Neural Machine Translation

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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/

1. Processing the Data

- **Preprocessing**: to lower case, remove punctuation, remove non-printable chars.

deu.txt

I survived.	Ich habe überlebt.
I survived.	Ich überlebte.
I think so.	Ich stimme dem zu.
I threw up.	Ich habe gekotzt.
I threw up.	Ich habe mich übergeben.
I threw up.	Ich habe erbrochen.
I use this.	Ich verwende das.
I use this.	Ich benutze das.
I want Tom.	Ich will Tom.
I want one!	Ich will einen!
I want one!	Ich will eins!
I want one!	Ich will eine!
I want one.	Ich will eins.
I want you.	Ich will dich.
I want you.	Ich will dich!
I was busy.	Ich war beschäftigt.
I was good.	Ich war gut.
I was rude.	Ich war ruppig.
I was sick.	Ich war krank.

2. Tokenization

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

Use 2 different tokenizers for the 2 languages

2. Tokenization

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

Eng_Tokenizer

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

Deu_Tokenizer

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

2. Tokenization

Question: Why 2 different tokenizers?

Answer: In the char-level, languages have different alphabet/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).

2. Tokenization

Question: Why 2 different tokenizers?

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.
```

3. Encoding

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

3. Encoding

"I_am_okay."

Eng_Tokenizer

['i', '_', 'a', 'm', '_', 'o', 'k', 'a', 'y']

Encoding using Eng_Dictionary

[9, 27, 1, 13, 27, 15, 11, 1, 25]

3. Encoding

```
"Es geht mir gut"
```

Deu_Tokenizer

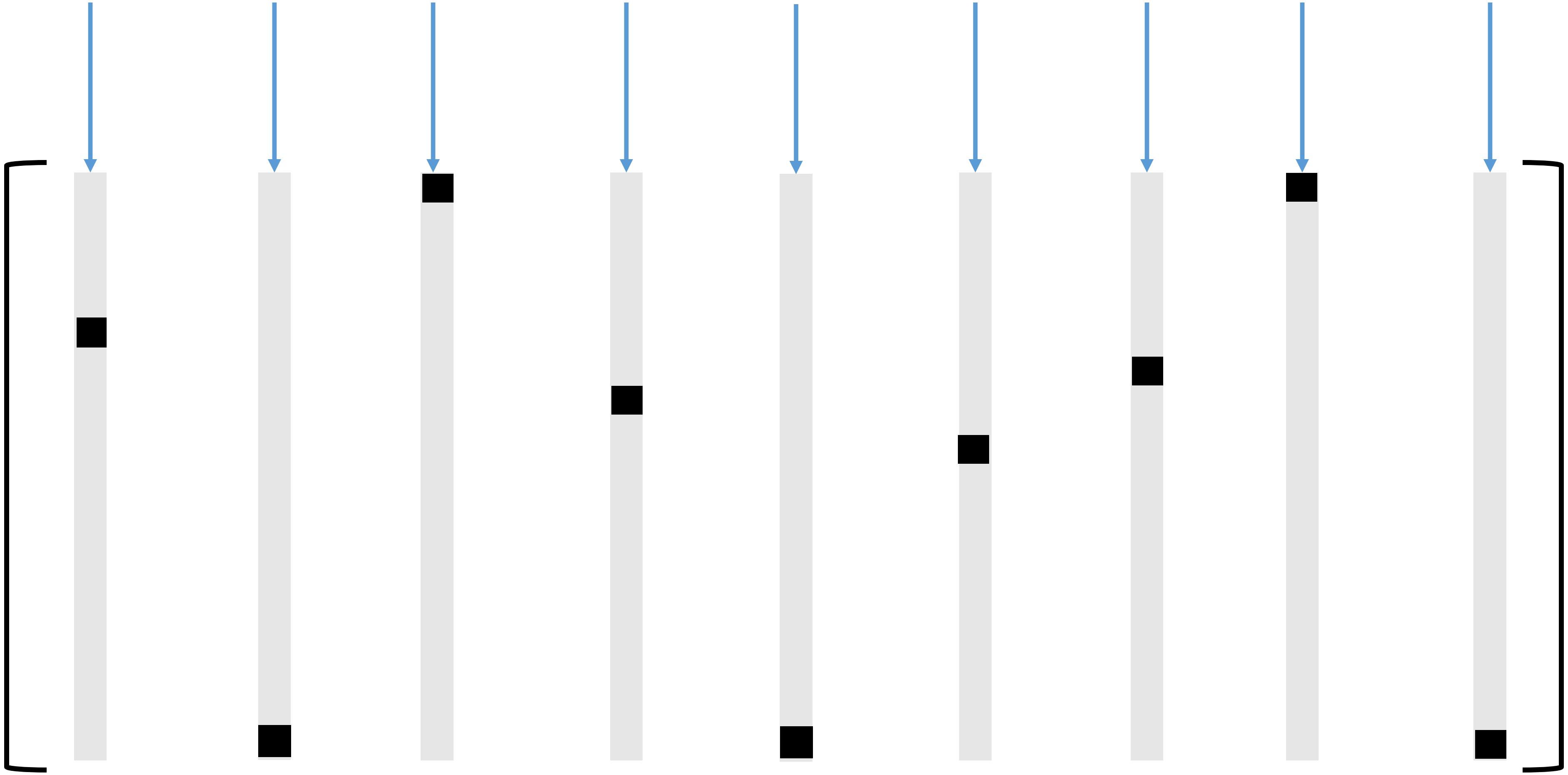
```
['e', 's', '_', 'g', 'e', ..., 'g', 'u', 't']
```

Encoding using Deu_Dictionary

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

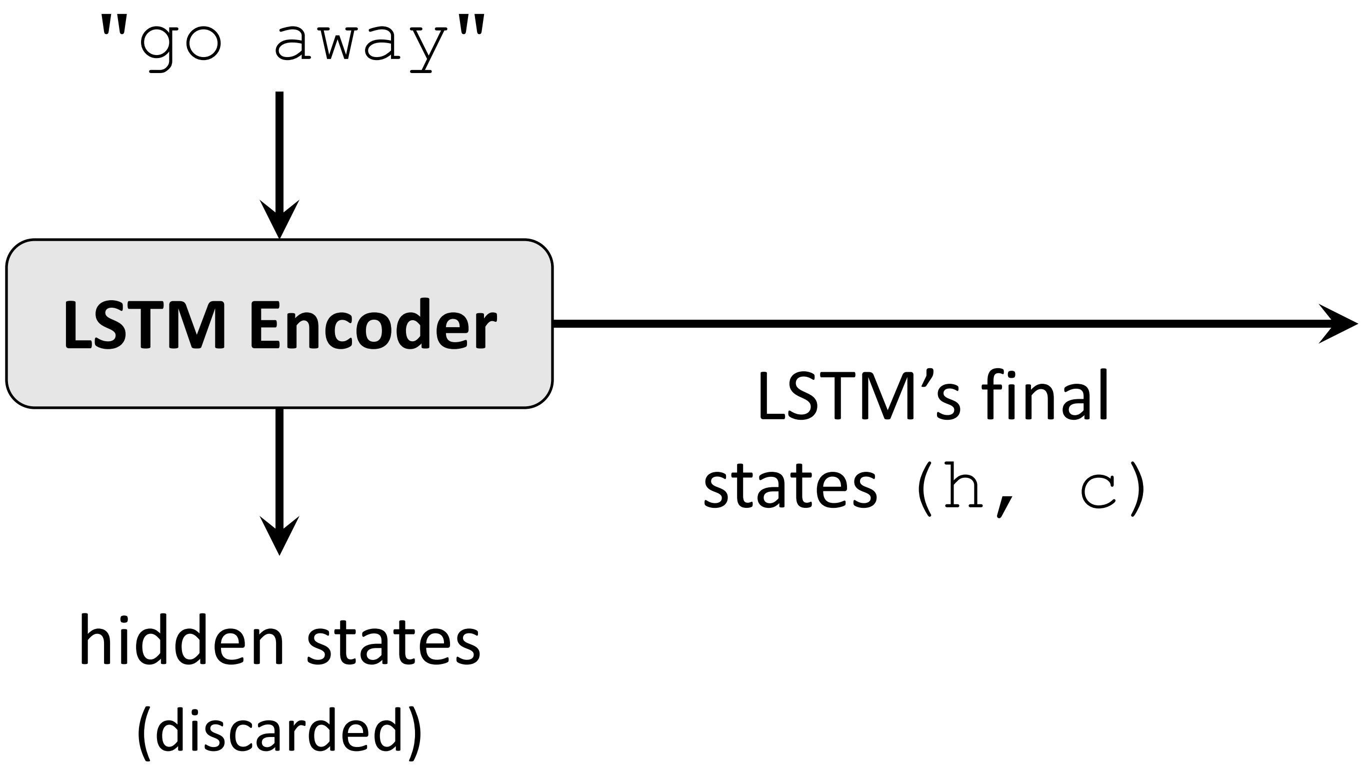
4. Embedding (One-Hot Encoding)

```
['i', '_', 'a', 'm', '_', 'o', 'k', 'a', 'y']
[ 9,   27,  1,   13,  27,  15,  11,  1,   25]
```

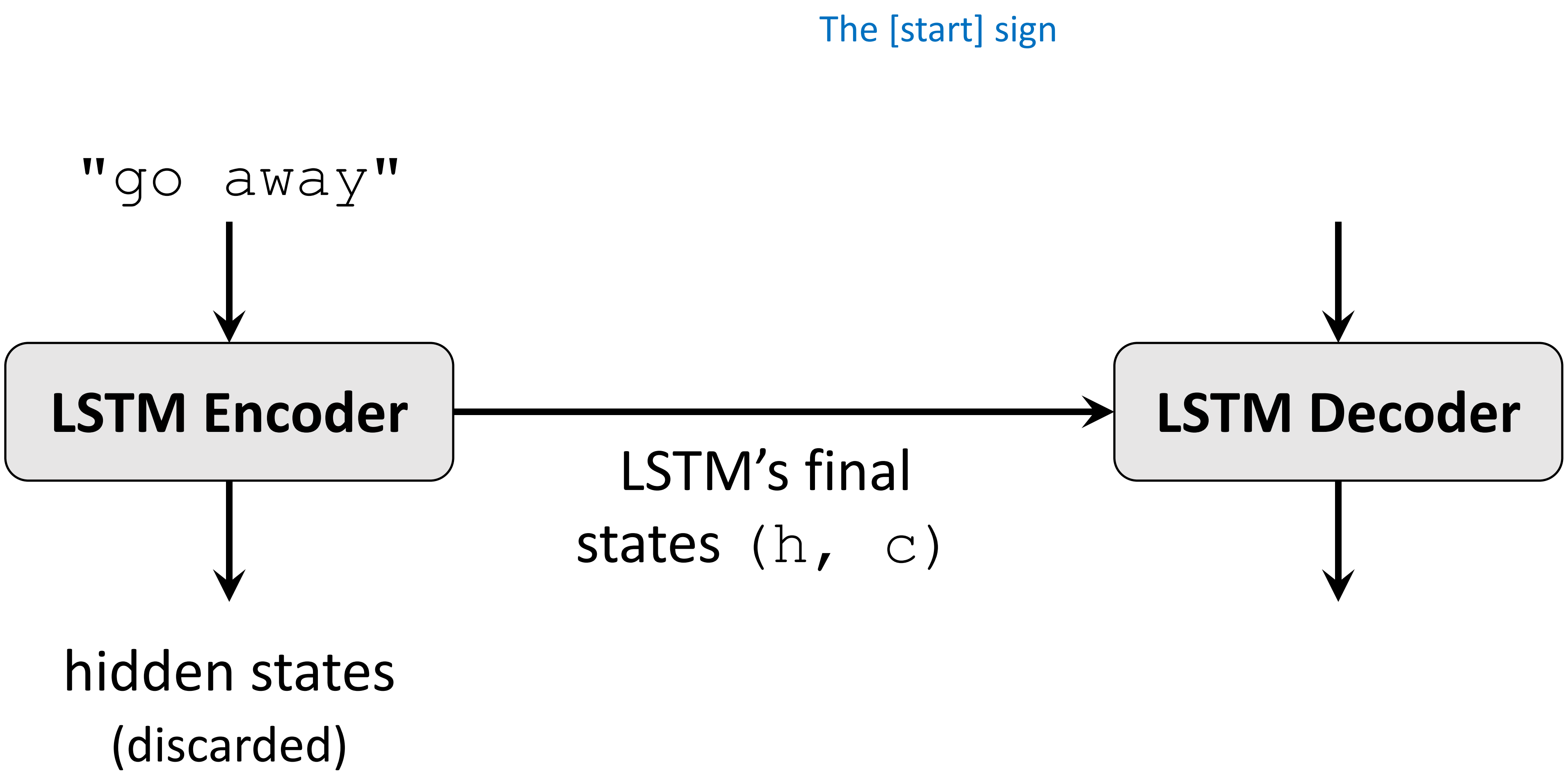


Seq2Seq Model

Training of the Seq2Seq Model



Training of the Seq2Seq Model



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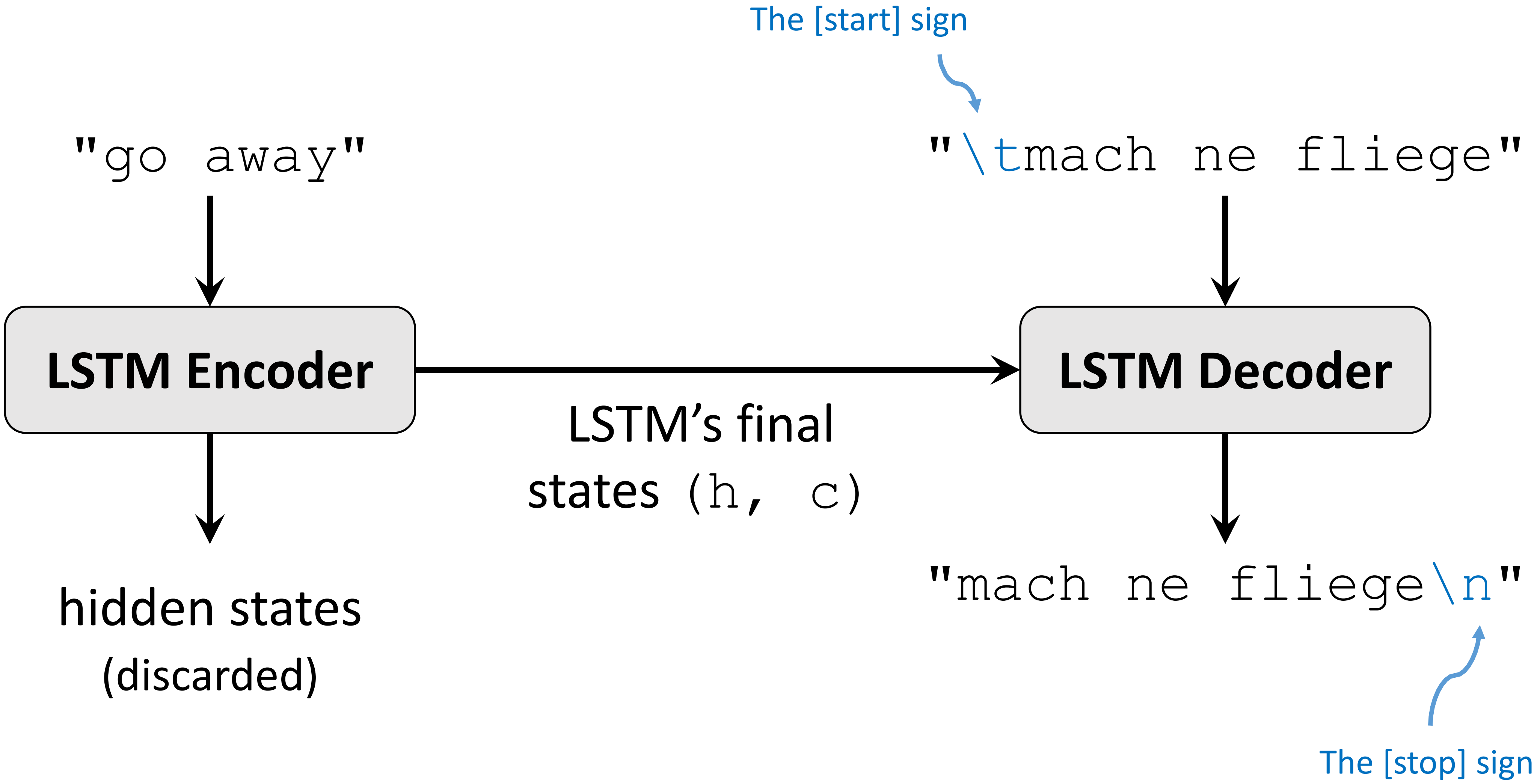

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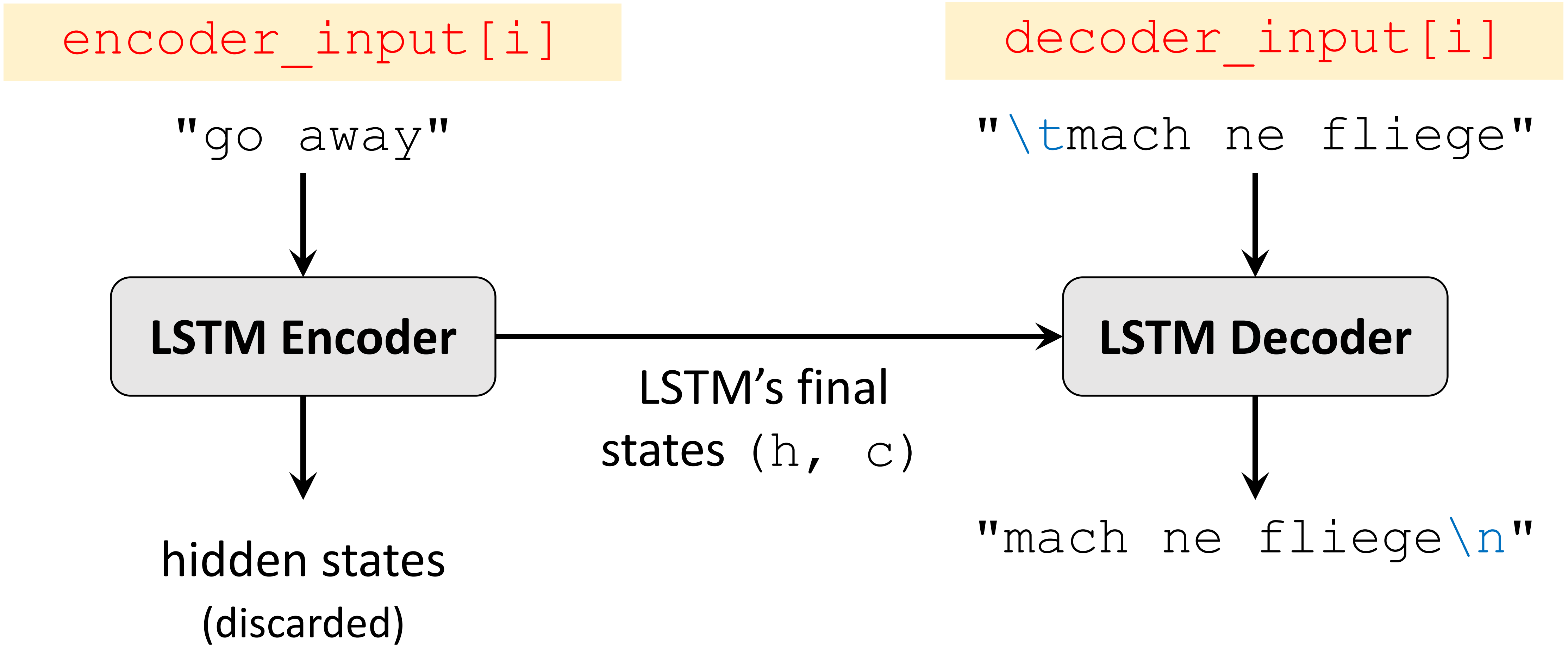

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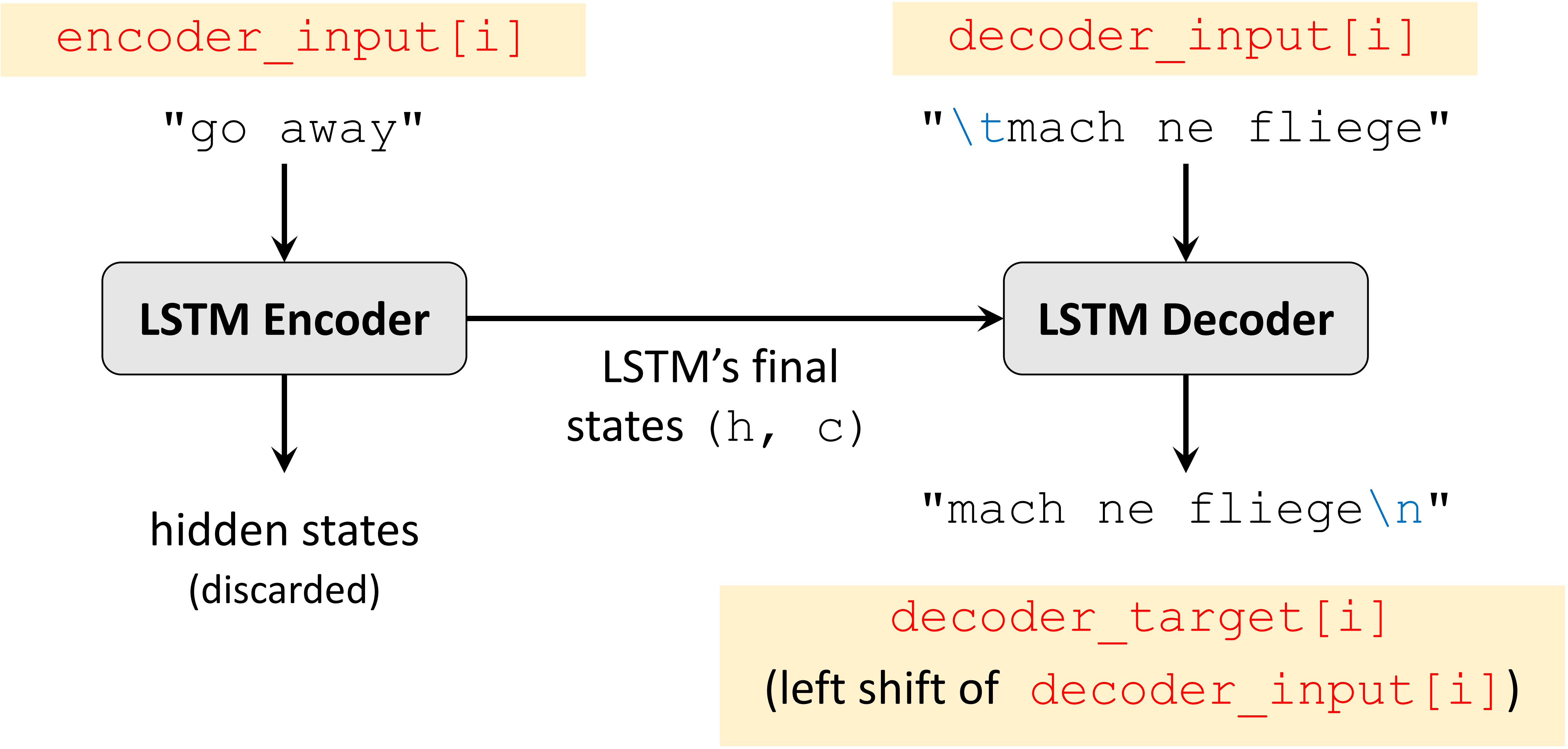
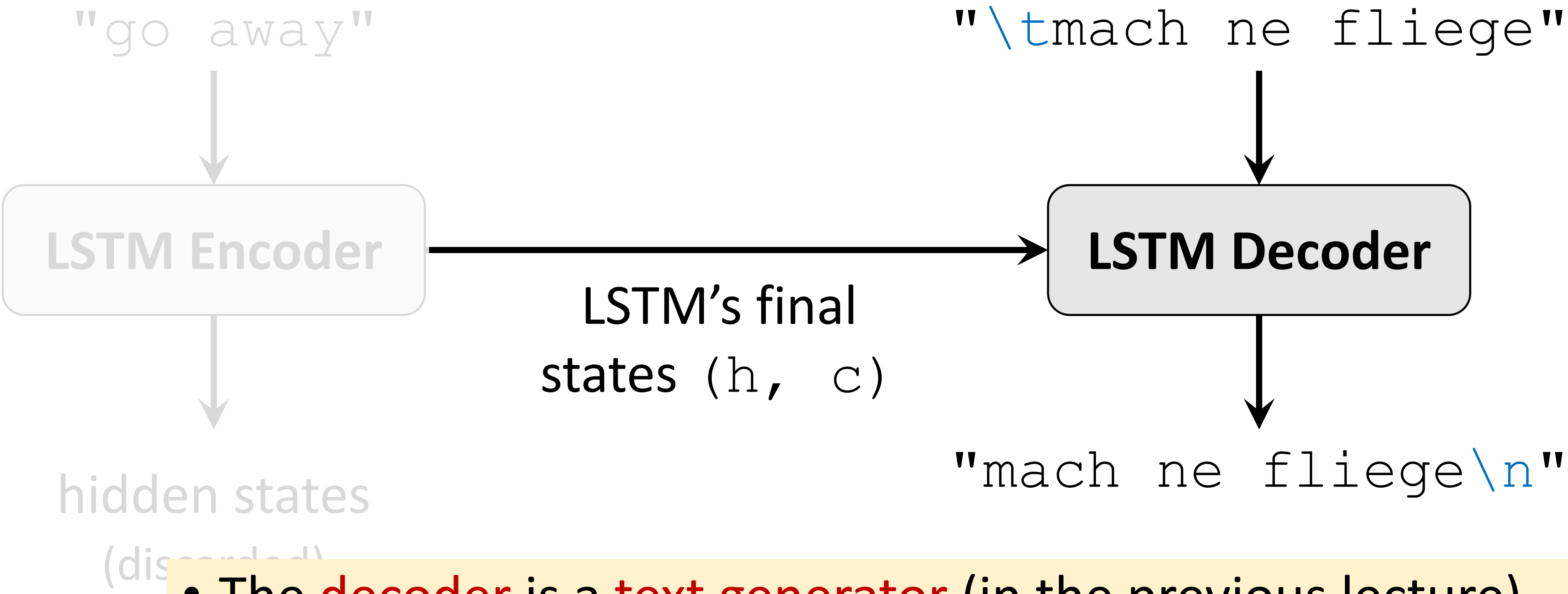
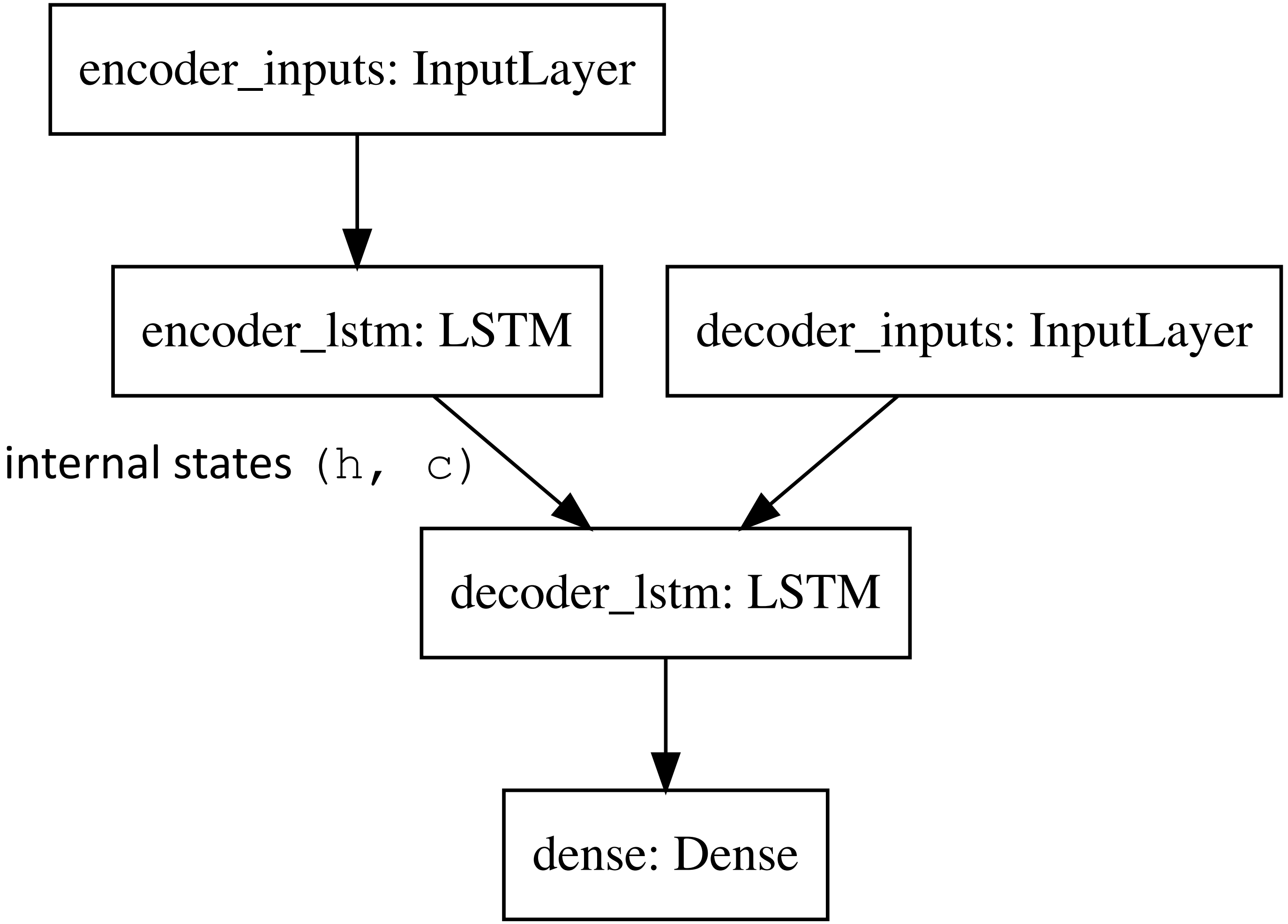


Training of the Seq2Seq Model



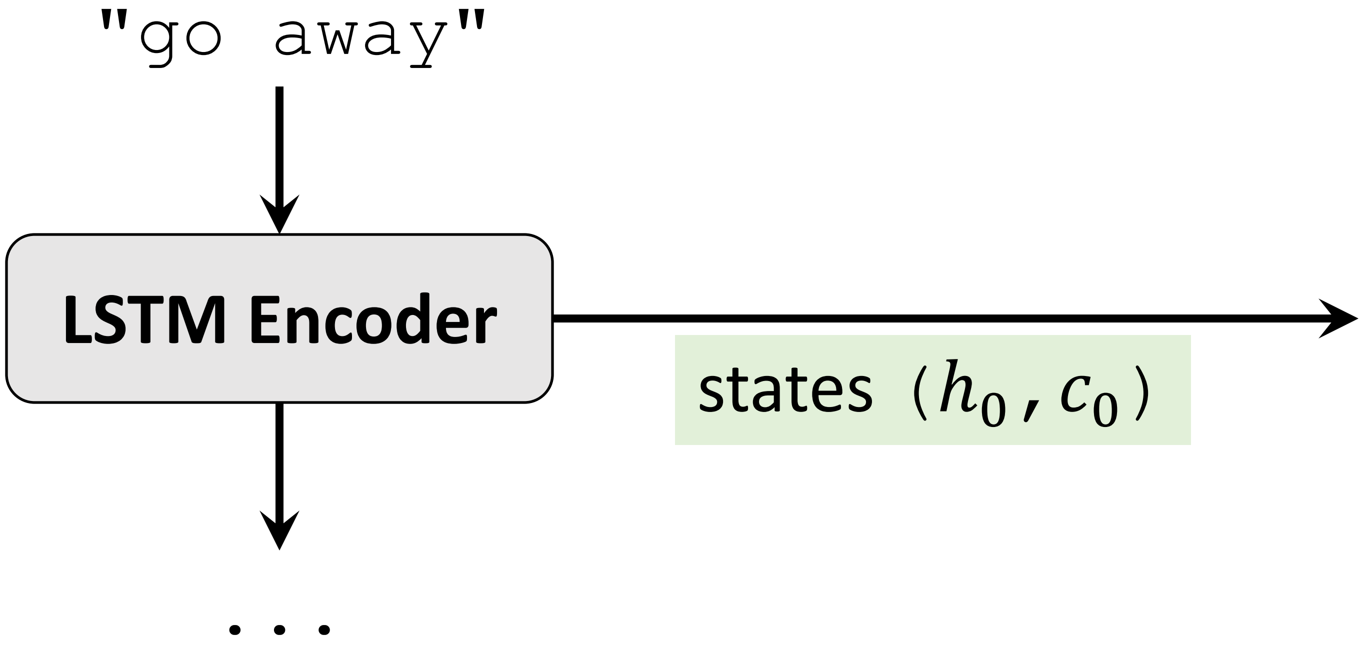
- The decoder is a text generator (in the previous lecture).
- Difference from the simple text generator: the initial states are determined by the encoder.

Seq2Seq Model in Keras

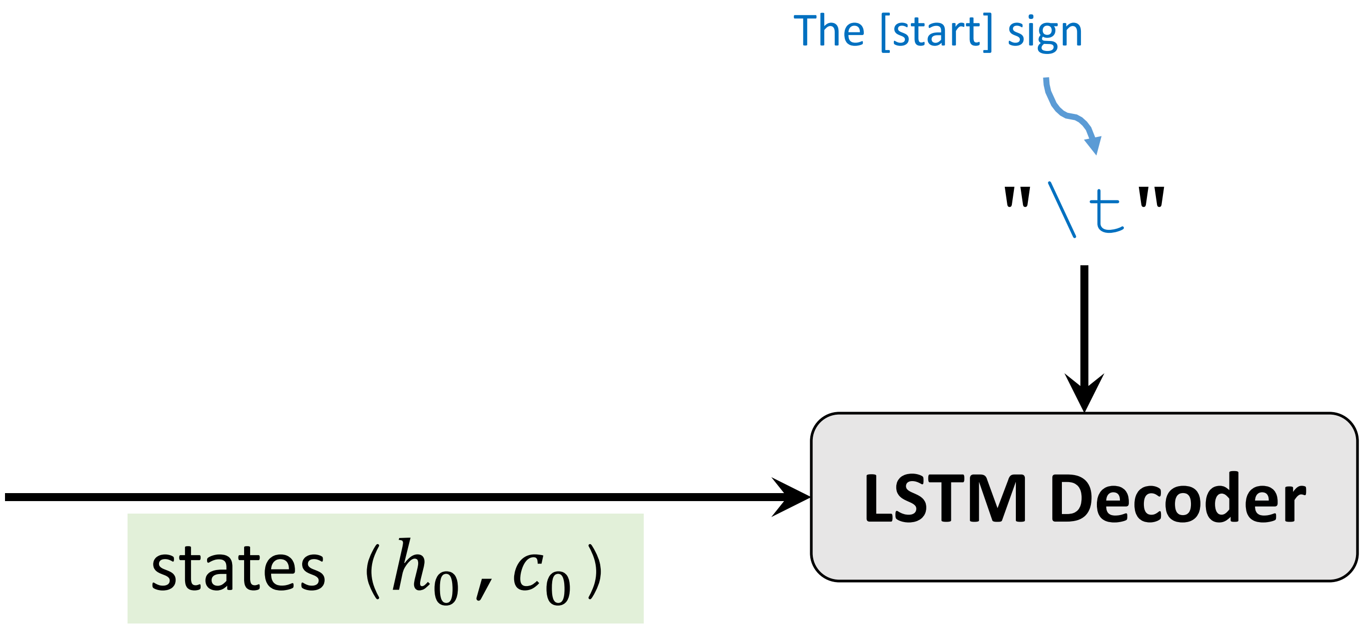


Inference Using the Seq2Seq Model

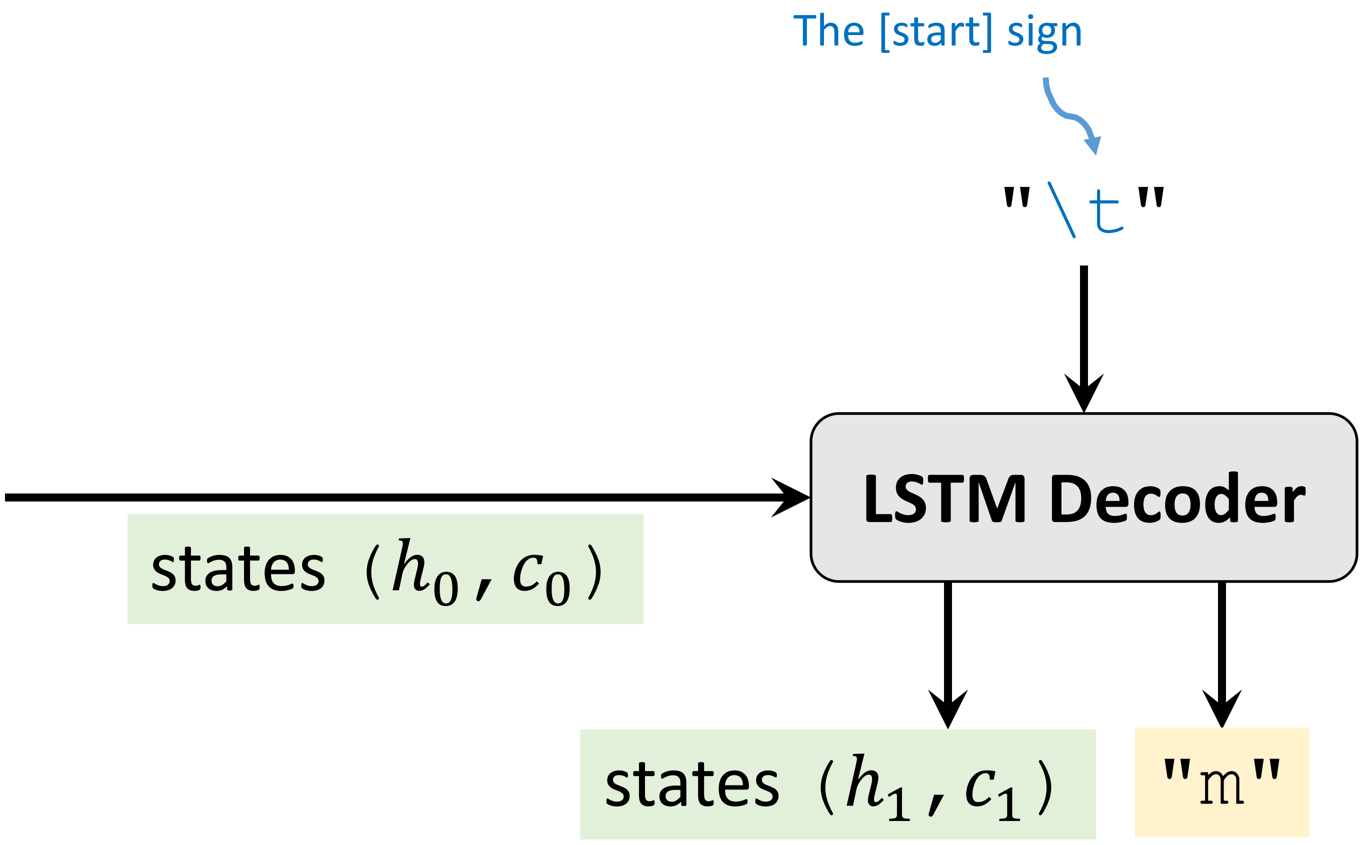
Inference



Inference

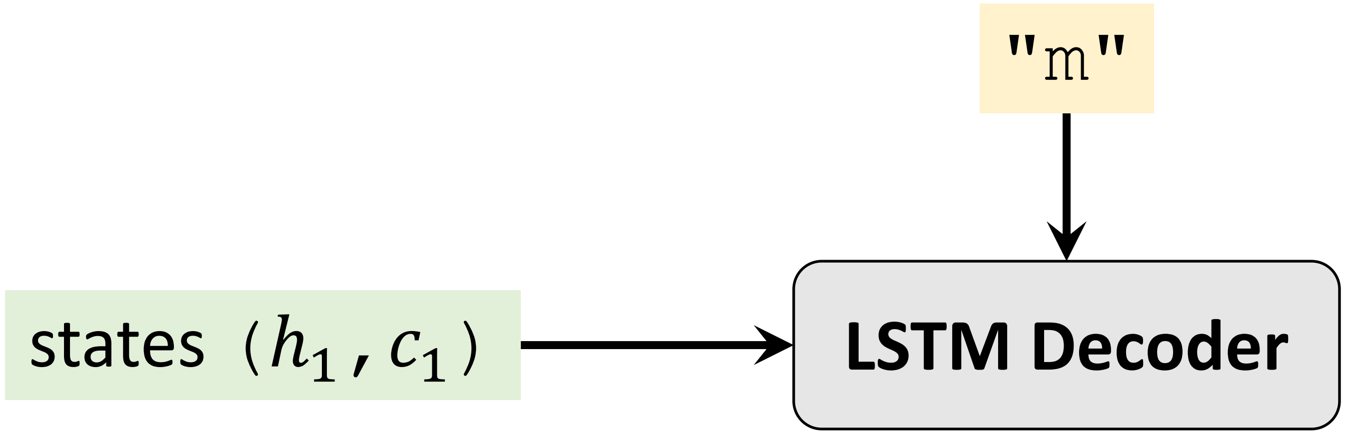


Inference



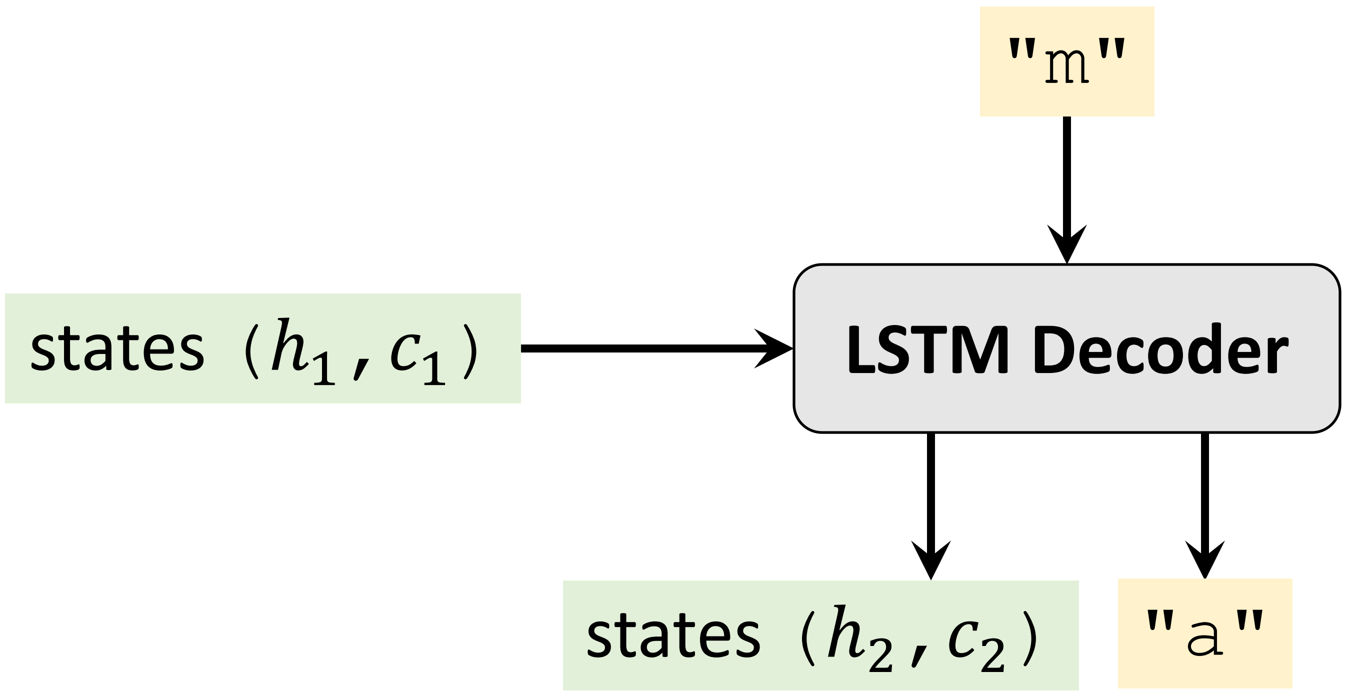
Record: "m"

Inference



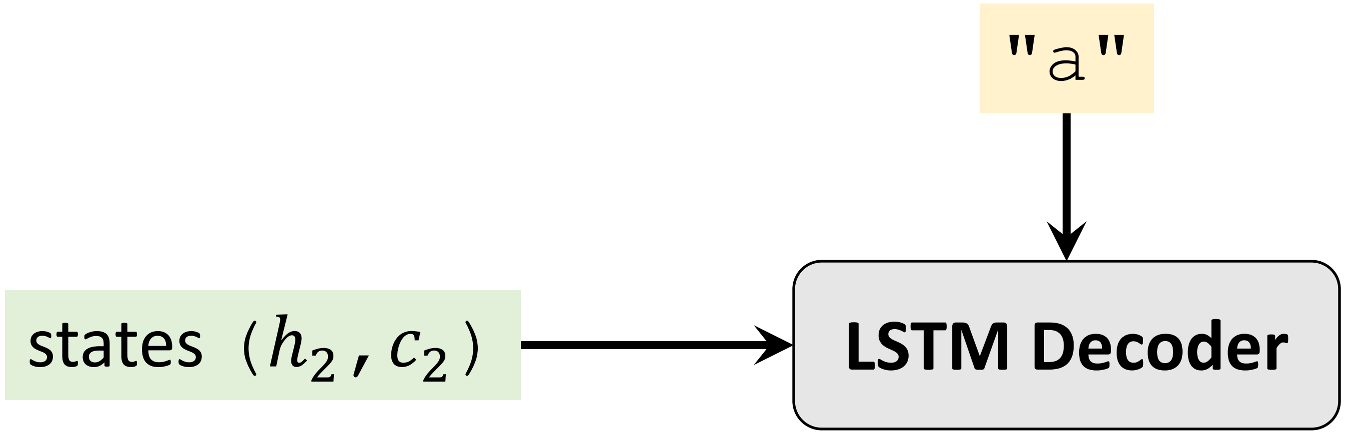
Record: "m"

Inference



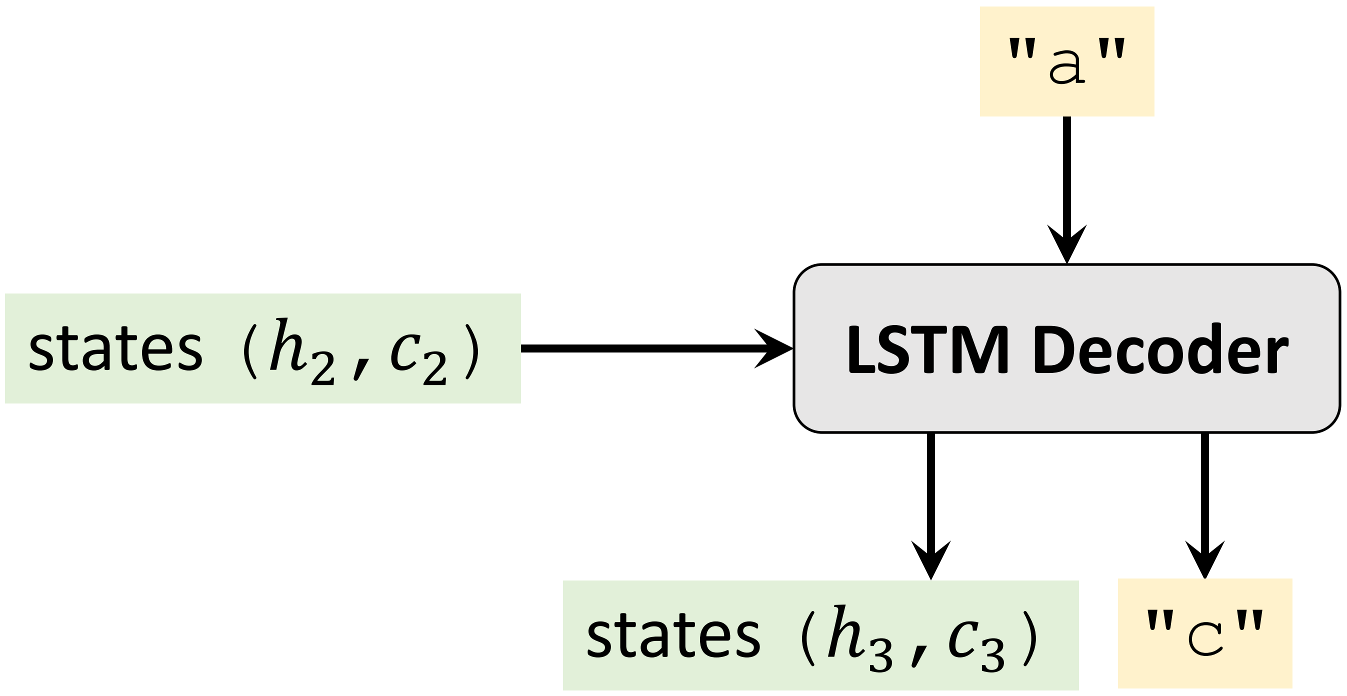
Record: `"ma"`

Inference



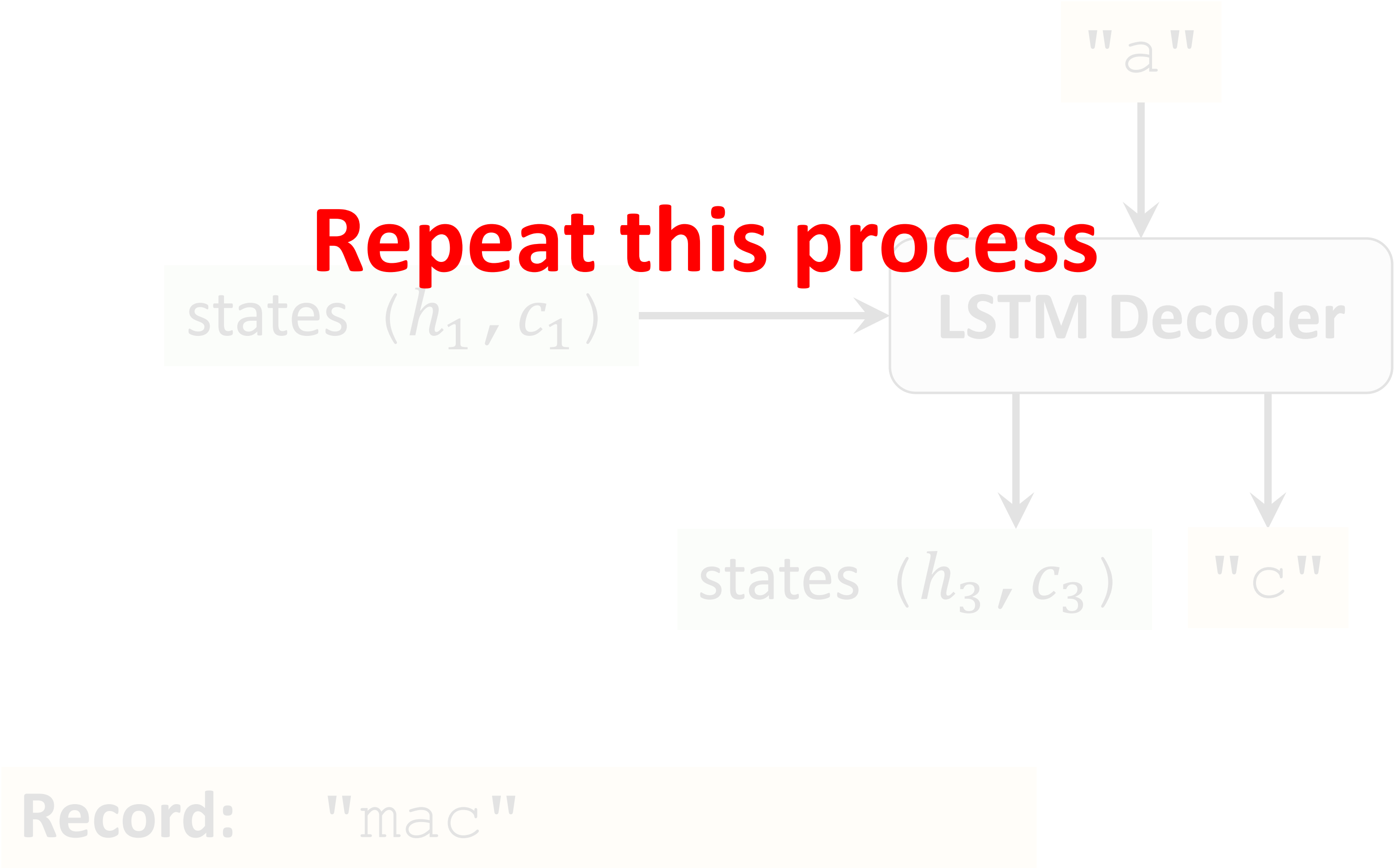
Record: "ma"

Inference



Record: "mac"

Inference



Repeat this process

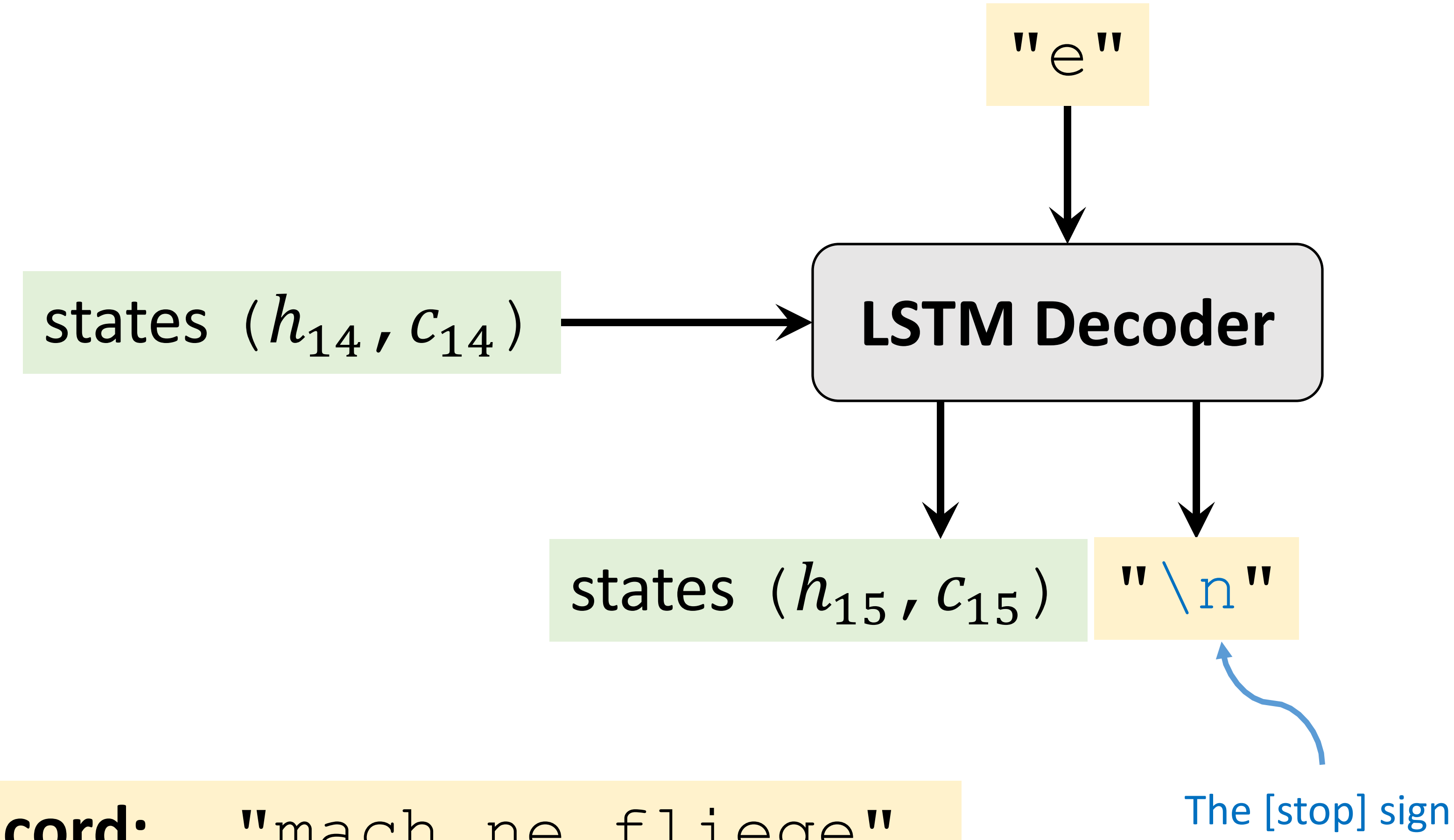
Inference

"e"

states (h_{14}, c_{14}) → **LSTM Decoder**

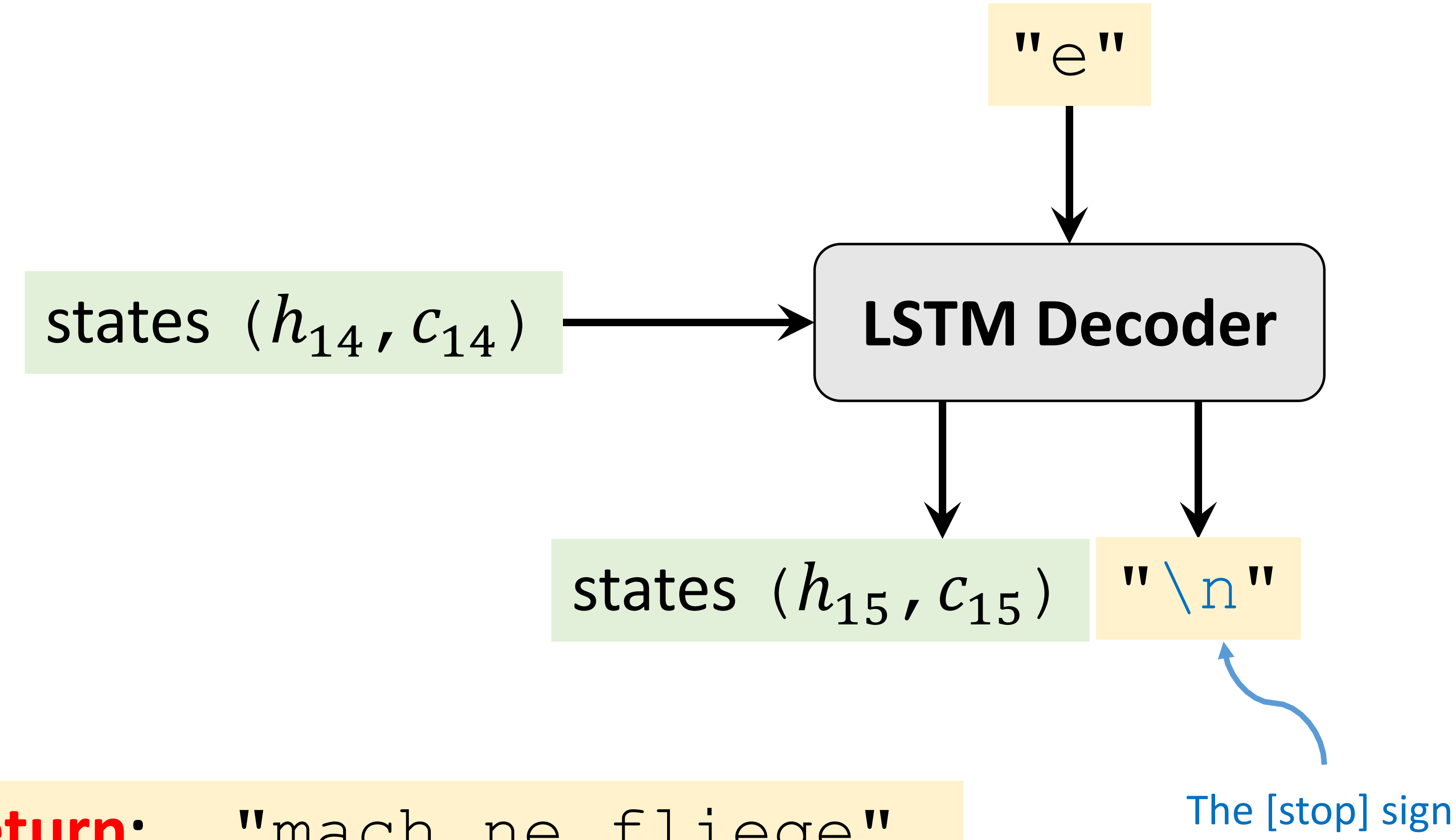
Record: "mach ne fliege"

Inference



Record: "mach ne fliege"

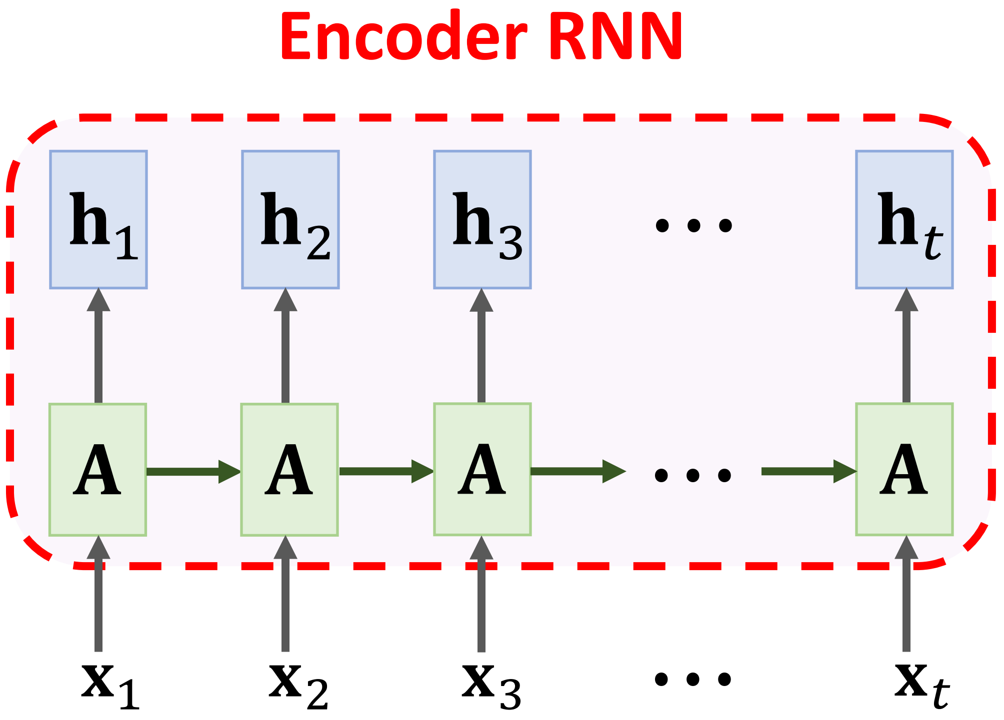
Inference



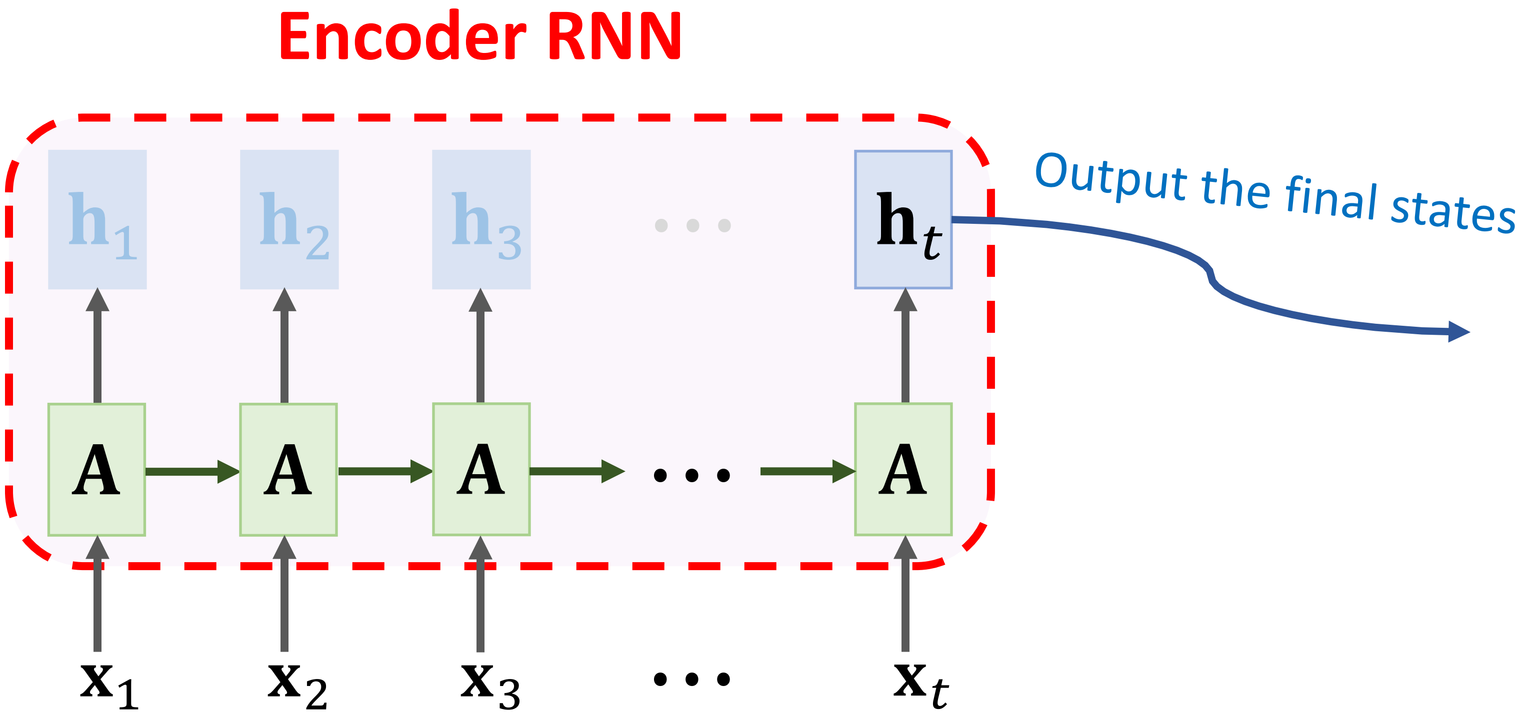
Return: `"mach ne fliege"`

Summary

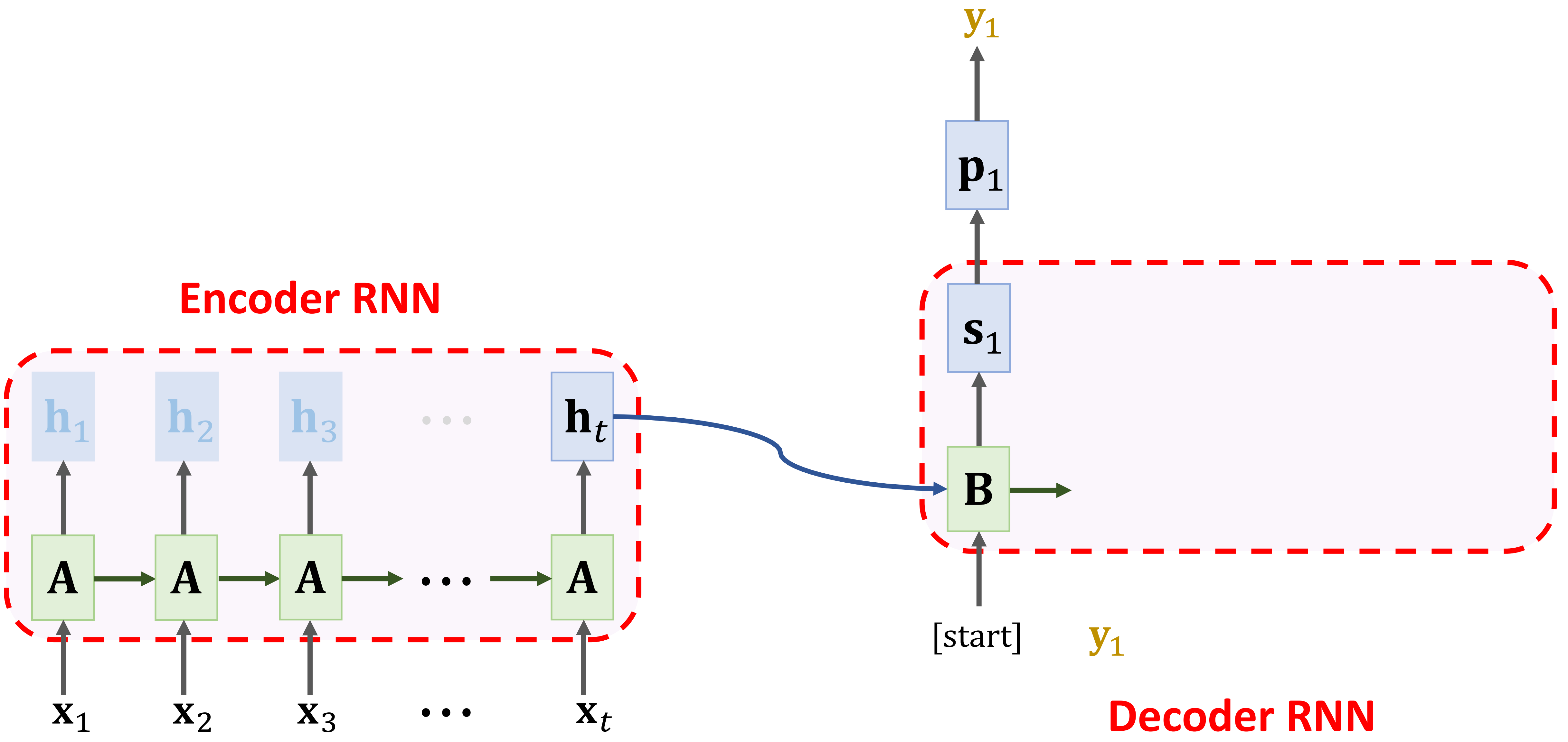
Seq2Seq Model



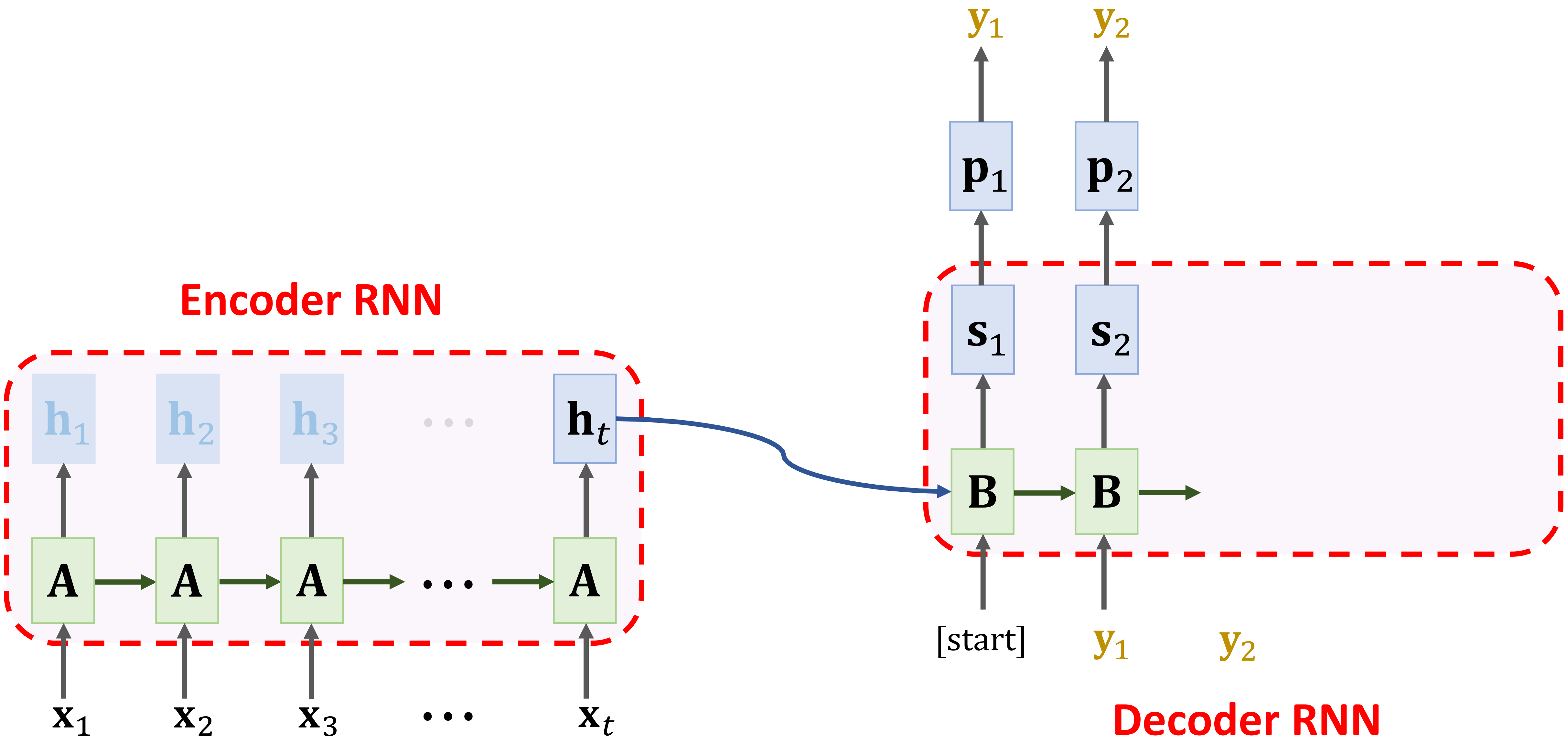
Seq2Seq Model



Seq2Seq Model



Seq2Seq Model



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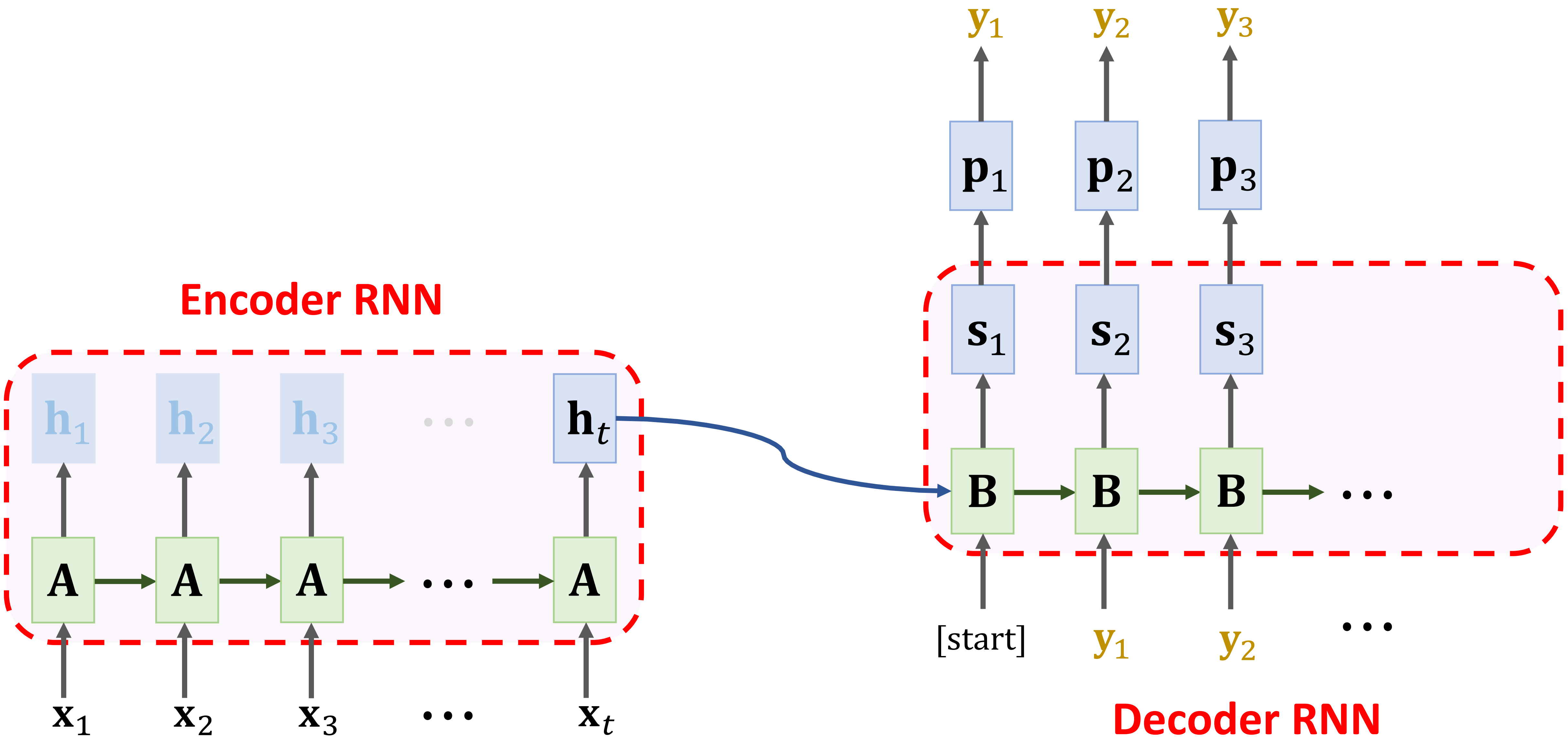

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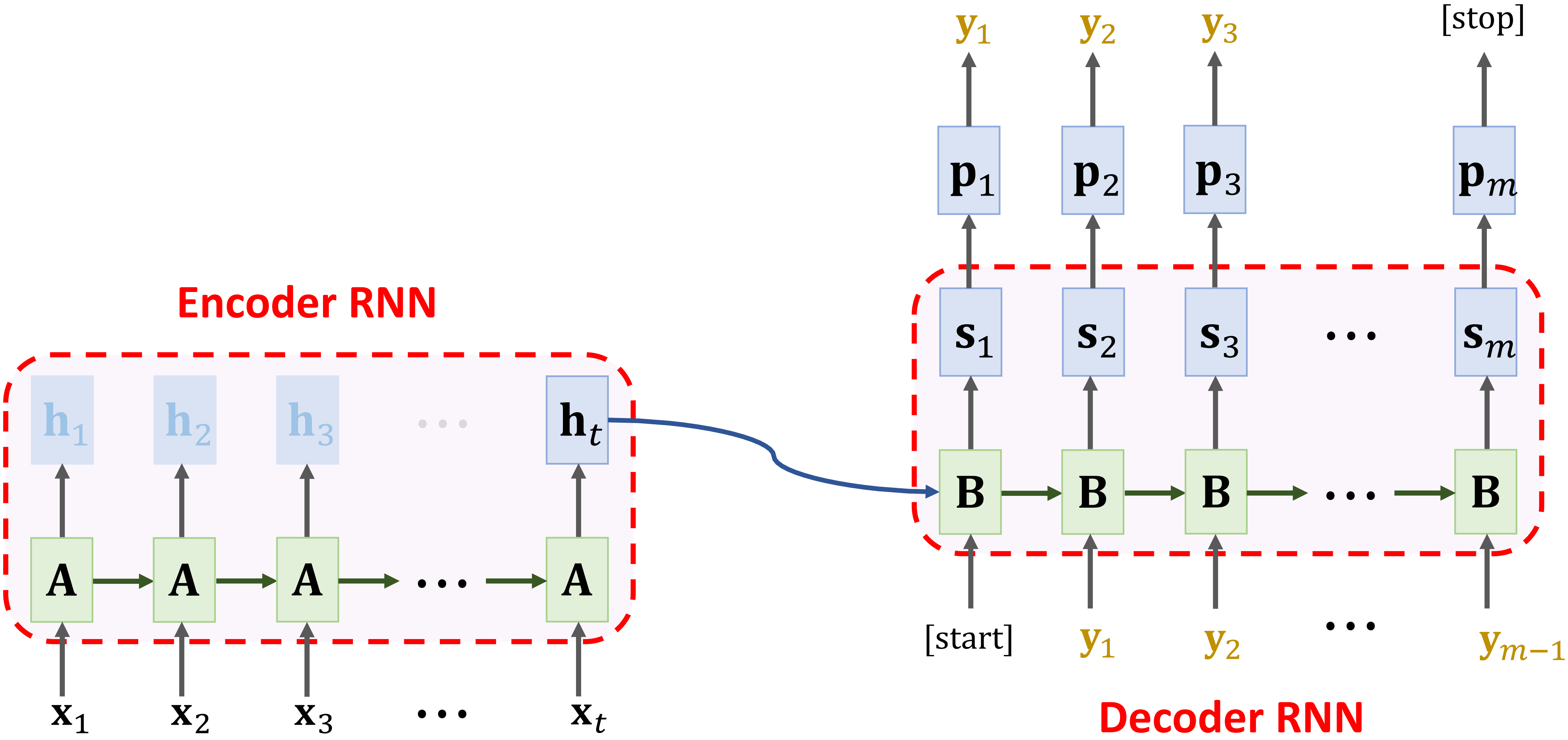
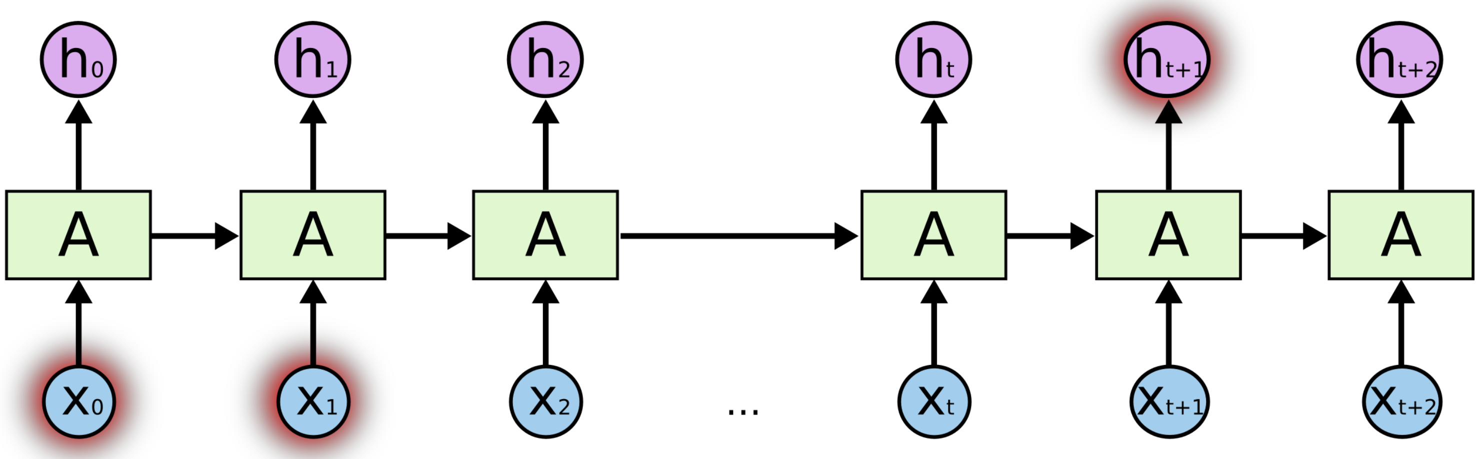


How to Improve?

1. Bi-LSTM instead of LSTM

- The final states ($\mathbf{h}_t$ and $\mathbf{c}_t$) of the Encoder have all the information of the English sentence.
- Really?
  - If the sentence is long (hundreds of tokens), the final states have forgotten the first tokens.



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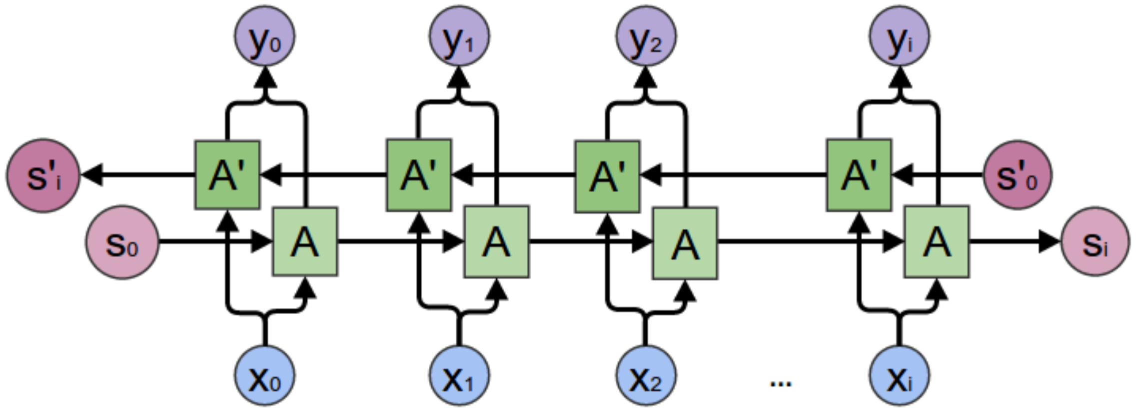
- The final states ($\mathbf{h}_t$ and $\mathbf{c}_t$) of the Encoder have all the information of the English sentence.
- Really?
  - If the sentence is long (hundreds of tokens), the final states have forgotten the first tokens.
- Bi-LSTM (left-to-right and right-to-left) remembers the first tokens.



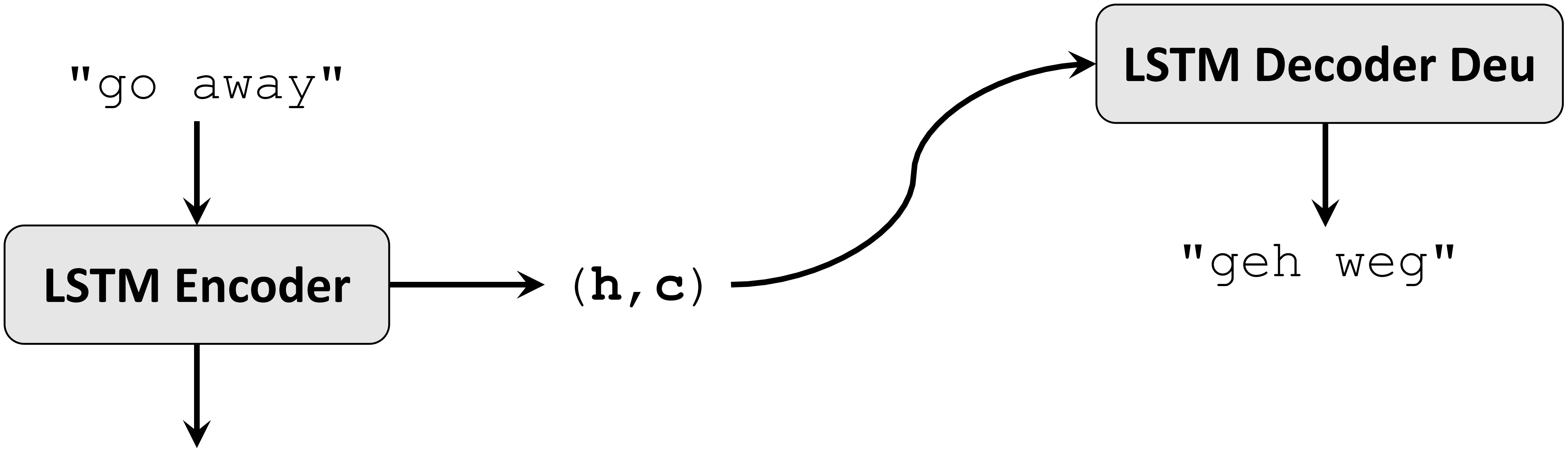
2. Word-Level Tokenization

- 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.

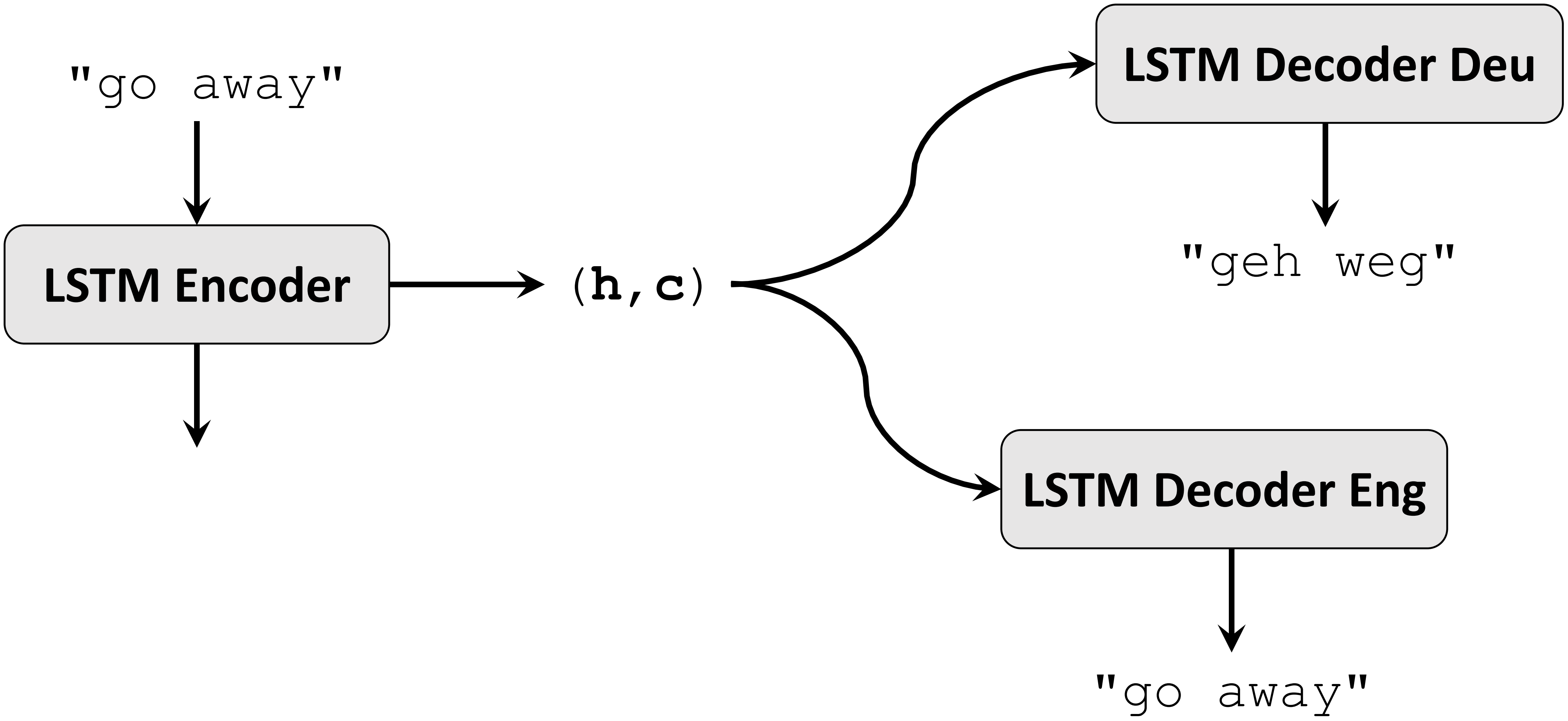
2. Word-Level Tokenization

- Word-level tokenization instead of char-level.
  - The average length of English words is 4.5 letters.
  - The sequences will be 4.5x shorter.
  - Shorter sequence, less likely to forget.
- But you will need a large dataset!
  - # of (frequently used) chars is $\sim 10^2$.
  - # of (frequently used) words is $\sim 10^4$.
  - Word Embedding Layer has many parameters ➔ overfitting!

3. Multi-Task Learning



3. Multi-Task Learning



3. Multi-Task Learning

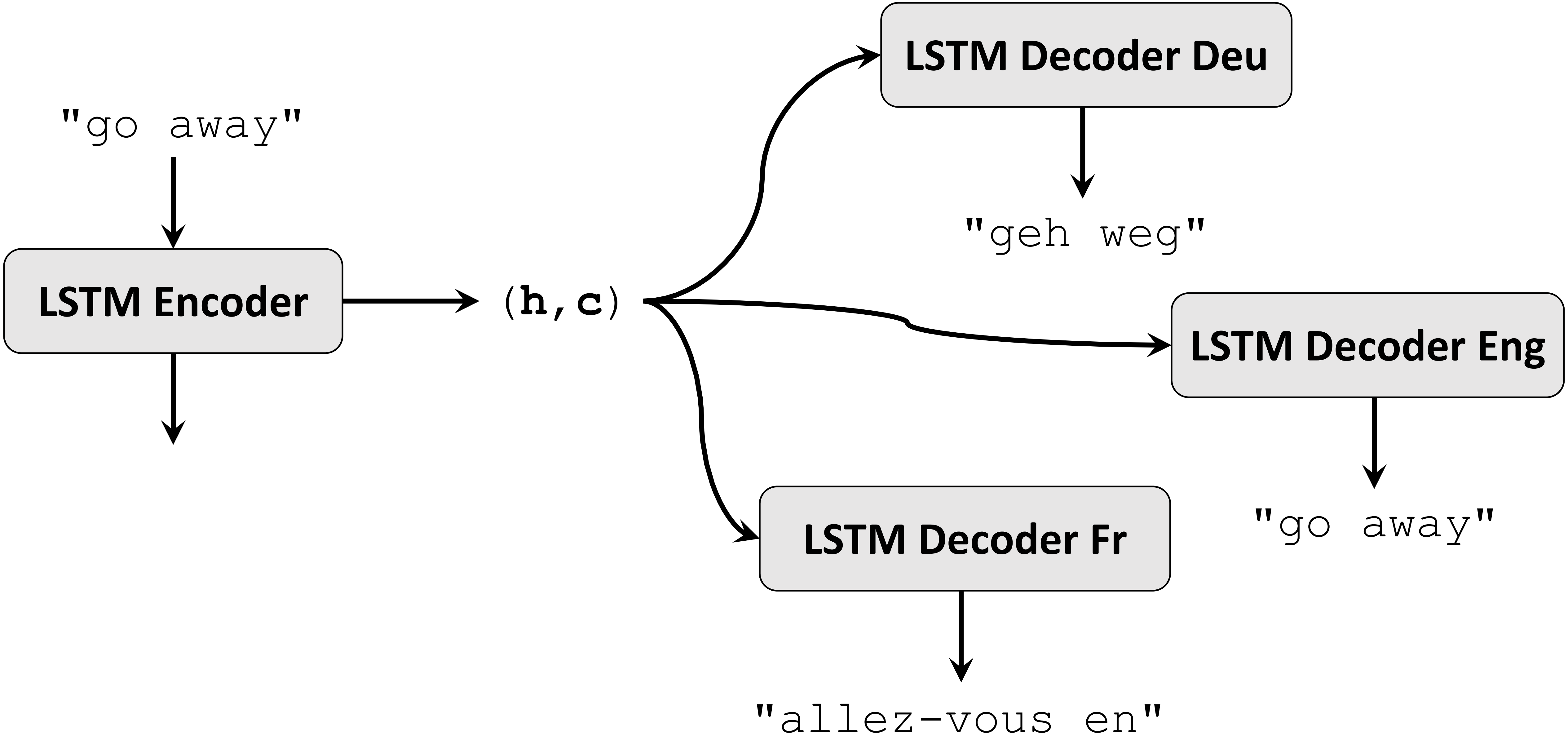
- Even if you want to translate English to German, you can use all the datasets:

- 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.
2. Tokenization in the word-level (rather than char-level.)
3. Multi-task learning.
4. Attention! (Future lectures, soon.)

Homework 4

- Build a seq2seq model for machine translation.
  - Anything languages except for [English ==> German].
  - Follow my IPython Notebook.
- Make as least one improvement over my naïve model.
  - E.g., Bi-LSTM, multi-task, attention, etc.
- Evaluate your model using BLEU score. (Optional.)
  - BLEU (BiLingual Evaluation Understudy).
  - Reference:
    - Wikipedia: https://en.wikipedia.org/wiki/BLEU
    - Blog: https://machinelearningmastery.com/calculate-bleu-score-for-text-python/