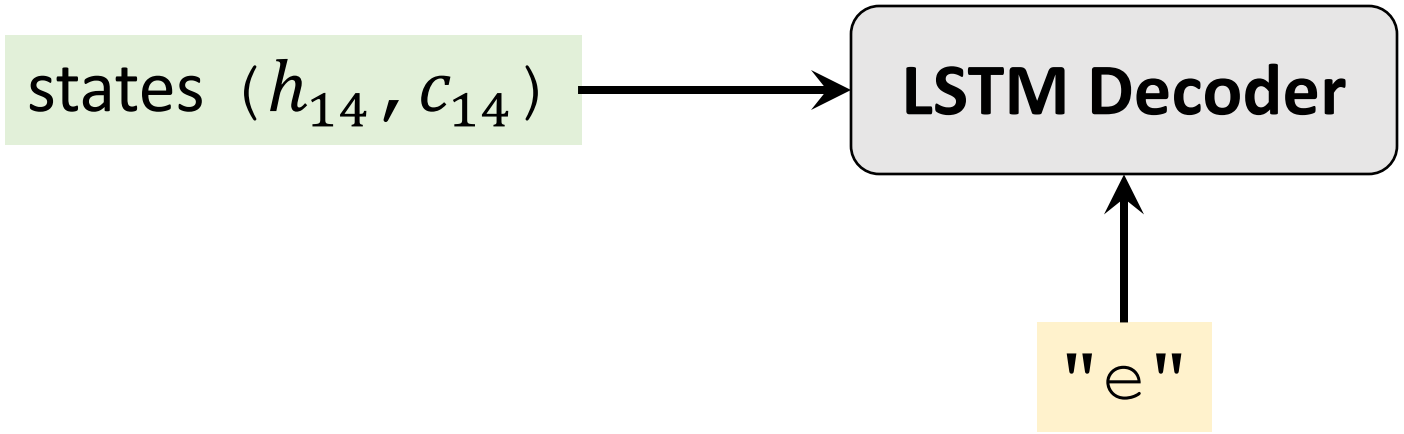
Record: "mac"

Inference



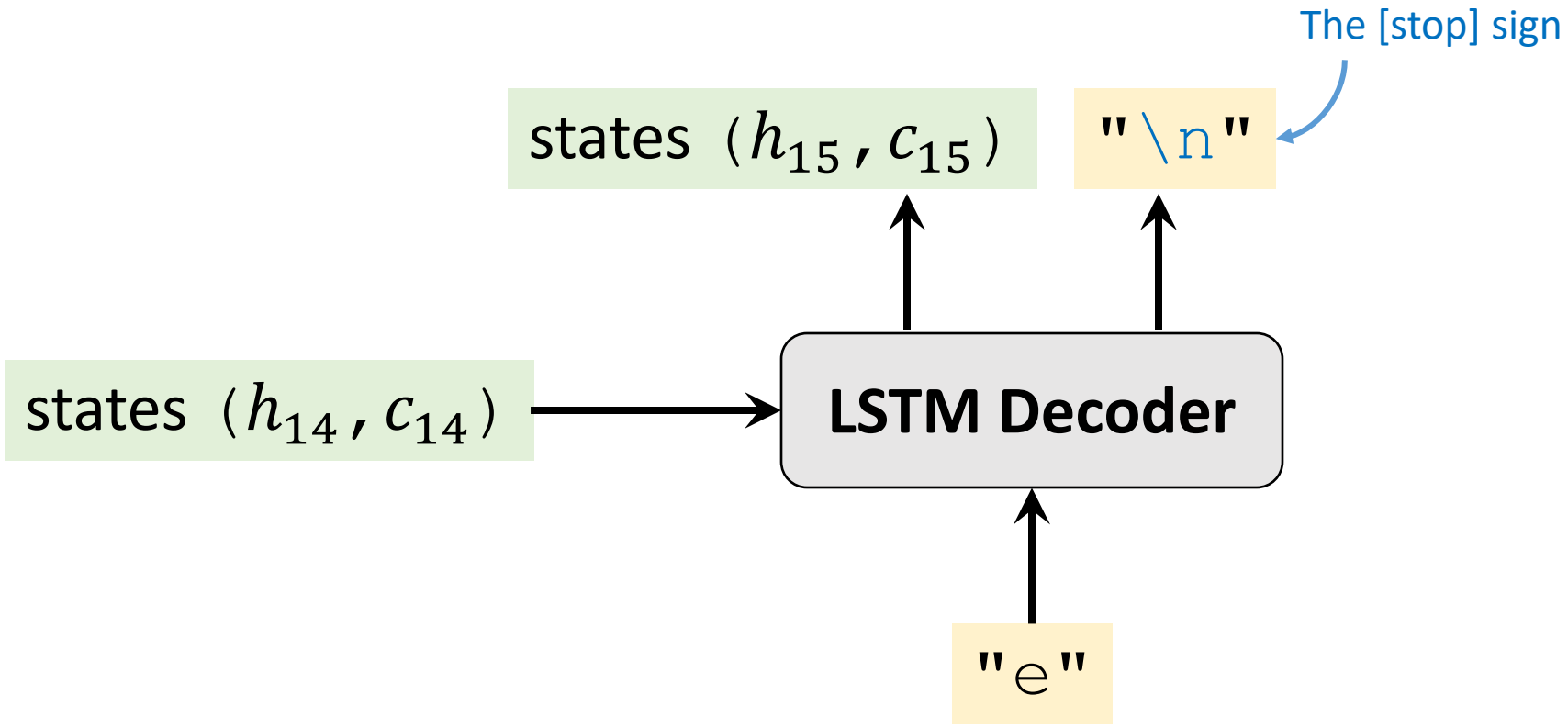
Record: "mac"

Inference



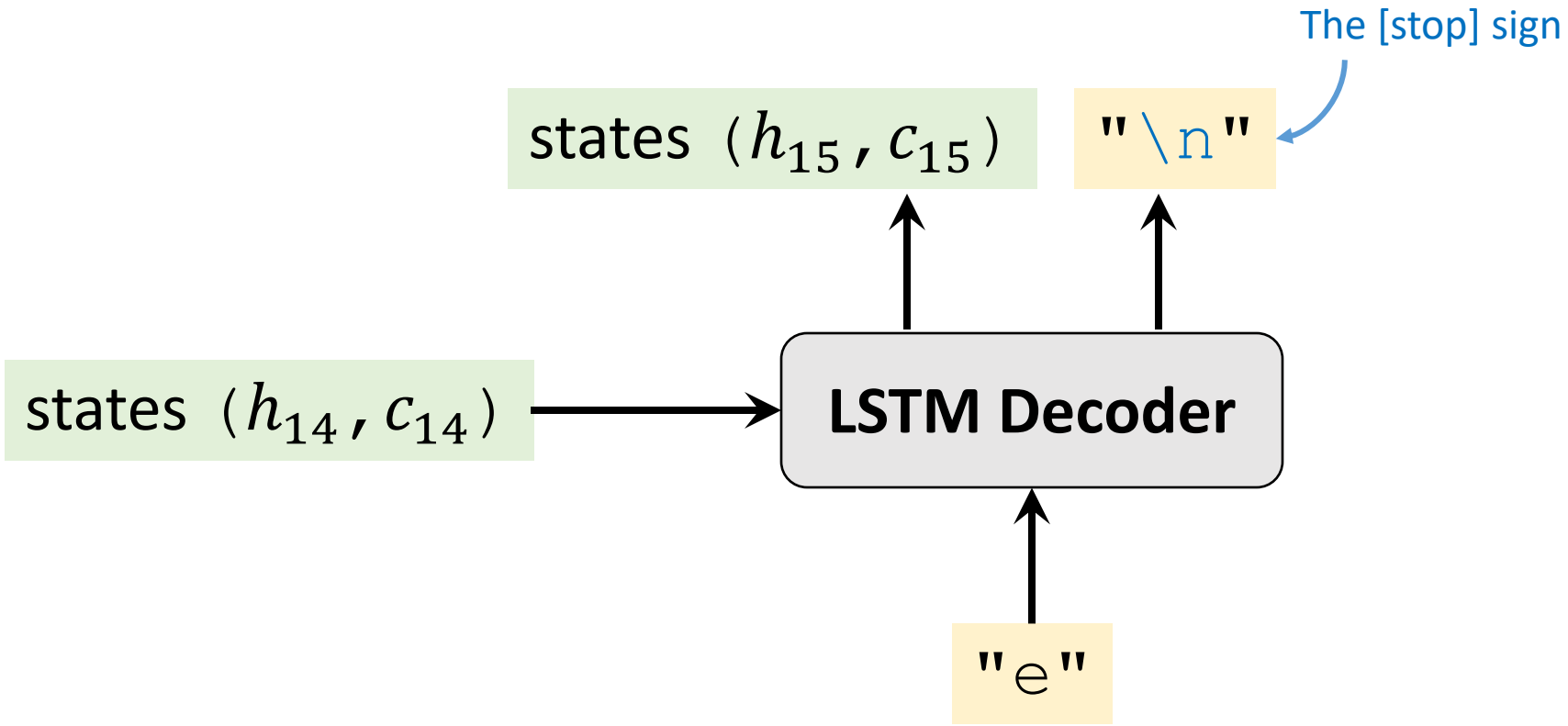
Record: `"mach ne fliege"`

Inference



Record: "mach ne fliege"

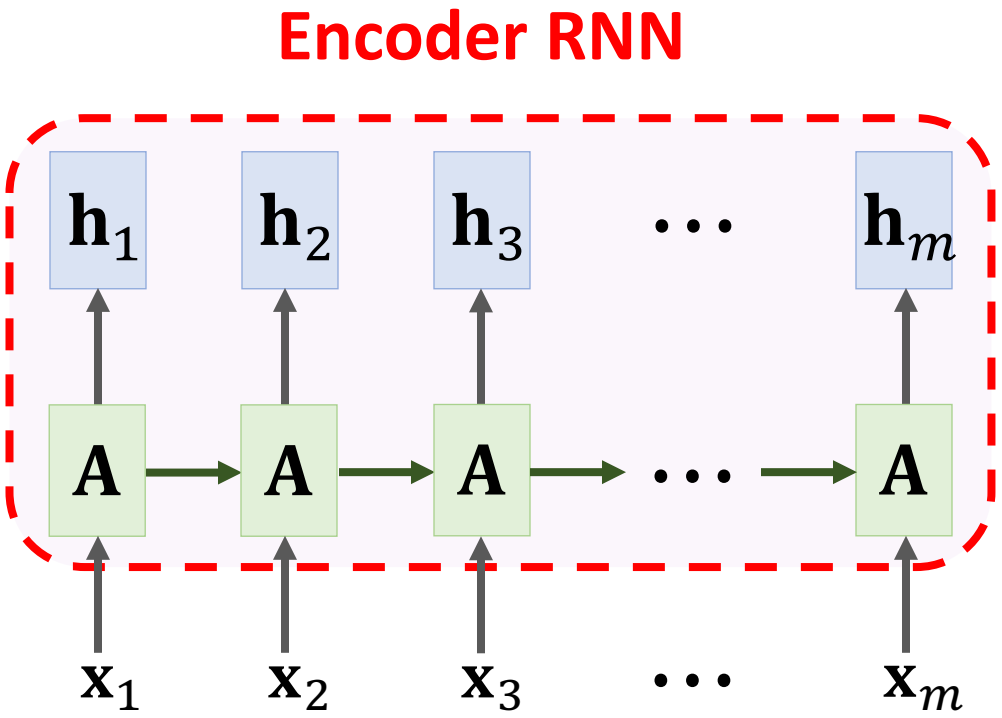
Inference



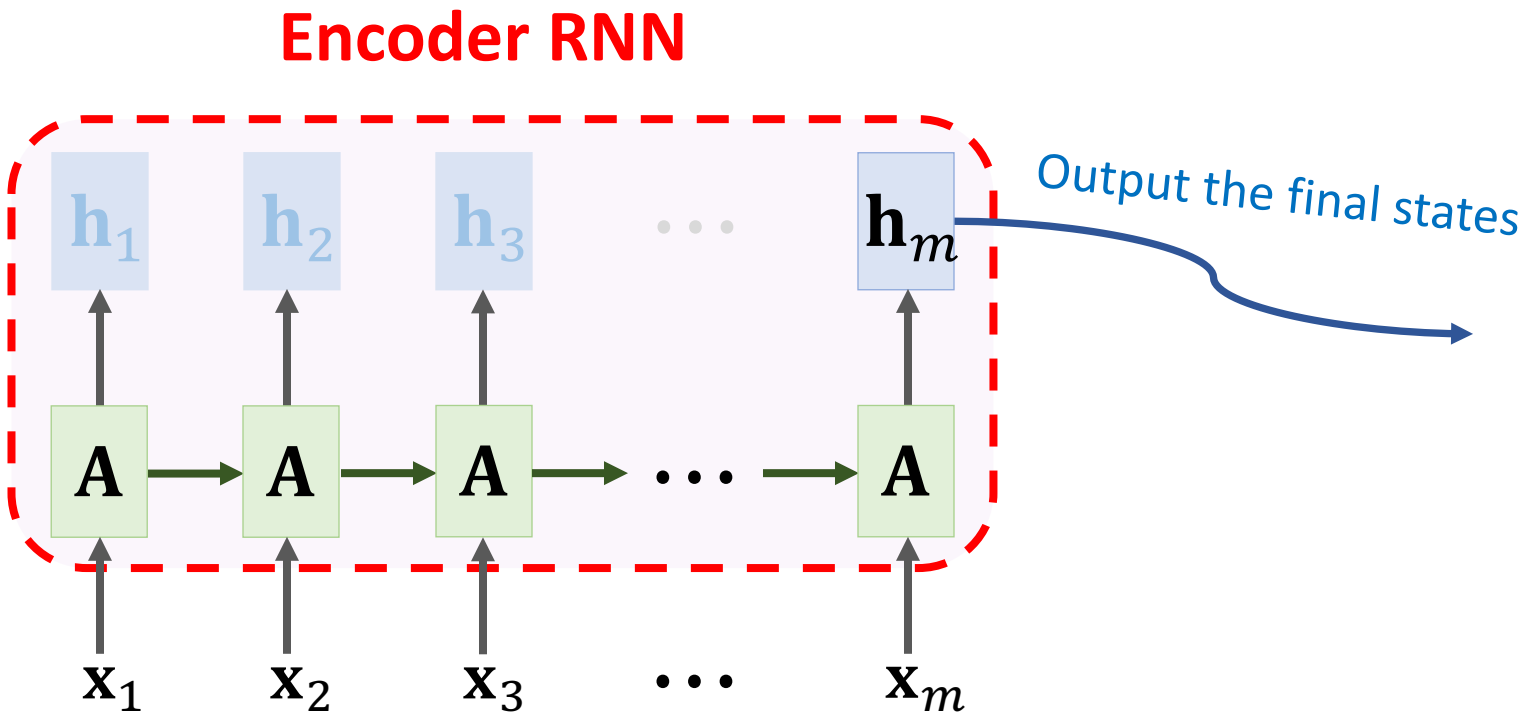
Return: "mach ne fliege"

Summary

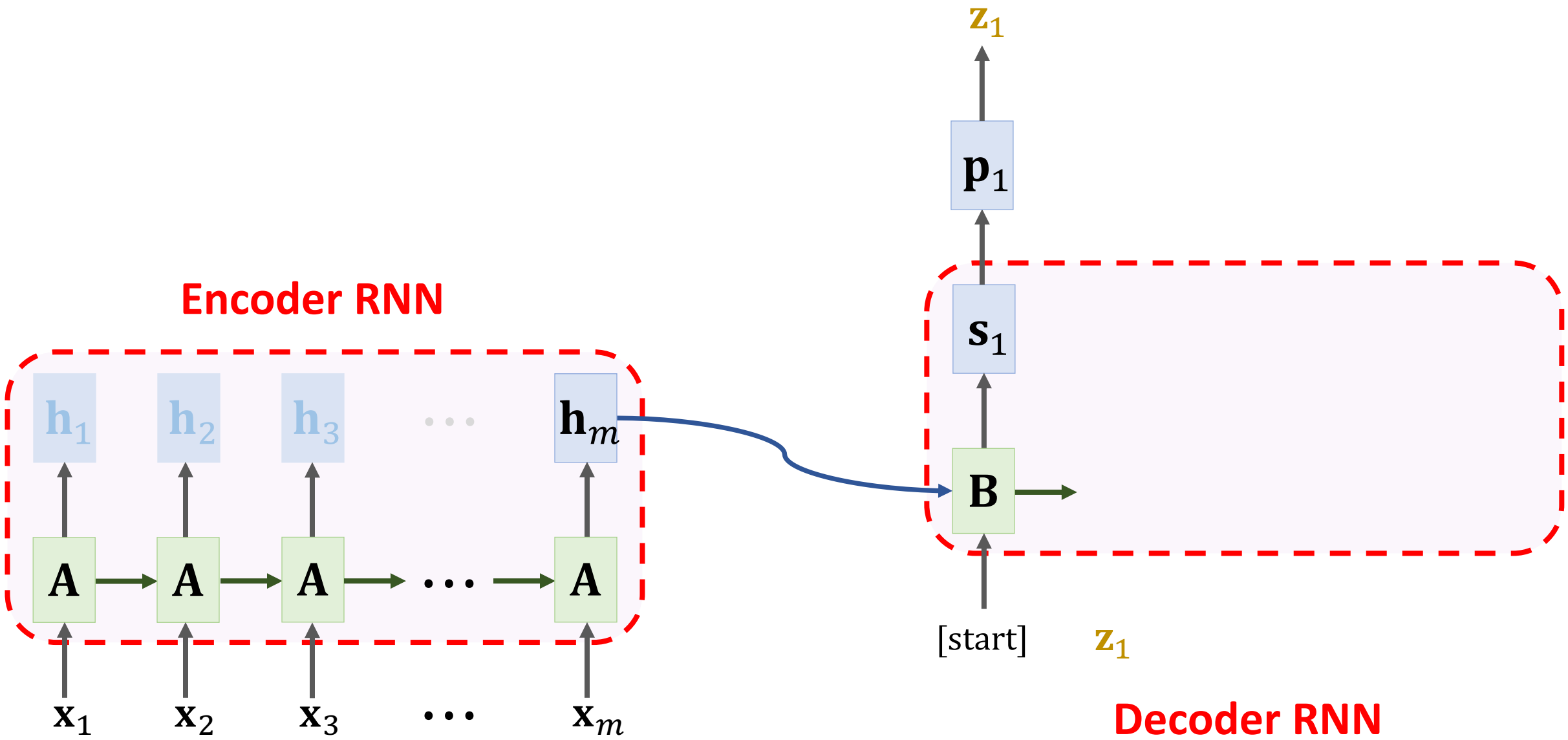
Seq2Seq Model



Seq2Seq Model



Seq2Seq Model



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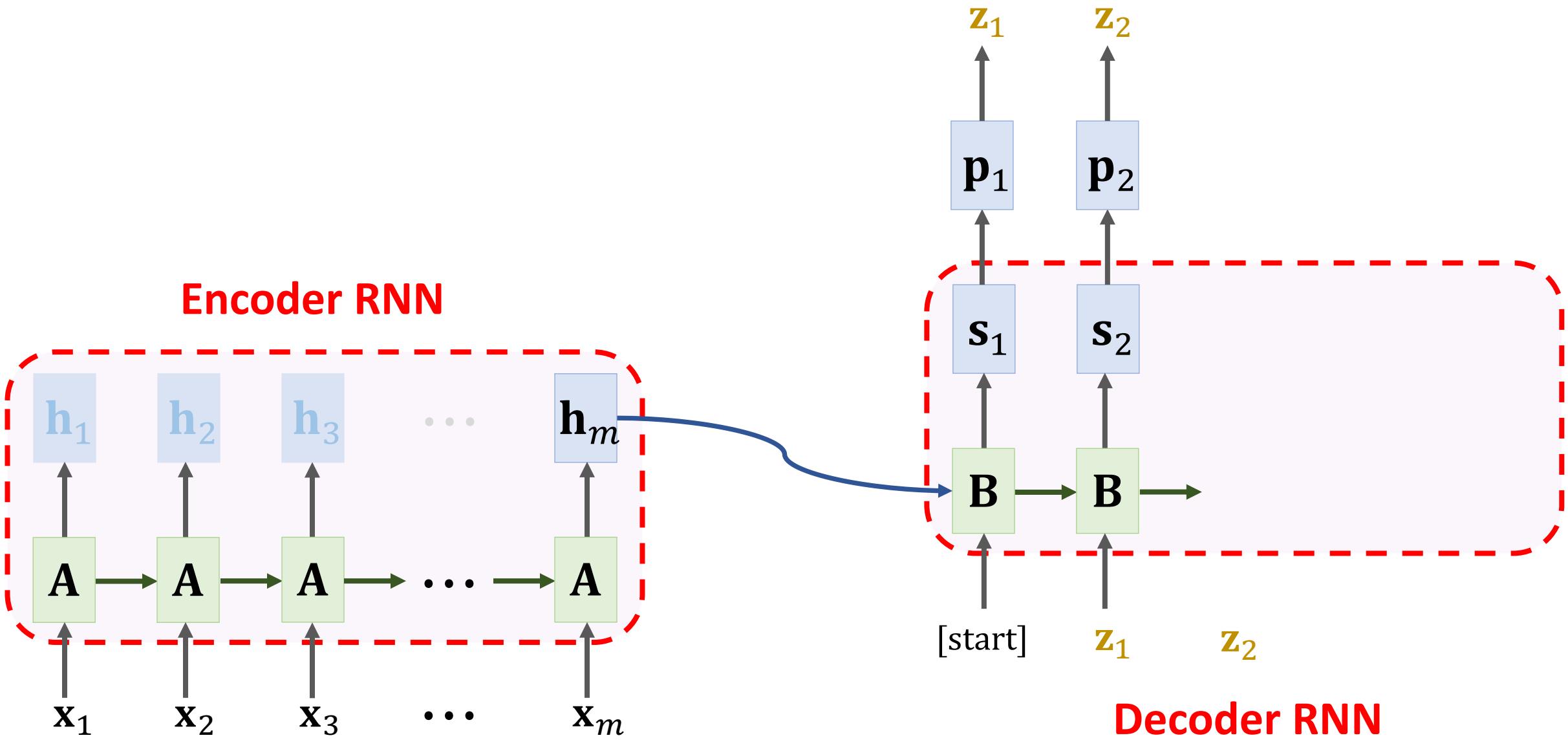
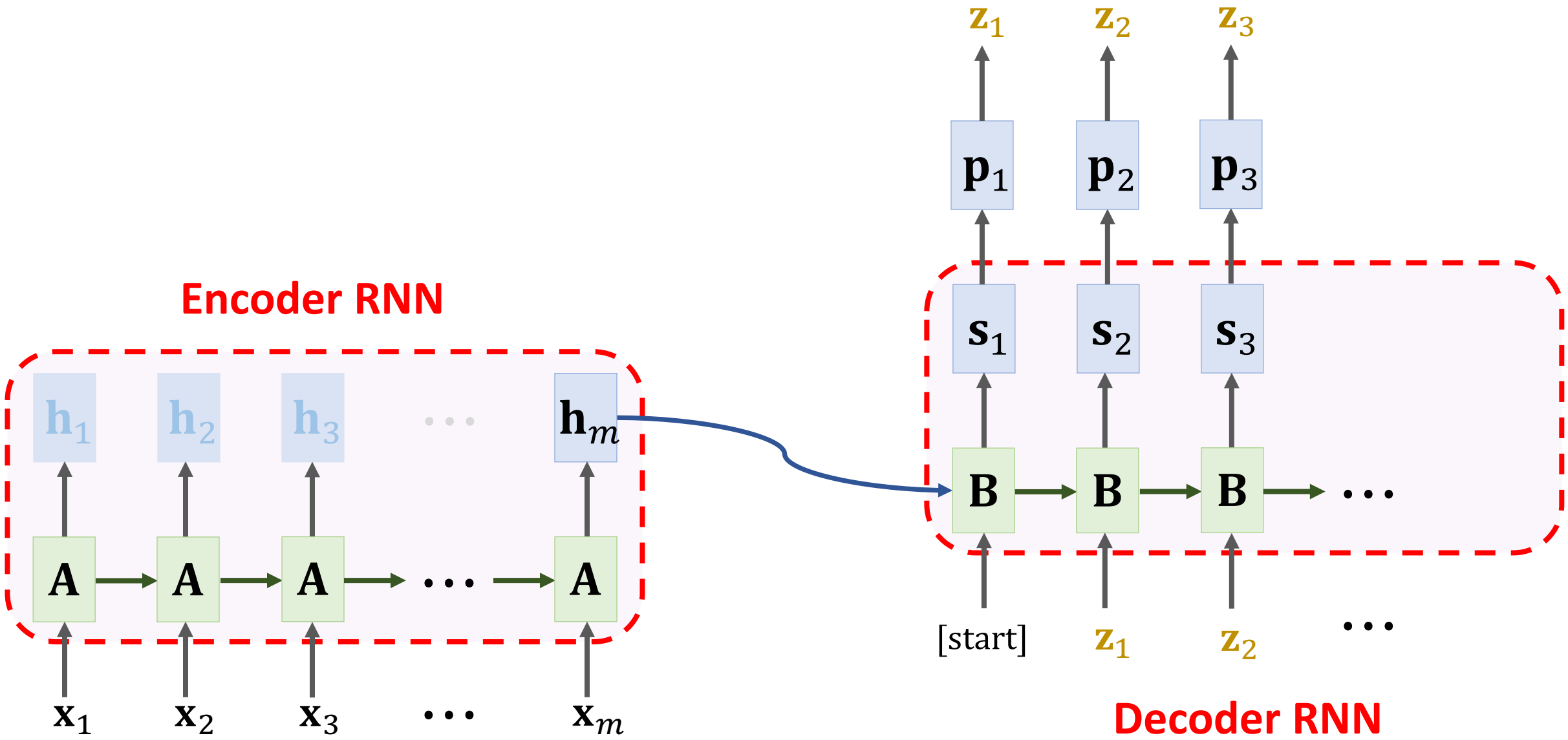
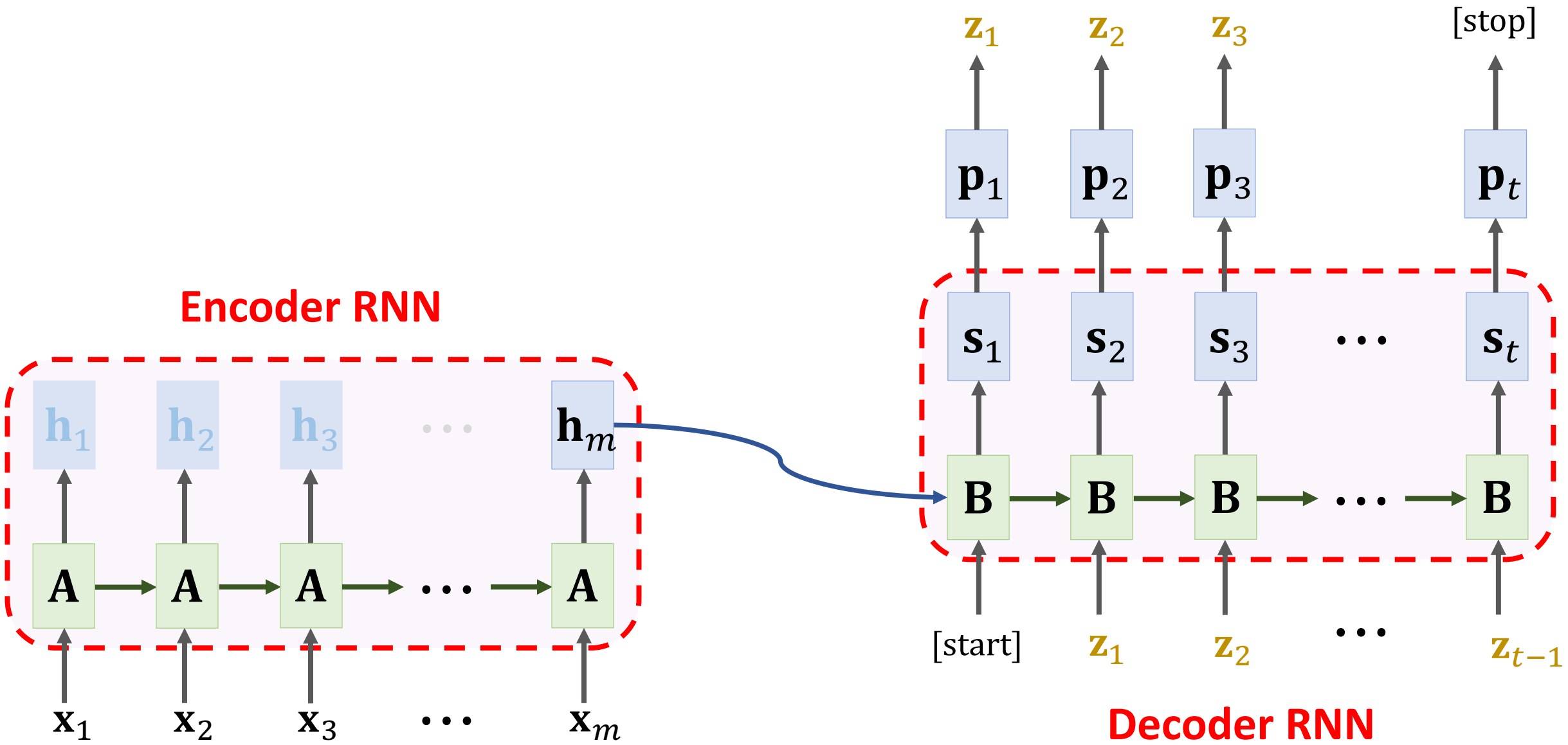


Seq2Seq Model



Seq2Seq Model



How to Improve?

1. Bi-LSTM instead of LSTM (Encoder only!)

- Encoder's final states ($\mathbf{h}_t$ and $\mathbf{c}_t$) have all the information of the English sentence.
- If the sentence is long, the final states have forgotten early inputs.

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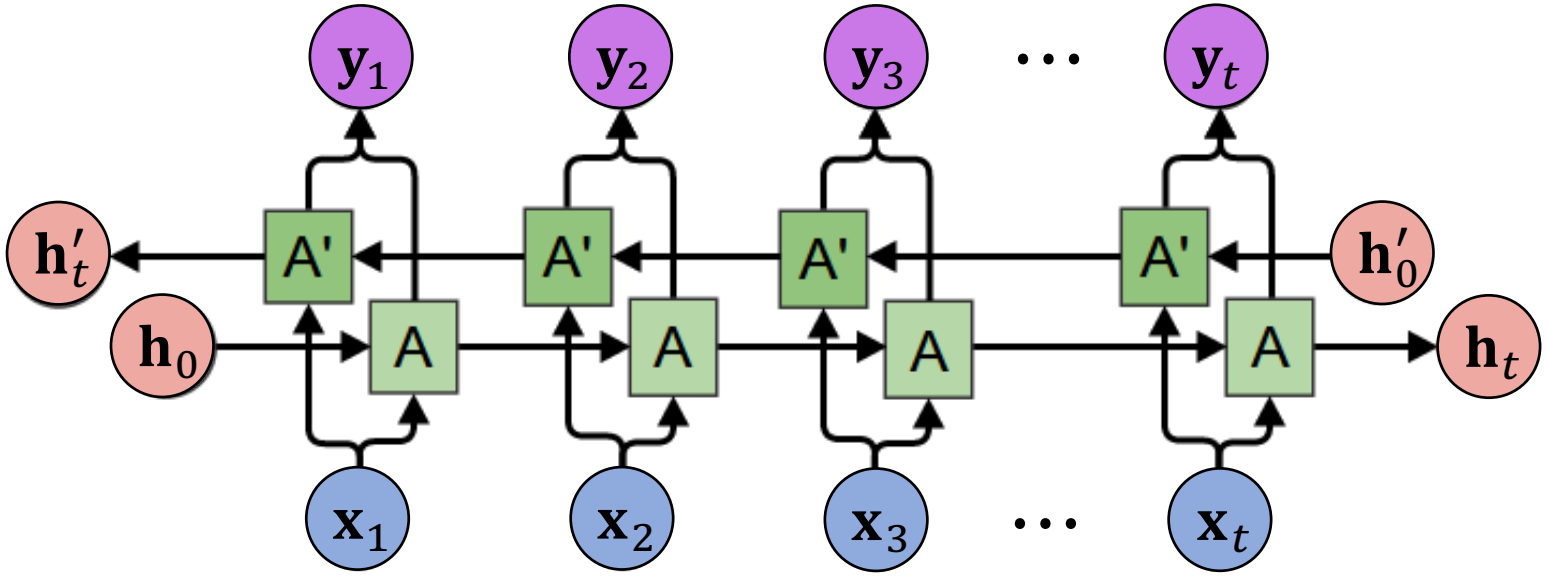

1. Bi-LSTM instead of LSTM (Encoder only!)

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- If the sentence is long, the final states have forgotten early inputs.
- Bi-LSTM (left-to-right and right-to-left) has longer memory.
- Use Bi-LSTM in the encoder; use unidirectional LSTM in the decoder.

2. Word-Level Tokenization

- Word-level tokenization instead of char-level.
  - The average length of English words is 4.5 letters.
  - The sequences will be 4.5x shorter.
  - Shorter sequence ➔ less likely to forget.

2. Word-Level Tokenization

- Word-level tokenization instead of char-level.
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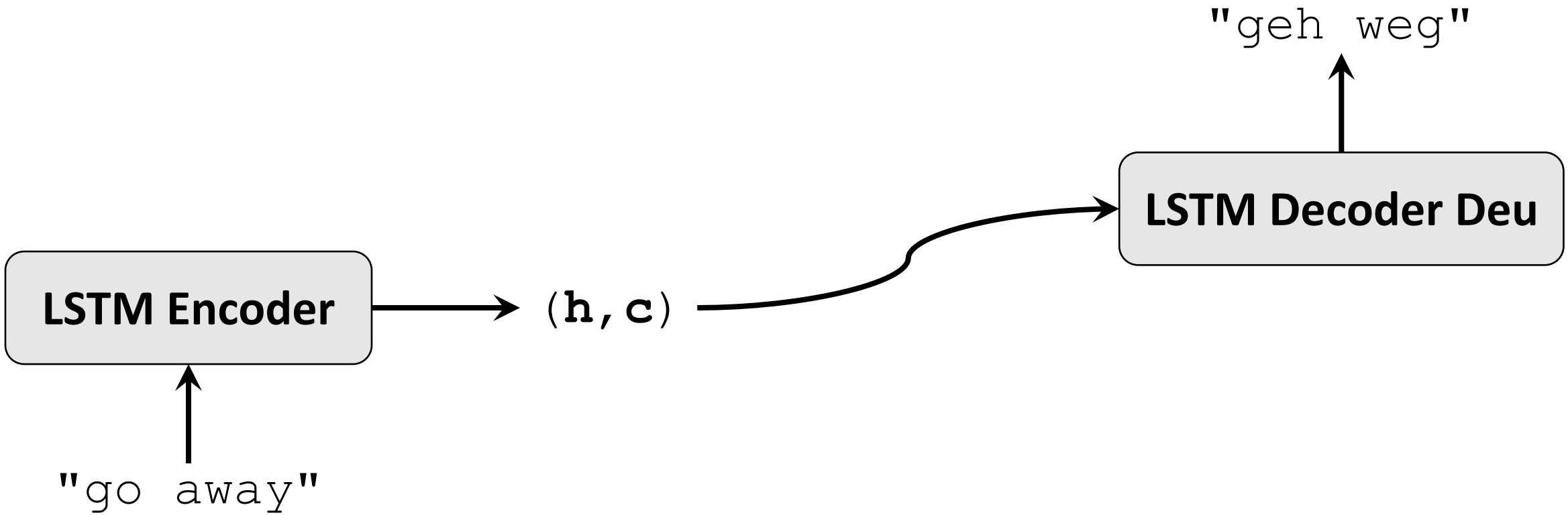
- But you will need a large dataset!
  - # of (frequently used) chars is ~10^2 ➔ one-hot suffices.
  - # of (frequently used) words is ~10^4 ➔ must use embedding.
  - Embedding Layer has many parameters ➔ overfitting!

3. Multi-Task Learning



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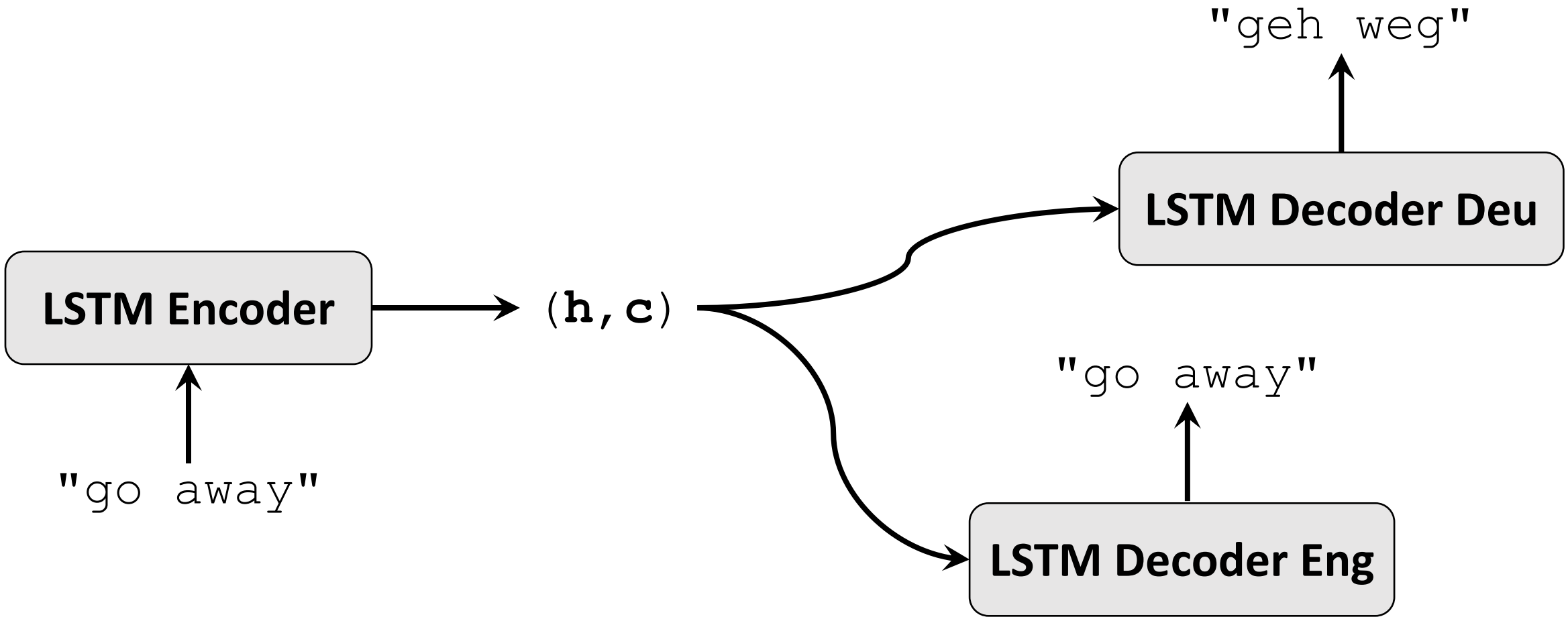


3. Multi-Task Learning

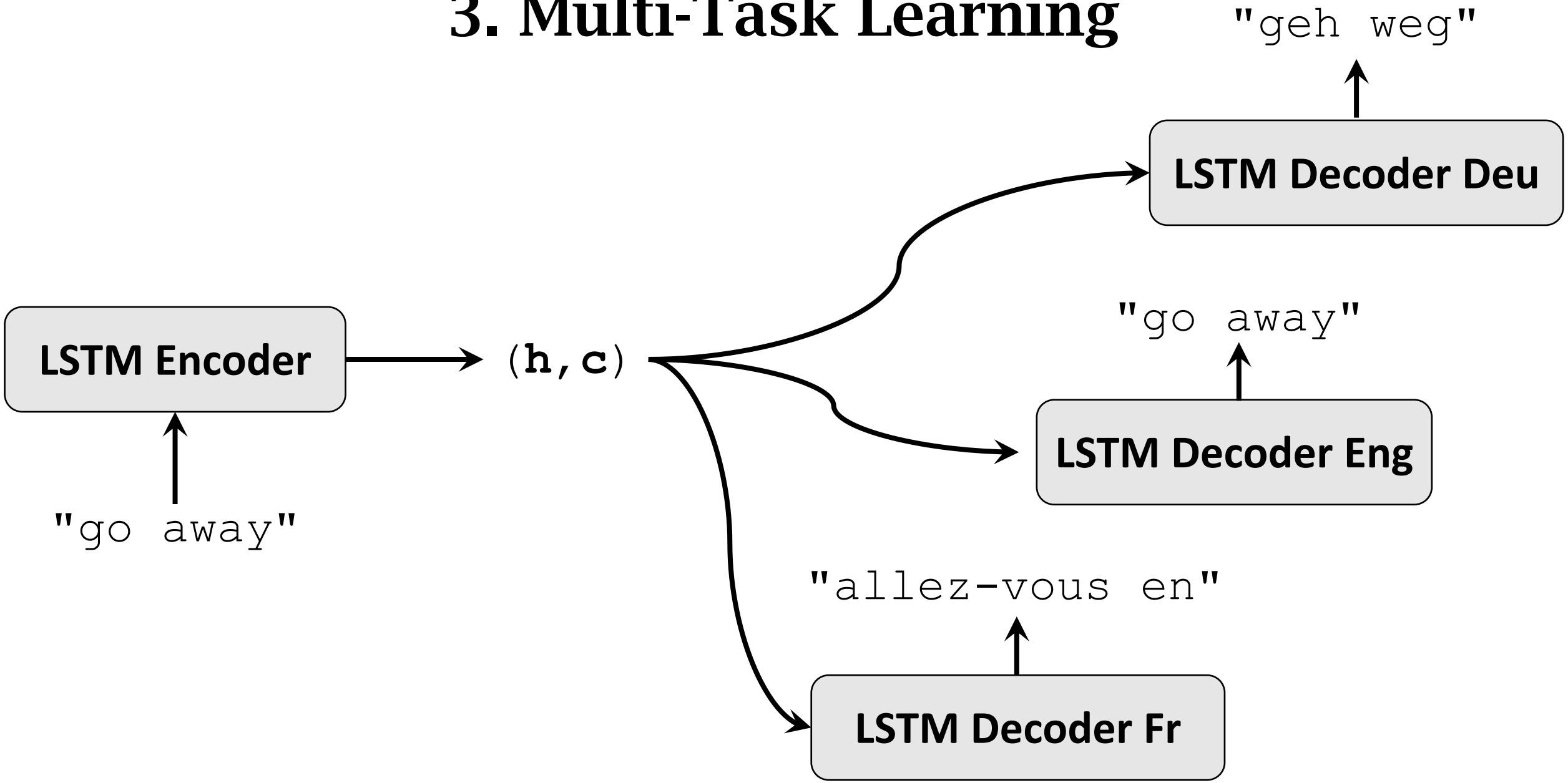
- Even if you want to translate English to German, you can use all the datasets:

- Afrikaans - English afr-eng.zip (725)
- Aklanon - English akl-eng.zip (22)
- Albanian - English sqi-eng.zip (412)
- Algerian Arabic - English arq-eng.zip (156)
- Arabic - English ara-eng.zip (11009)
- Arabic (Gulf) - English afb-eng.zip (28)
- Assamese - English asm-eng.zip (23)
- Asturian - English ast-eng.zip (23)
- Azerbaijani - English aze-eng.zip (2131)
- Basque - English eus-eng.zip (667)
- Belarusian - English bel-eng.zip (2698)
- Bengali - English ben-eng.zip (4399)
- Berber - English ber-eng.zip (54988)
- Bulgarian - English bul-eng.zip (14968)

• • •

- Spanish - English spa-eng.zip (120799)
- Swedish - English swe-eng.zip (17409)
- Tagalog - English tgl-eng.zip (3144)
- Tamil - English tam-eng.zip (197)
- Tatar - English tat-eng.zip (529)
- Telugu - English tel-eng.zip (138)
- Thai - English tha-eng.zip (110)
- Turkish - English tur-eng.zip (497249)
- Ukrainian - English ukr-eng.zip (113396)
- Urdu - English urd-eng.zip (1180)
- Uyghur - English uig-eng.zip (285)
- Vietnamese - English vie-eng.zip (3413)
- Waray - English war-eng.zip (1181)
- Zaza - English zza-eng.zip (345)

3. Multi-Task Learning



How to Improve?

1. Bi-LSTM instead of LSTM. (Encoder only!)
2. Tokenization in the word-level (instead of char-level.)
3. Multi-task learning.
4. Attention! (Next lecture.)

Thank you!