Neural Machine Translation

Shusen Wang

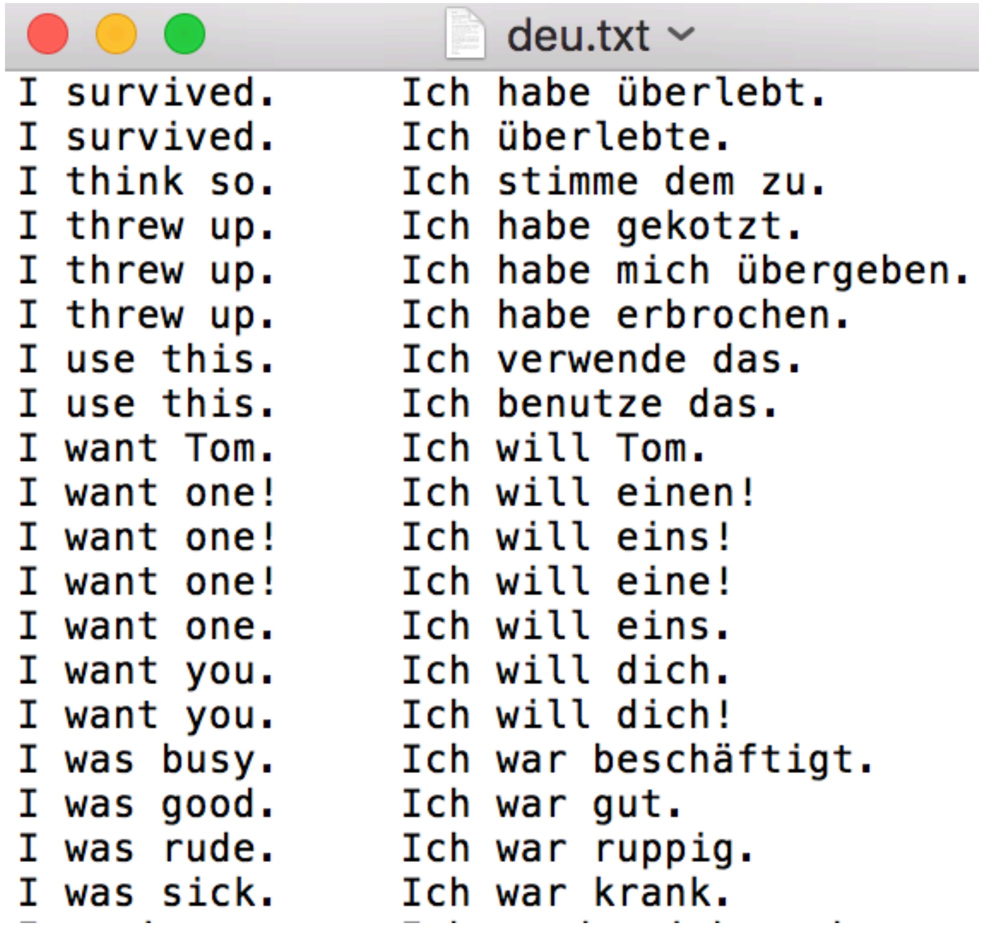
Sequence-to-Sequence Model (Seq2Seq)

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/


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.

1. Processing the Data

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

deu.txt

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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`

Tokenization in the char-level.

Tokenization in the word-level.

2. Tokenization

- `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']`

2. Tokenization

Question: Why 2 different tokenizers?

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).

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

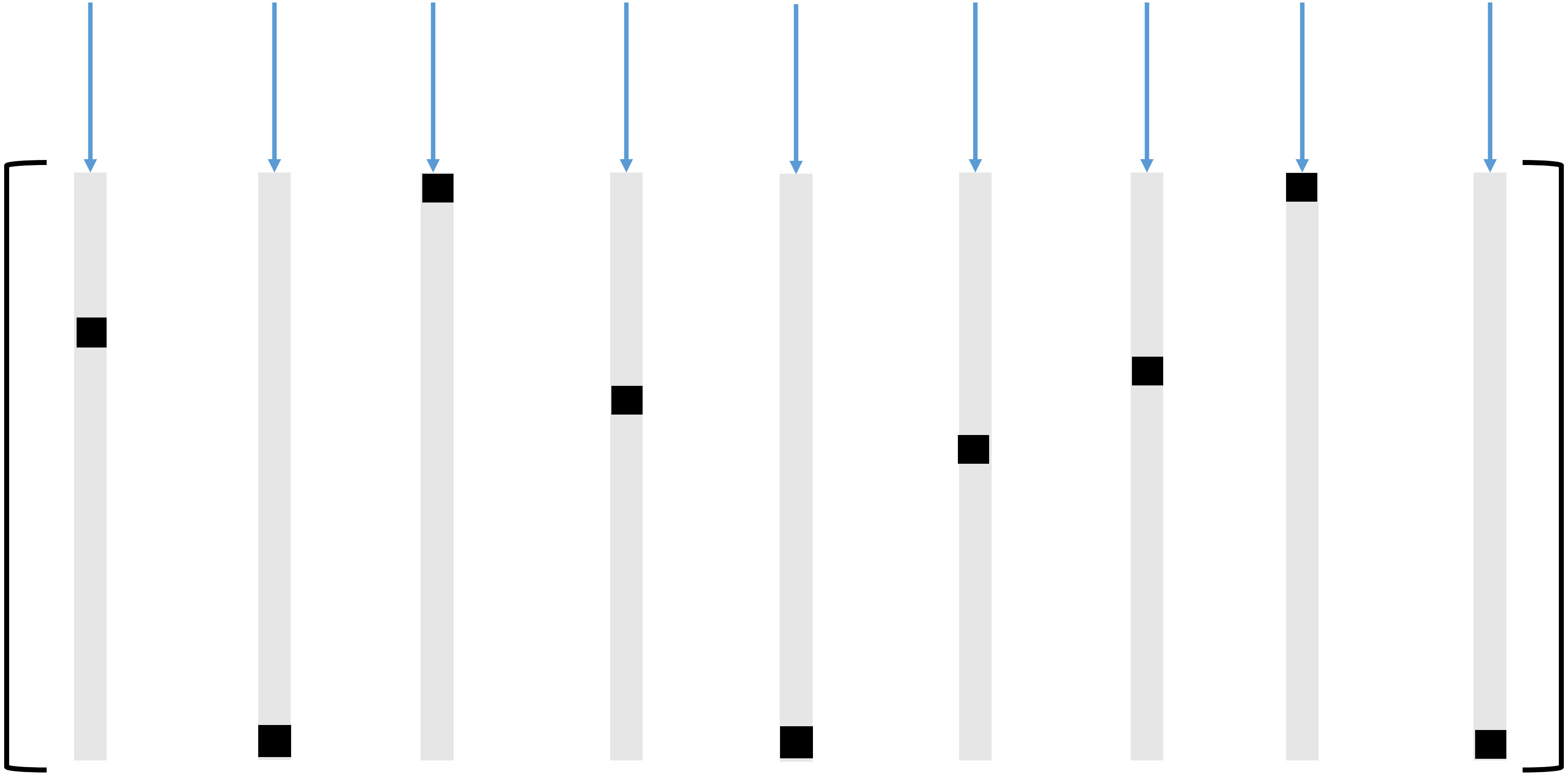
['e', 's', '_', 'g', 'e', ..., 'g', 'u', 't']

Encoding using Deu_Dictionary

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

4. One-Hot Encoding (Char to Vector)

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



4. One-Hot Encoding v.s. Embedding

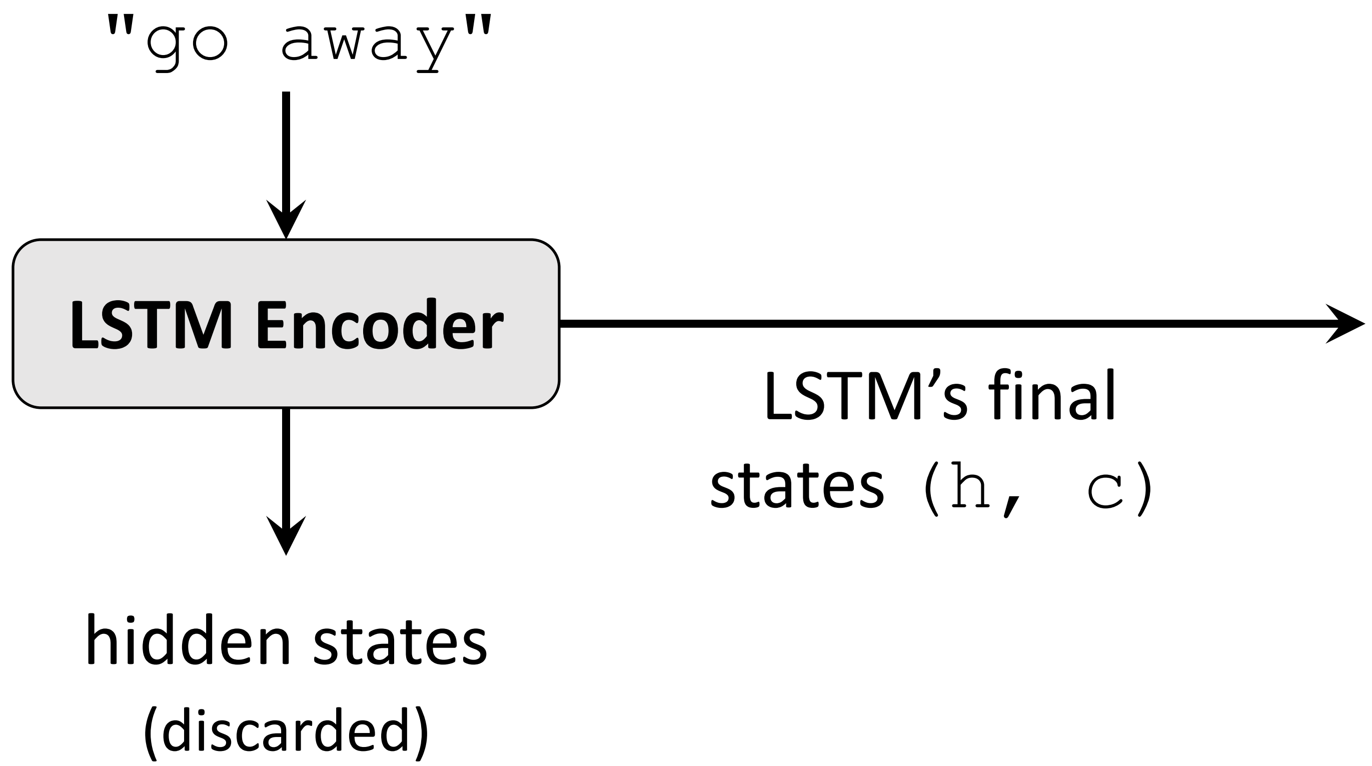
- There are around 100 frequent characters. (Vocabulary ≈ 100.)
- There are around $10K$ frequent English words. (Vocabulary $\approx 10K$.)

- One-hot converts a character to 100-dim vector.
- One-hot converts a word to $10K$-dim vector. (Too big.)

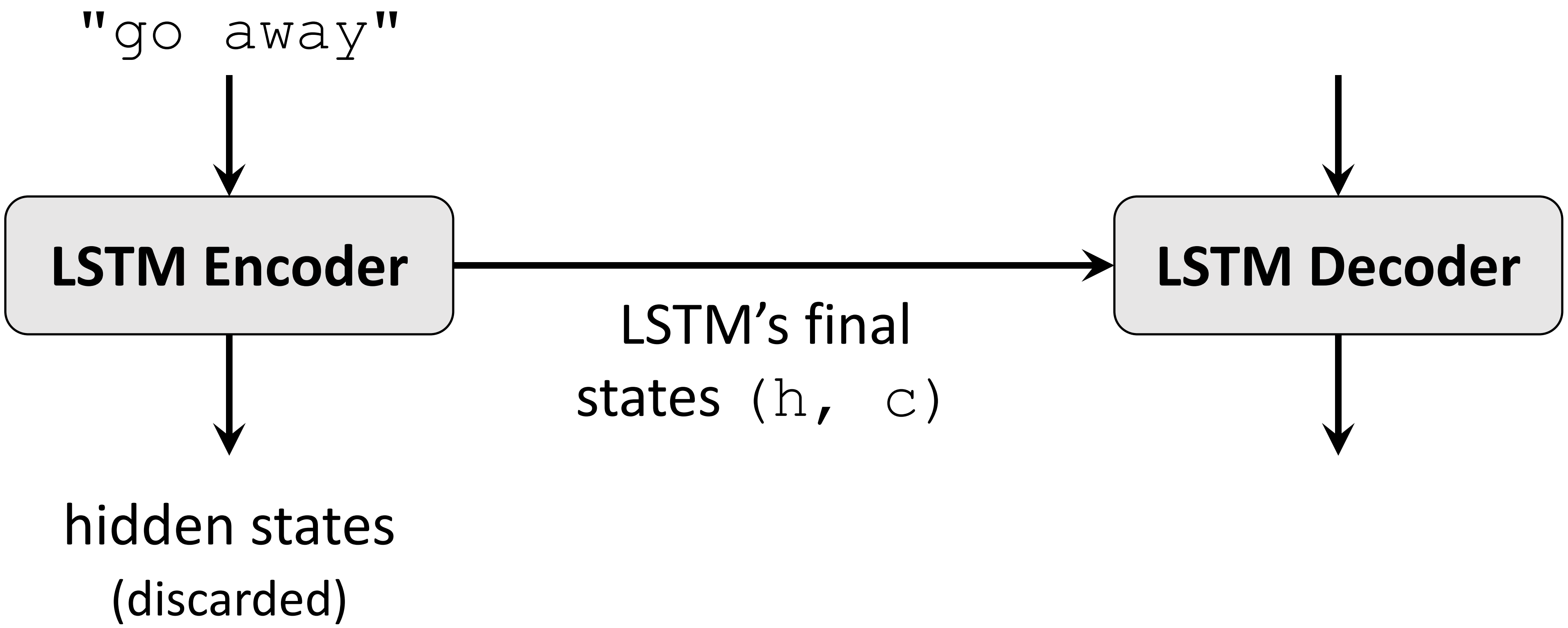
- Conclusion:
  - For char-level tokenization, use one-hot.
  - For word-level tokenization, use an embedding layer.

Seq2Seq Model: Training

Training of the Seq2Seq Model



Training of the Seq2Seq Model



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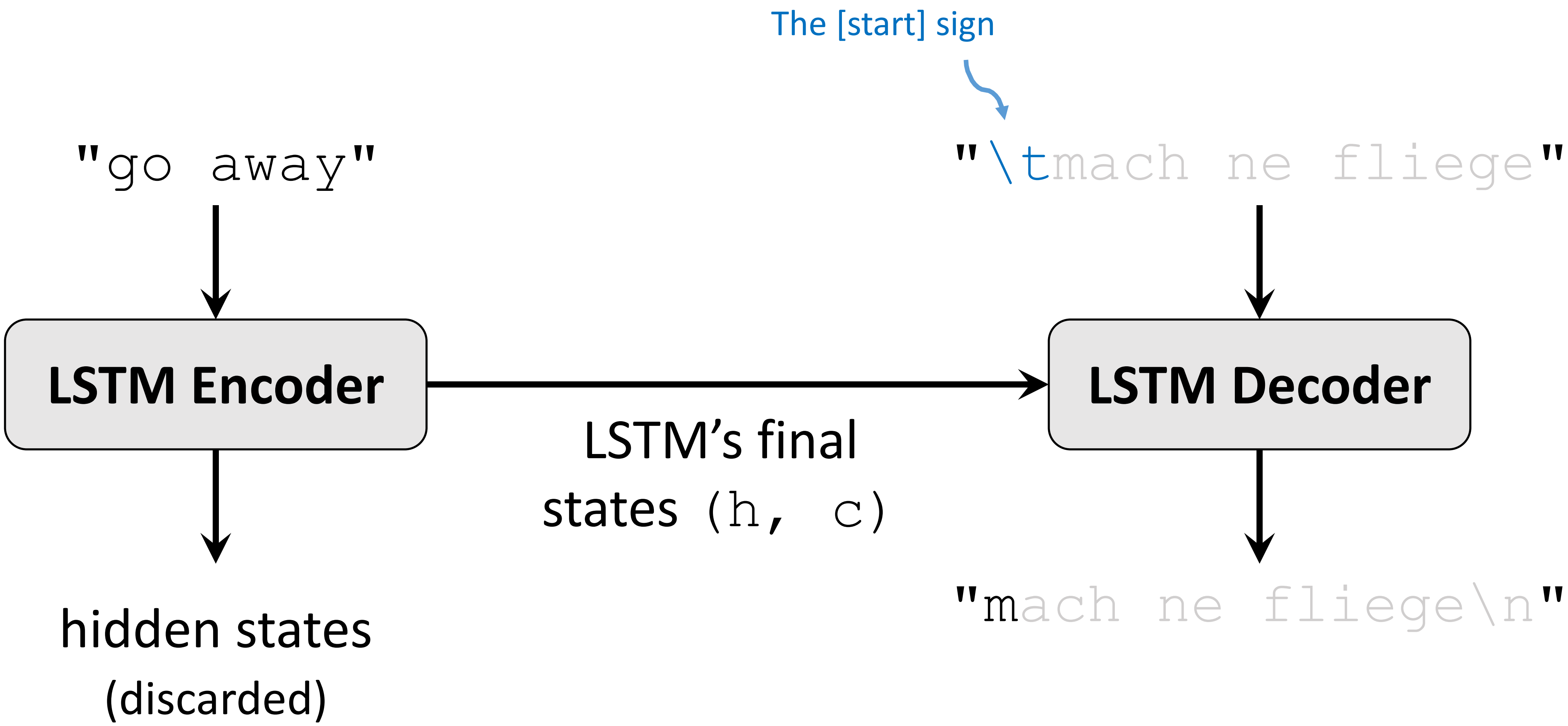

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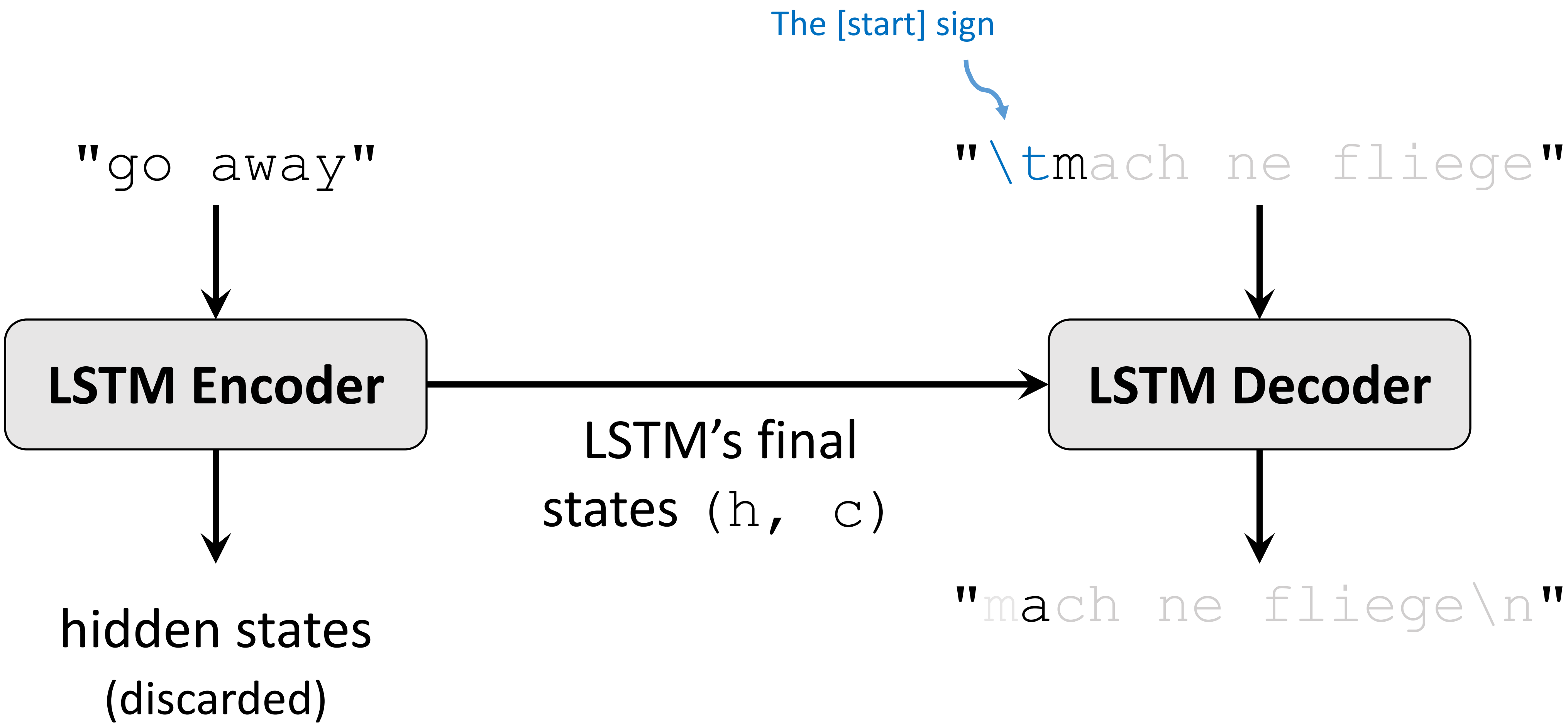

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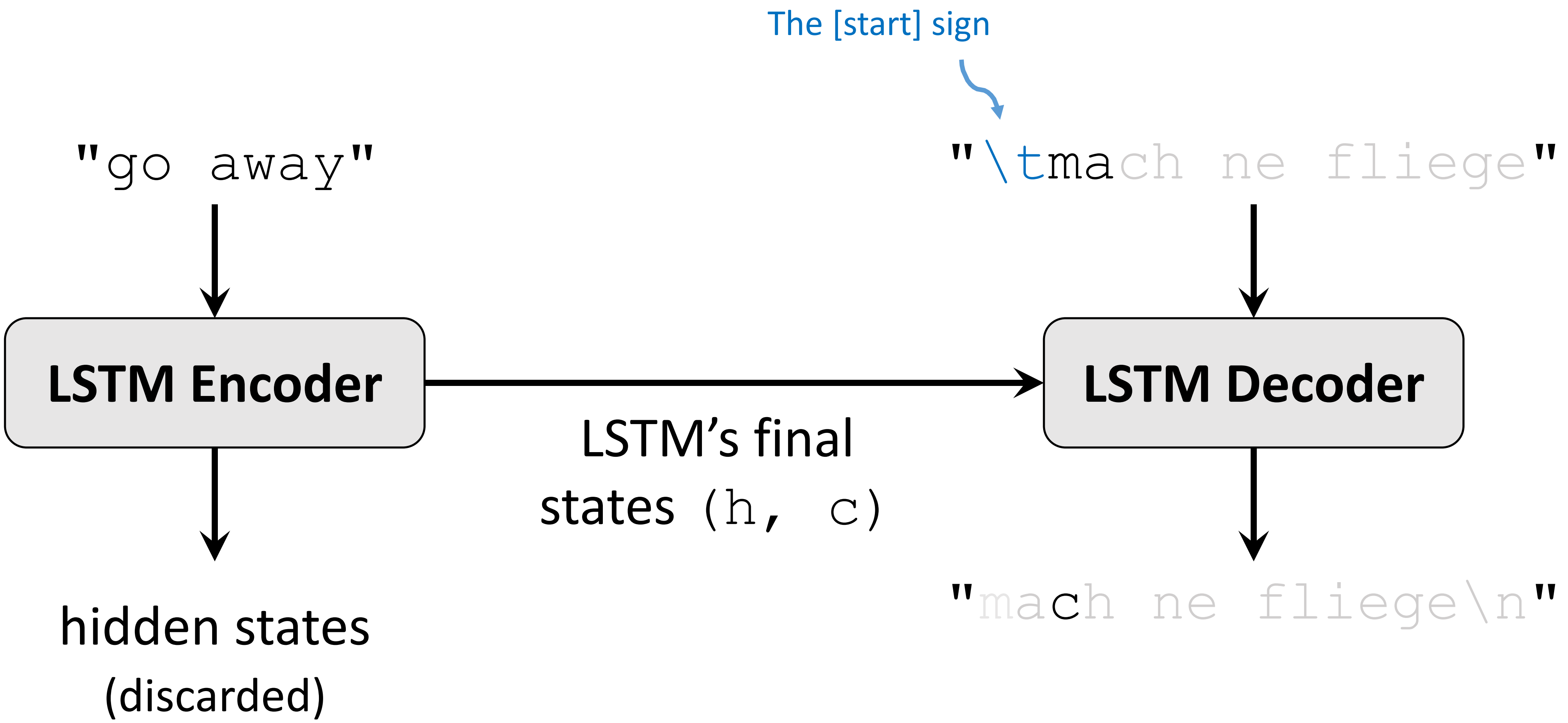
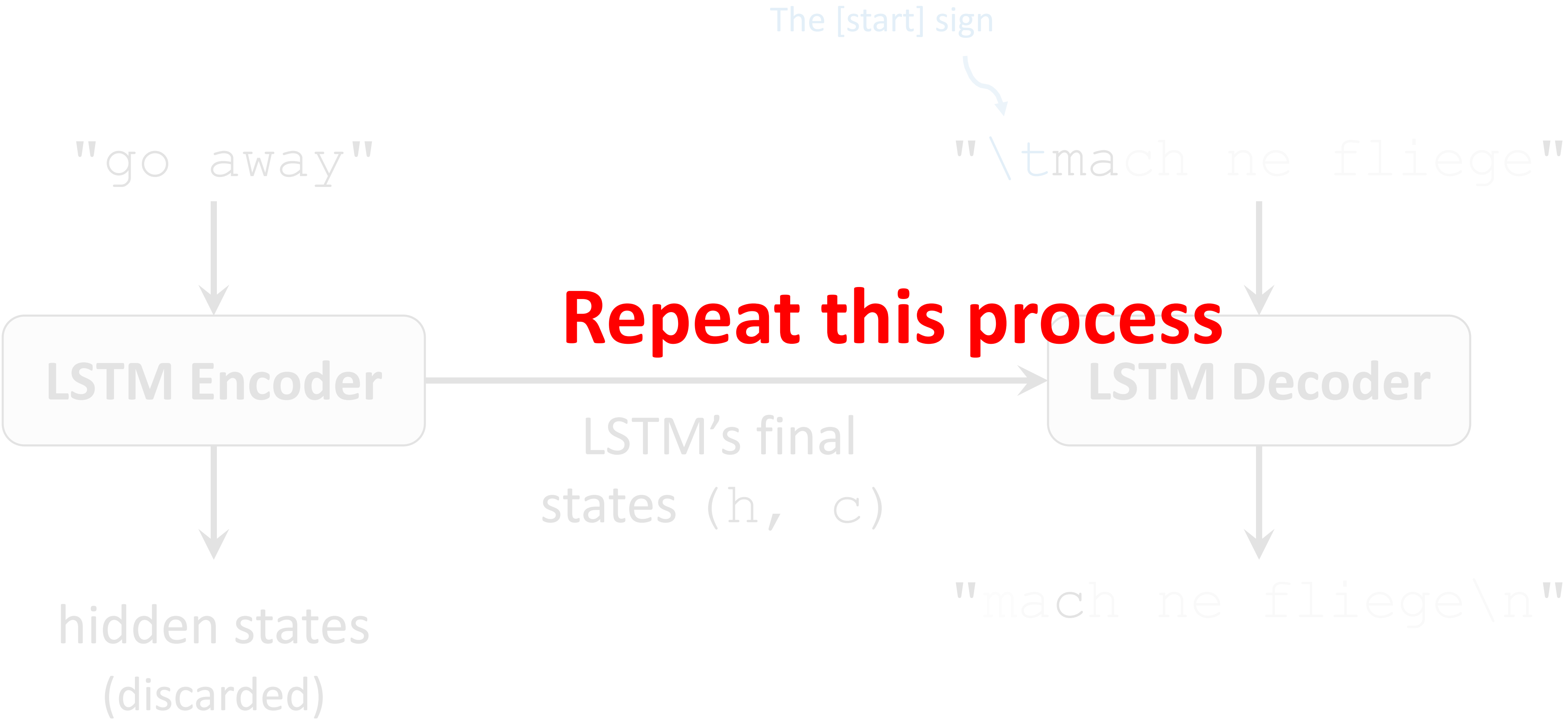
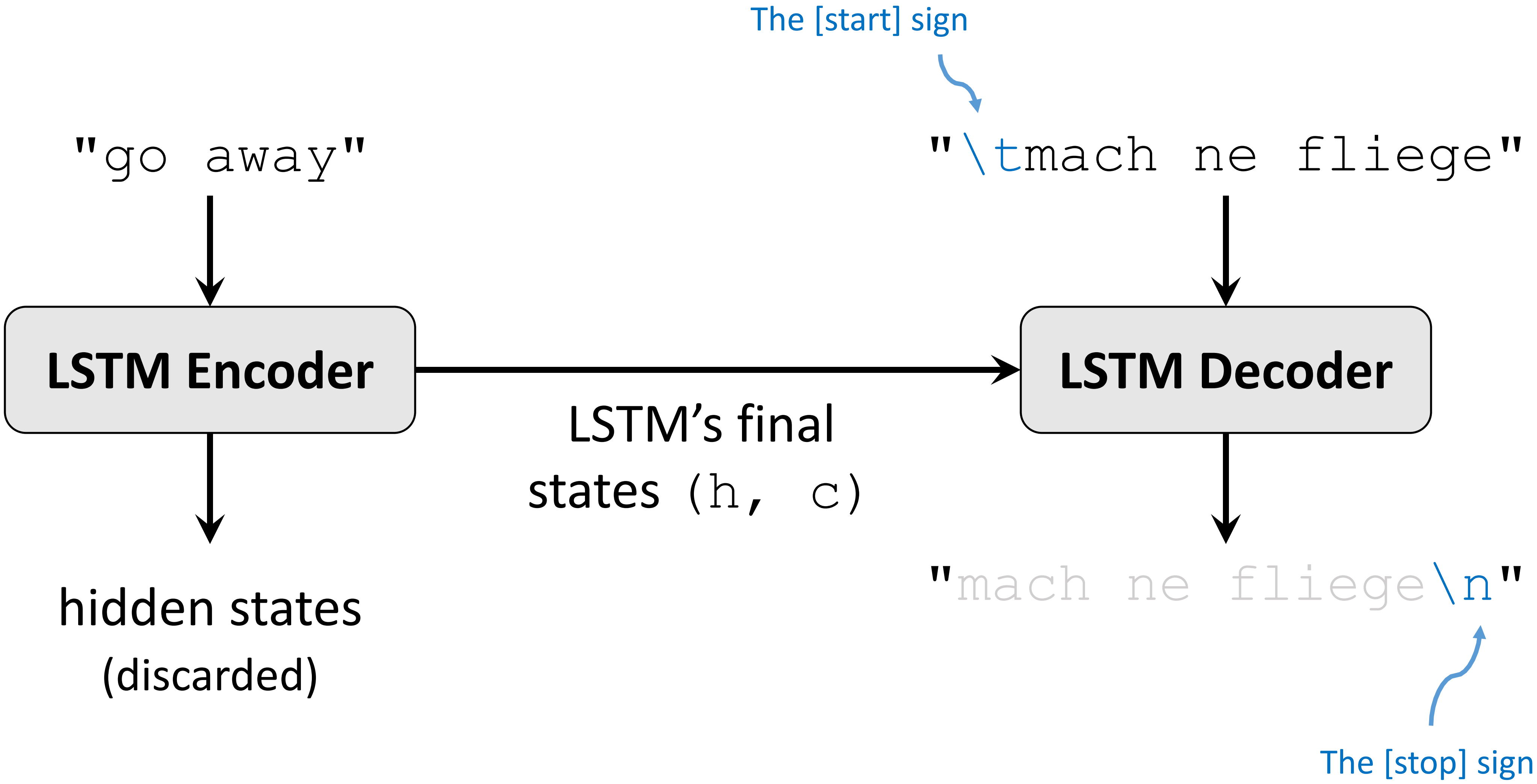


Training of the Seq2Seq Model



Repeat this process

Training of the Seq2Seq Model



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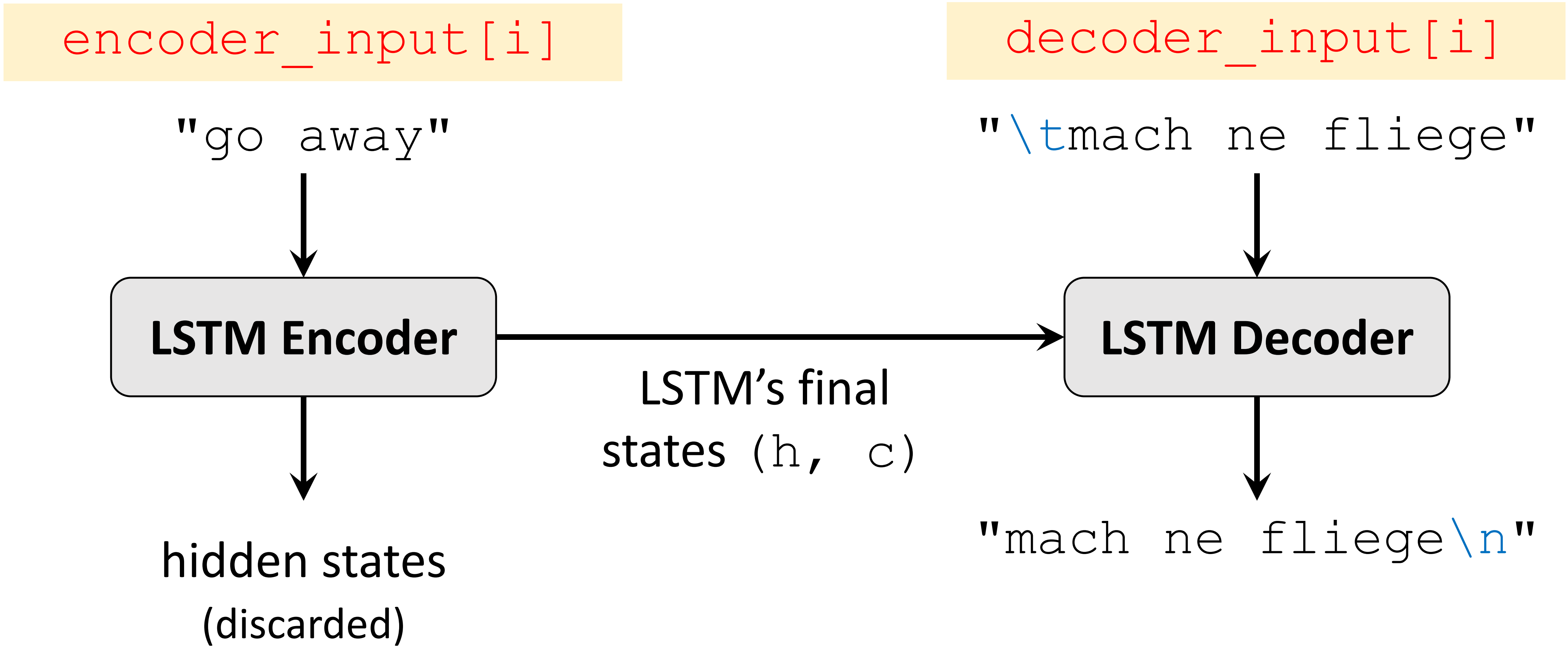

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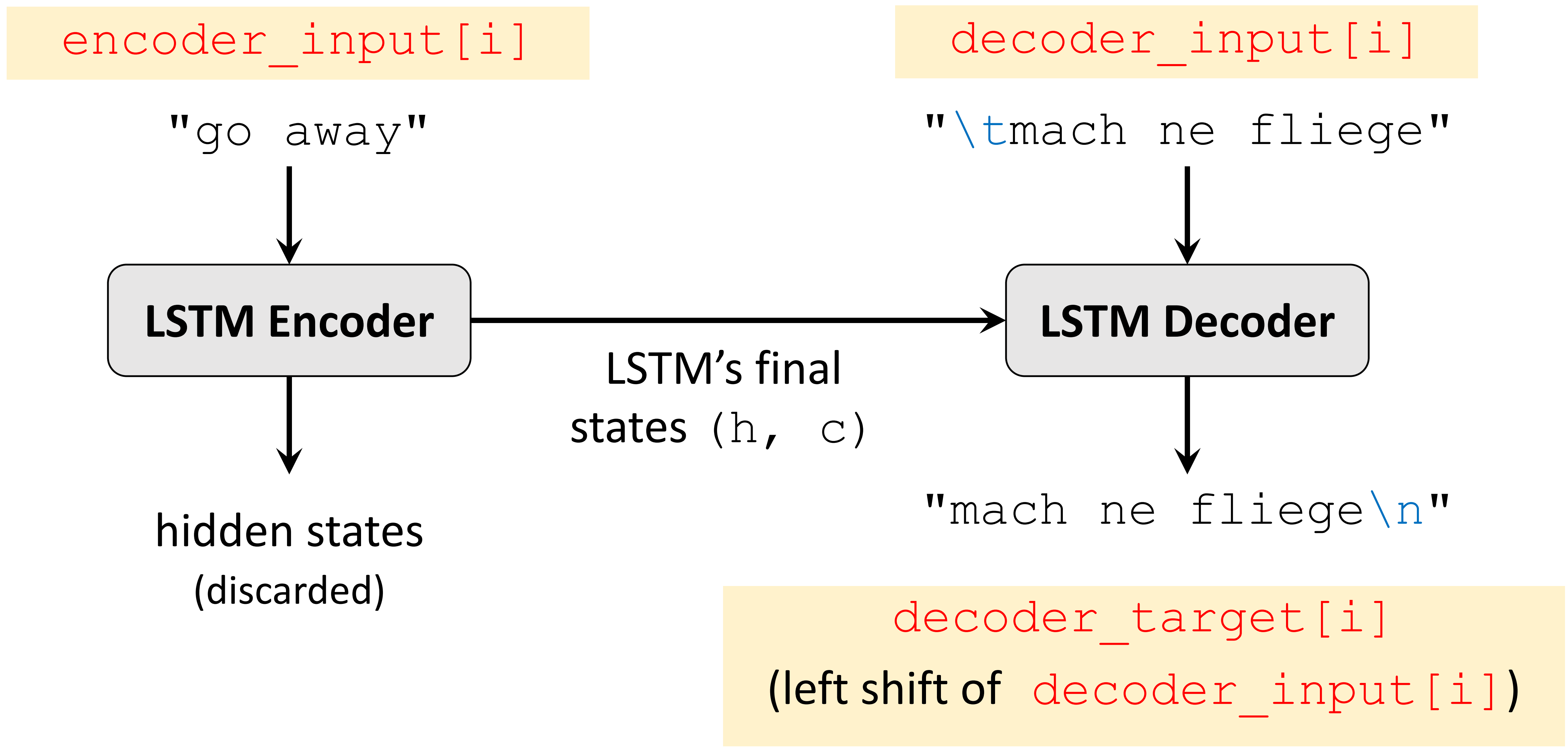

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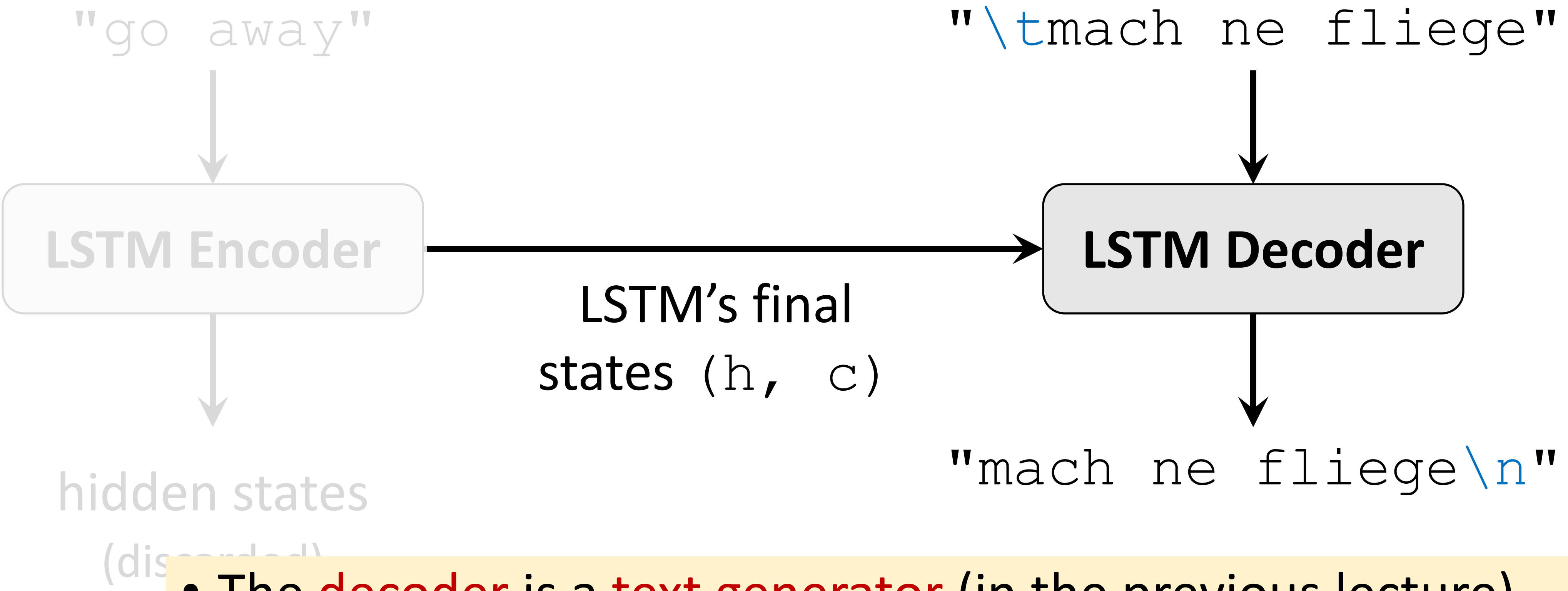
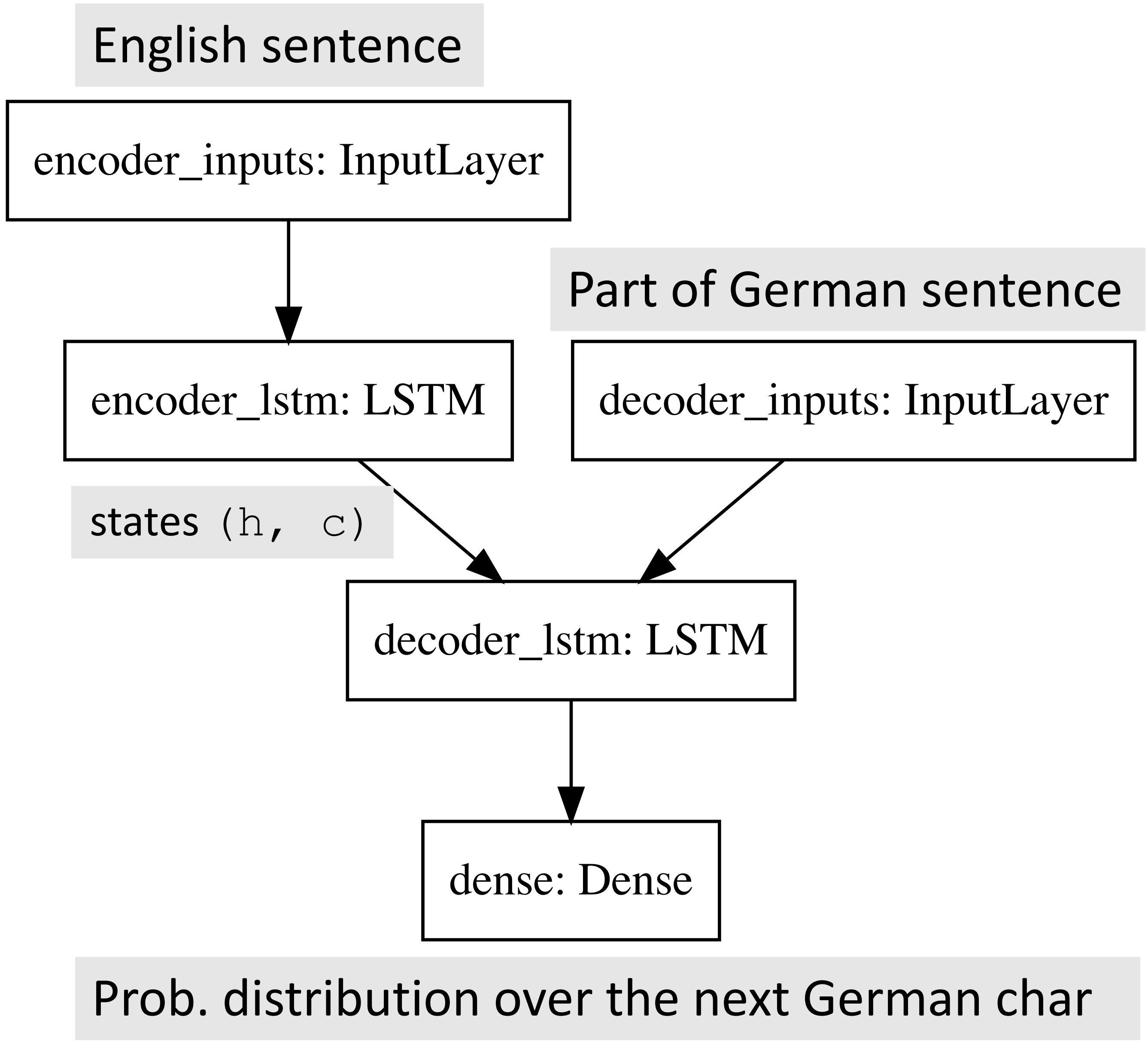


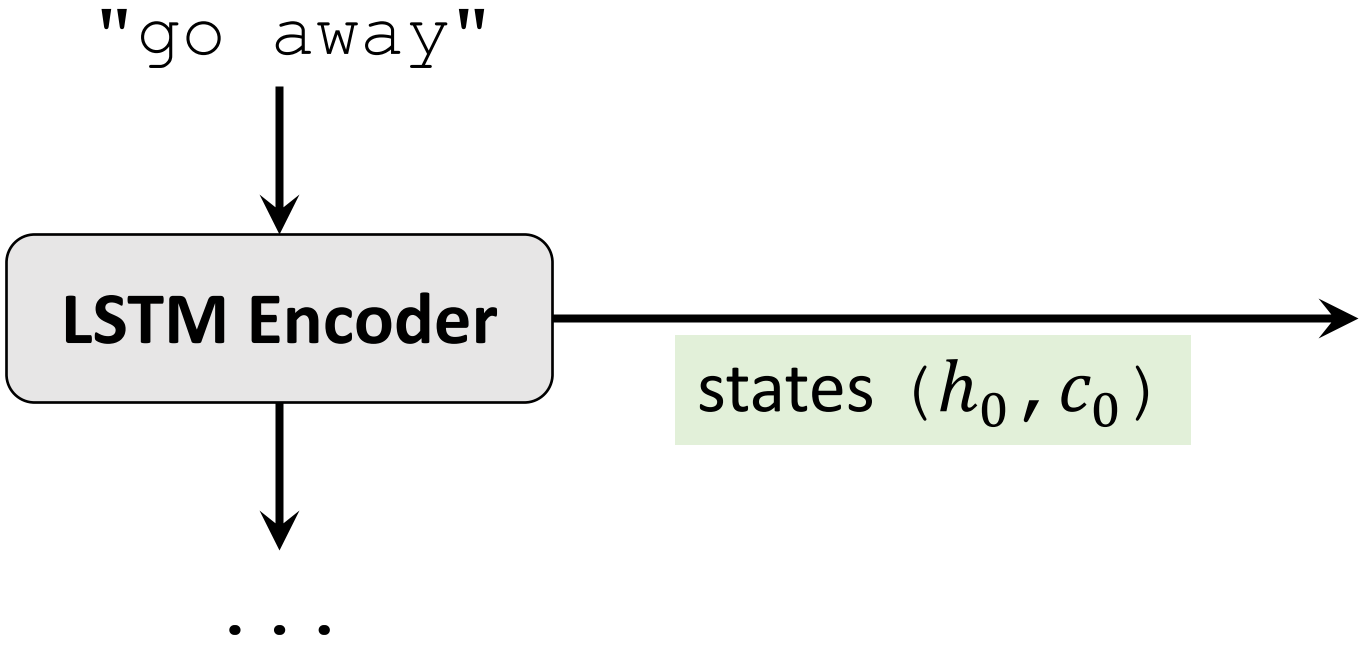
- The decoder is a text generator (in the previous lecture).
- Difference from the simple text generator: the initial states are determined by the encoder.

Seq2Seq Model in Keras

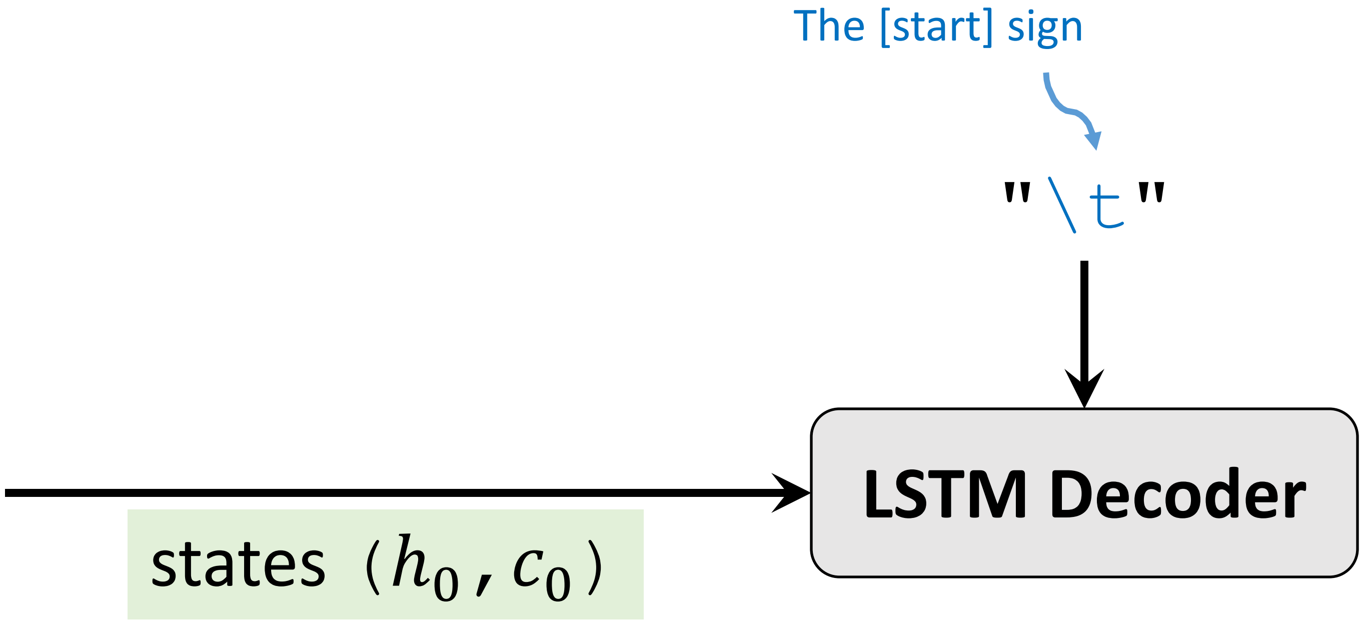


Inference Using the Seq2Seq Model

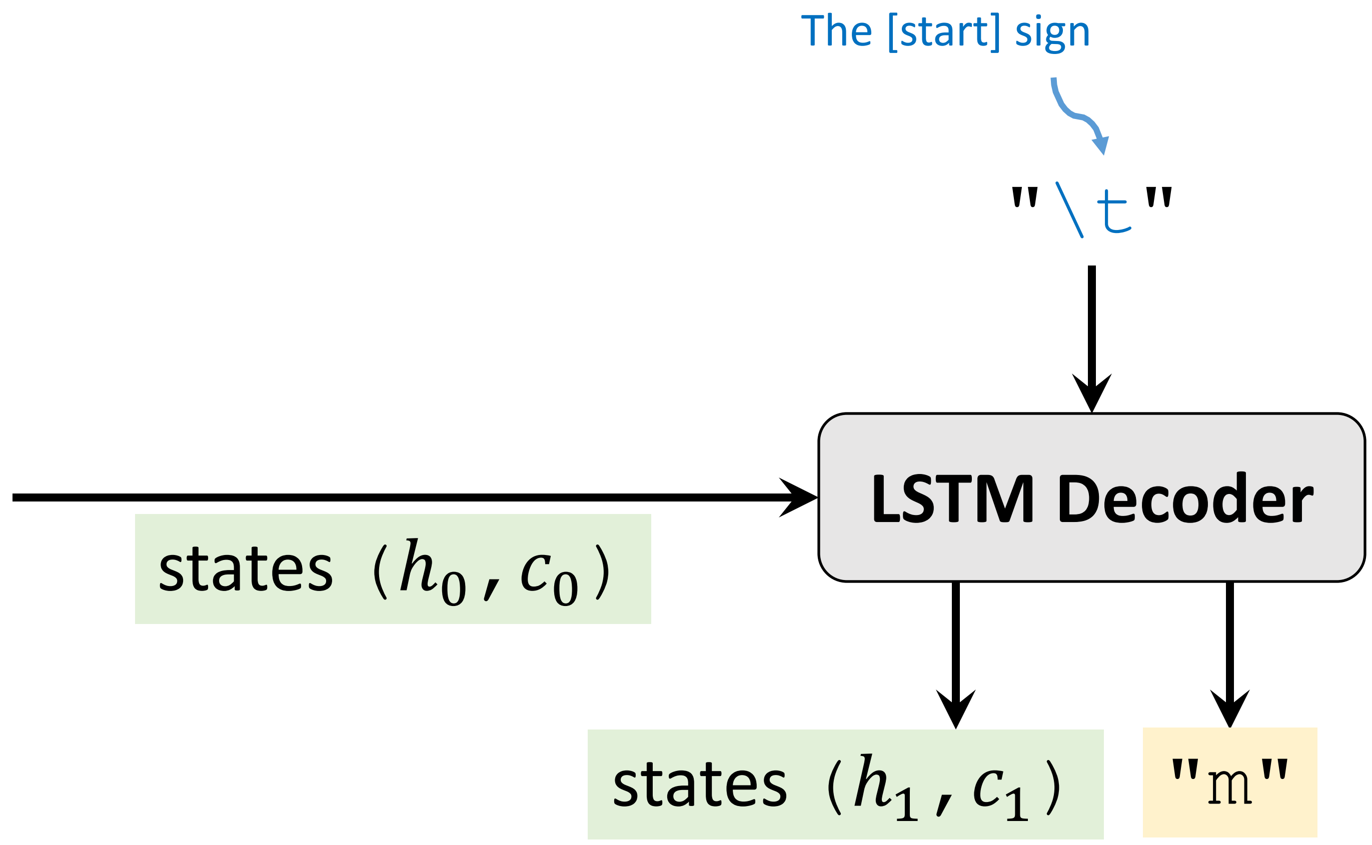
Inference



Inference

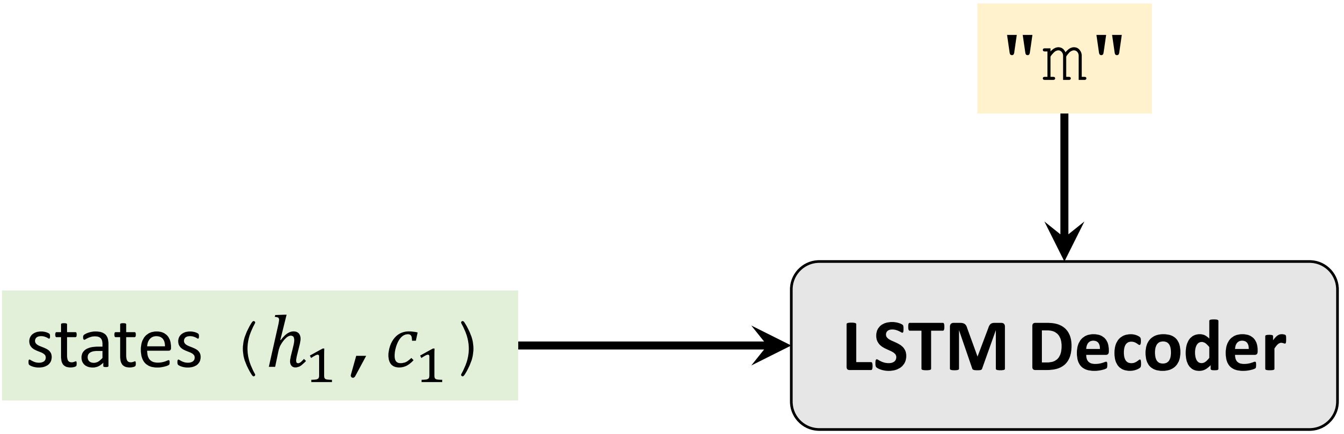


Inference



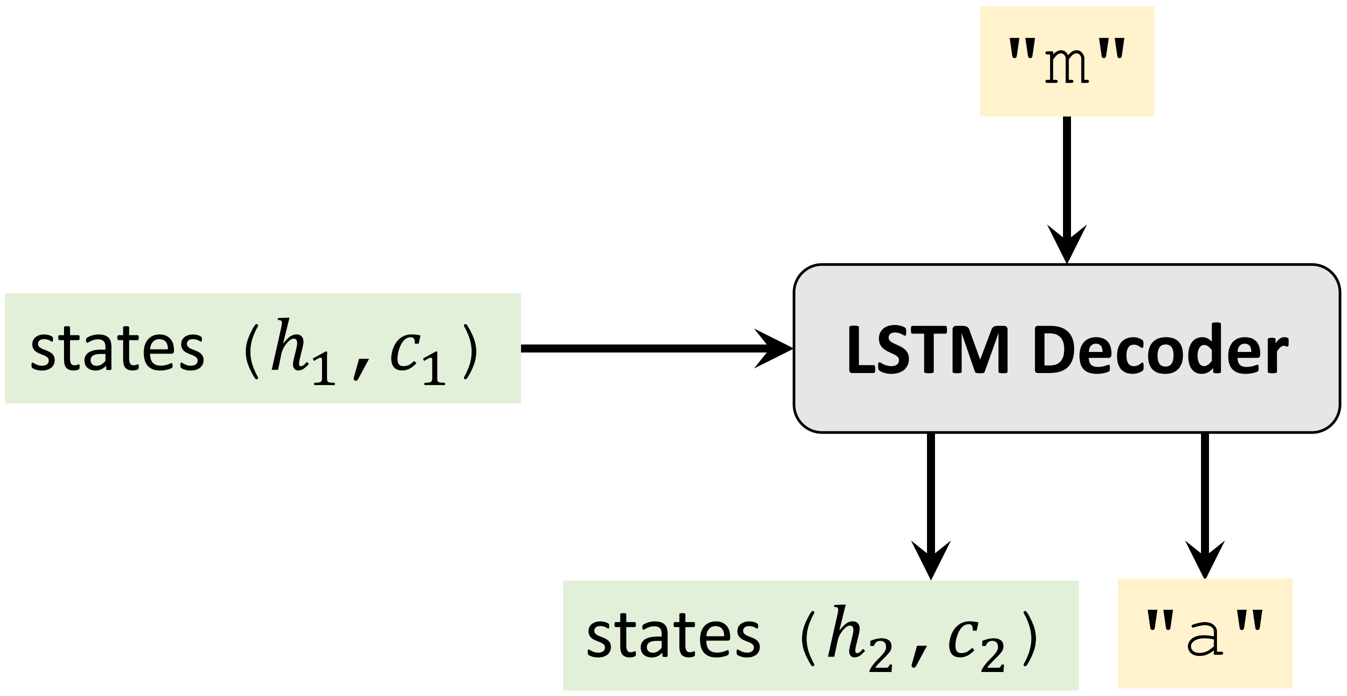
Record: "m"

Inference



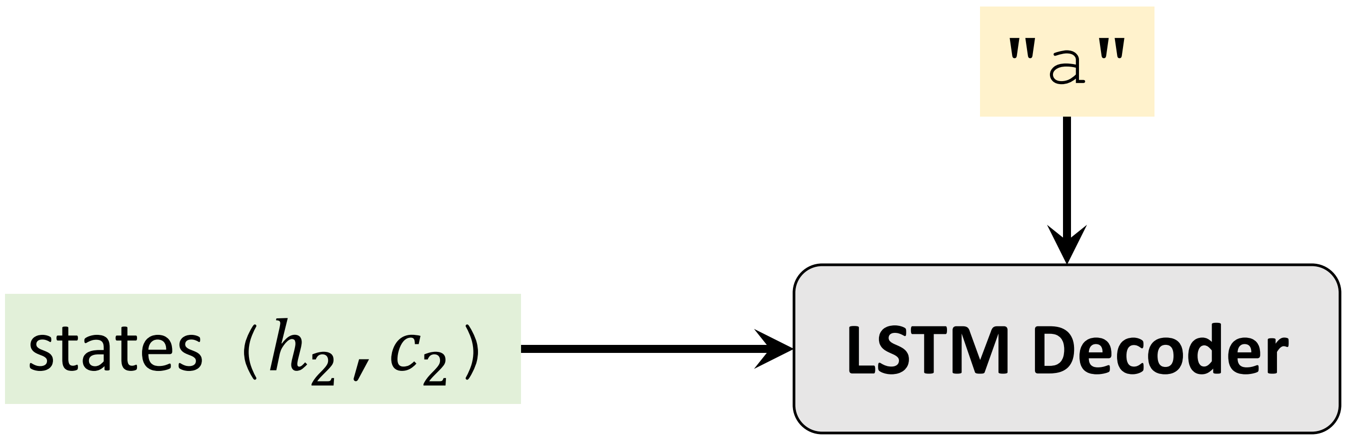
Record: "m"

Inference



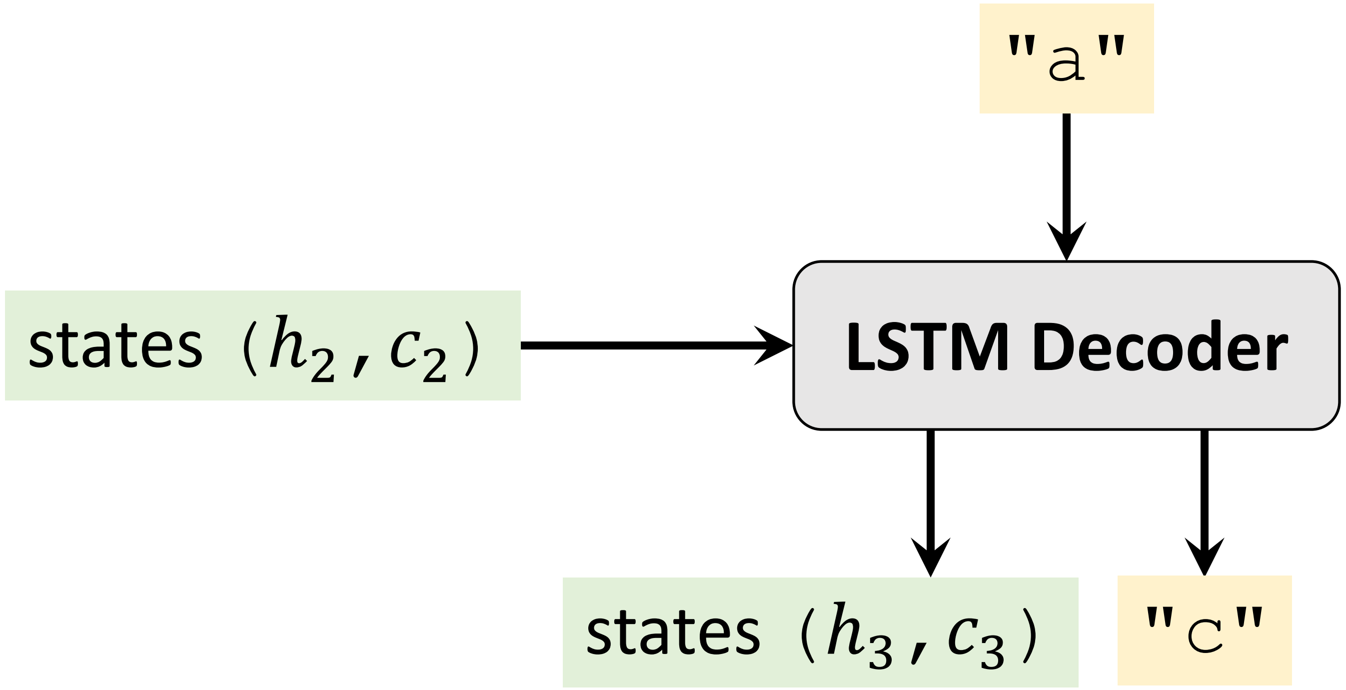
Record: `"ma"`

Inference



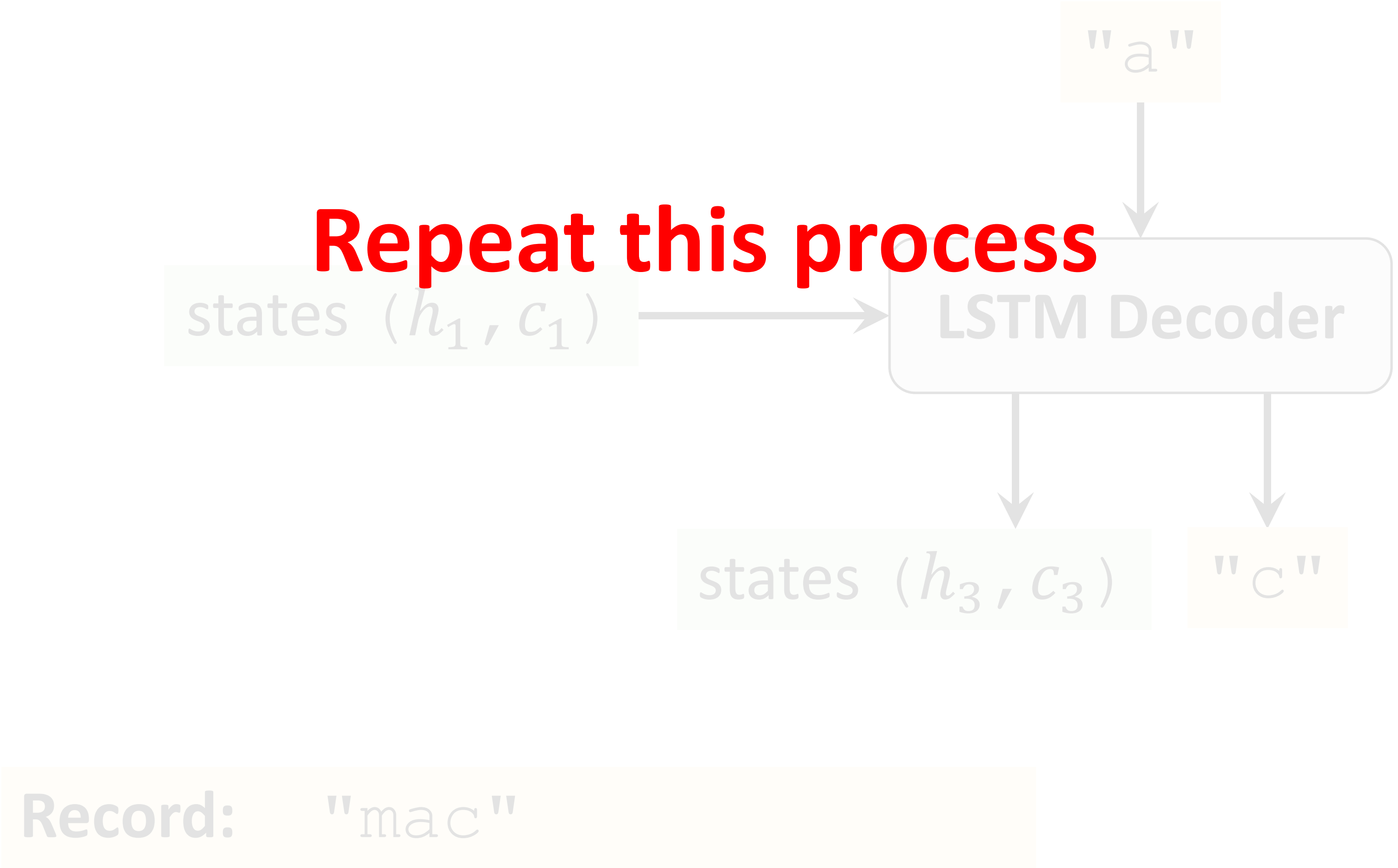
Record: "ma"

Inference

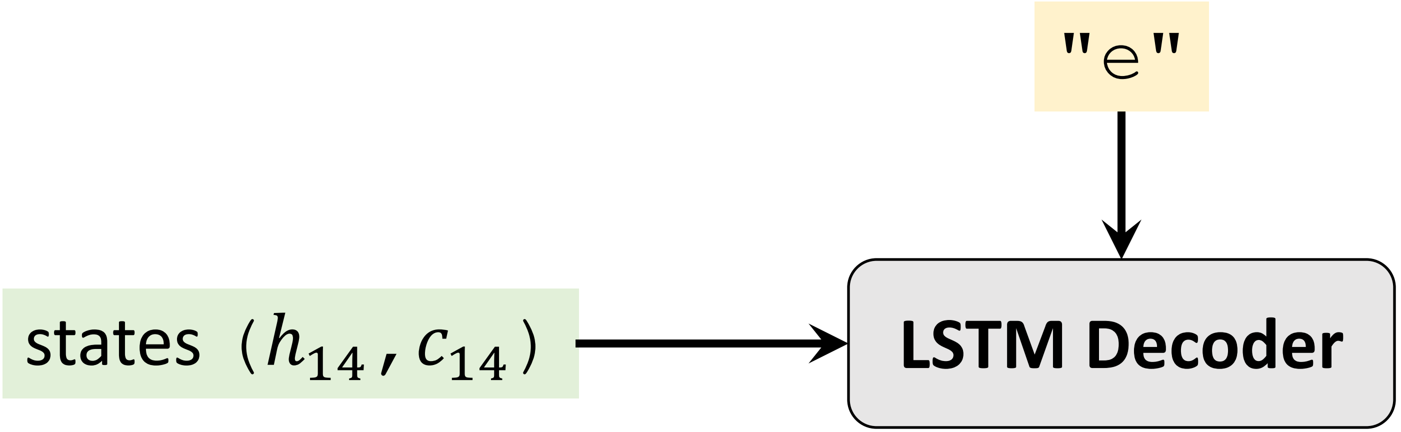


Record: `"mac"`

Inference

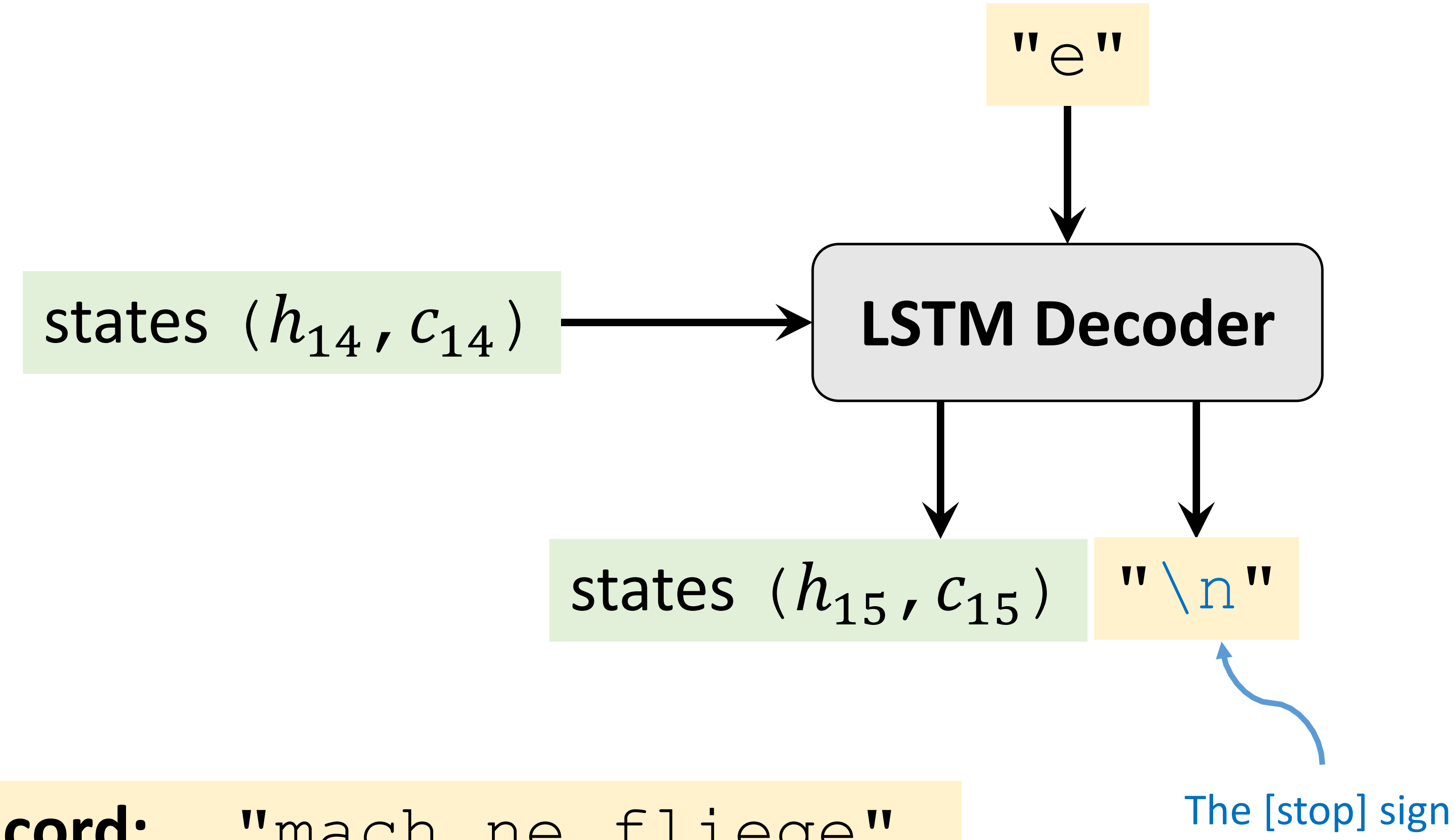

"a"
Repeat this process
states (h_1, c_1)
LSTM Decoder
states (h_3, c_3)
"c"
Record: "mac"

Inference



Record: `"mach ne fliege"`

Inference



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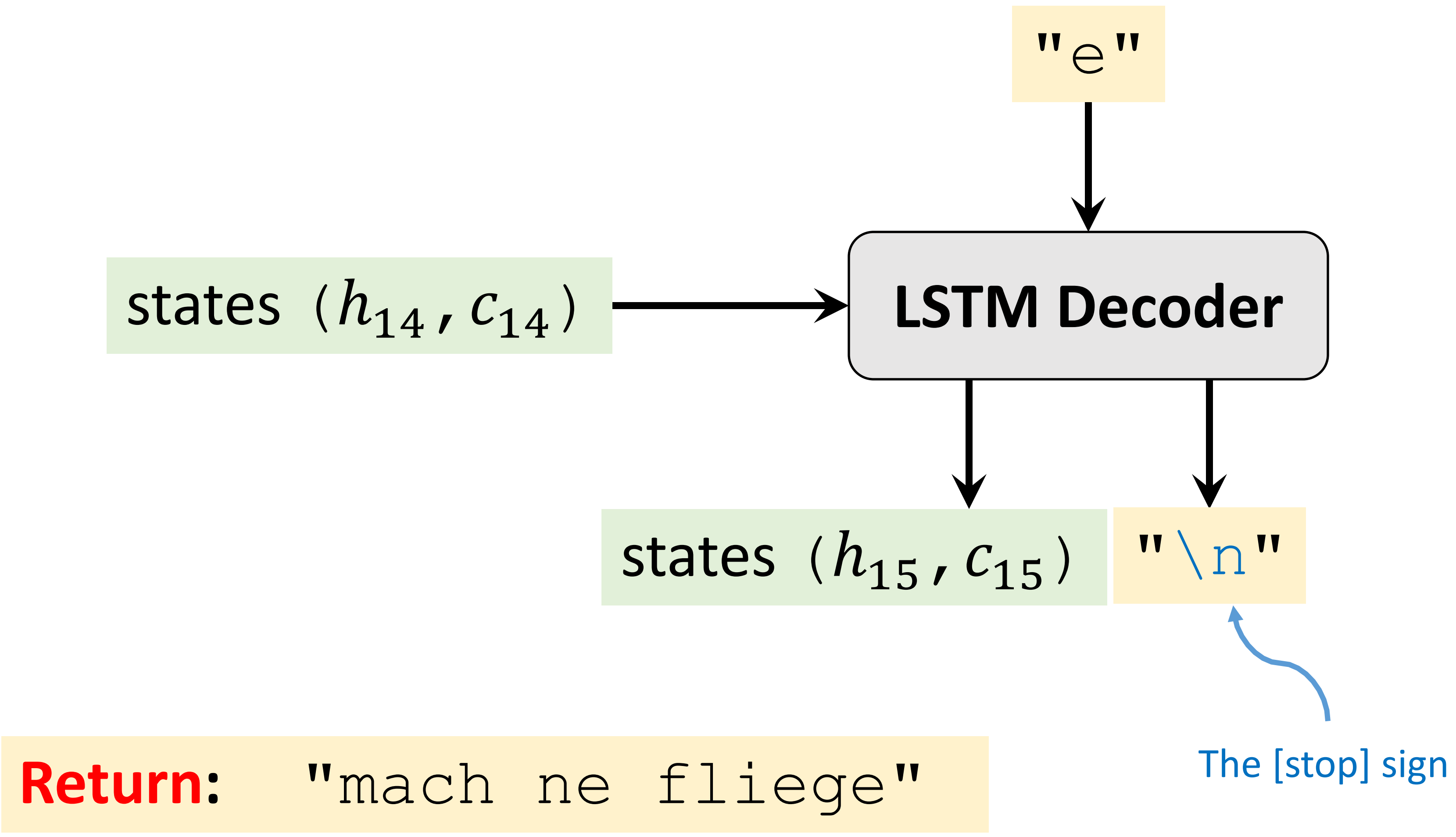
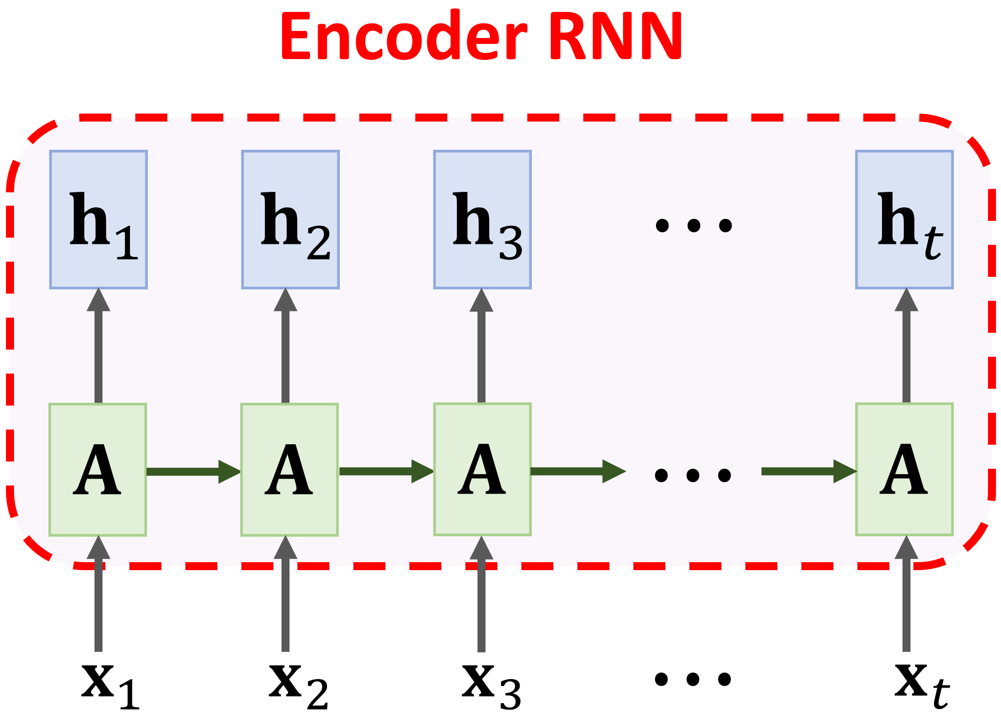


"e"
states (h_{14}, c_{14})
LSTM Decoder
states (h_{15}, c_{15})
"\n"
The [stop] sign
Return: "mach ne fliege"

Summary

Seq2Seq Model



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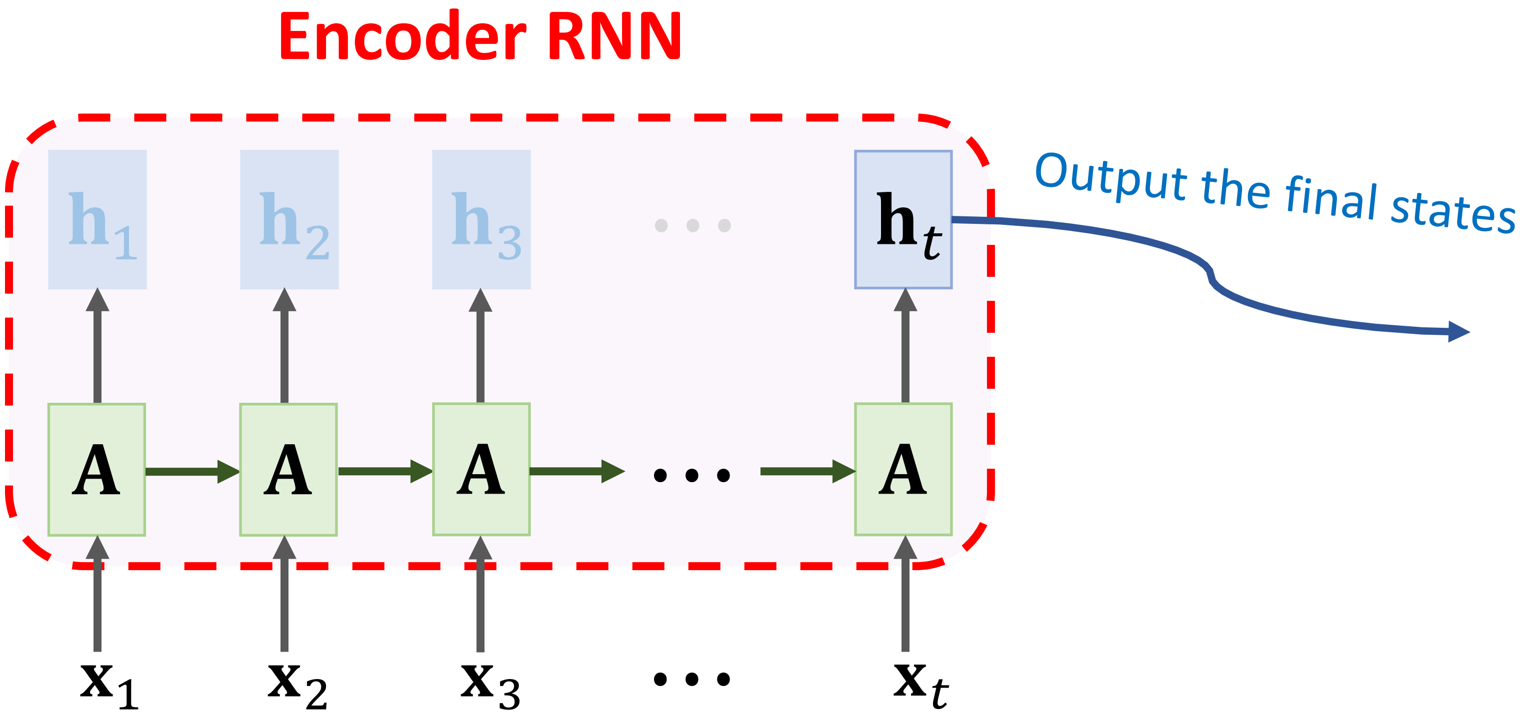

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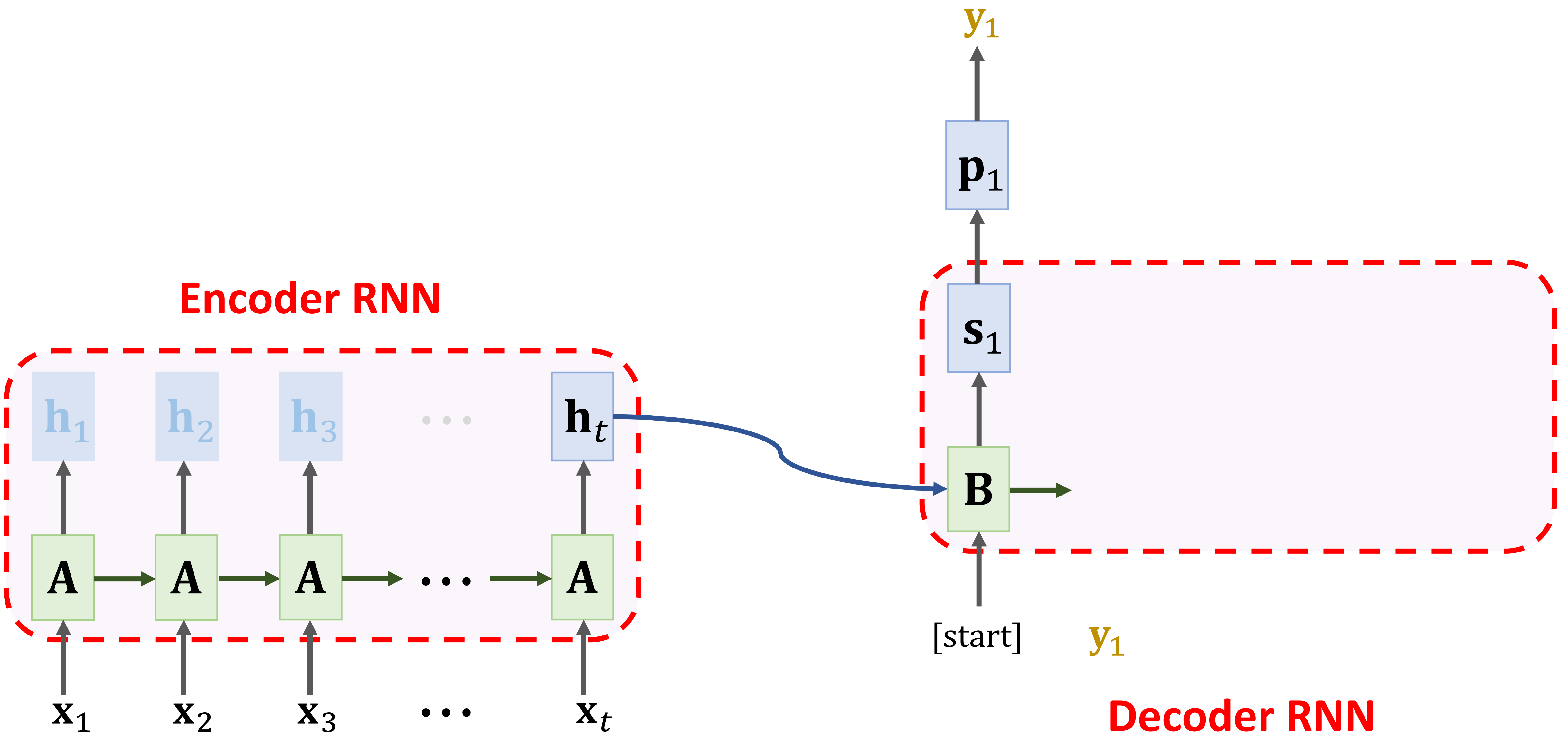

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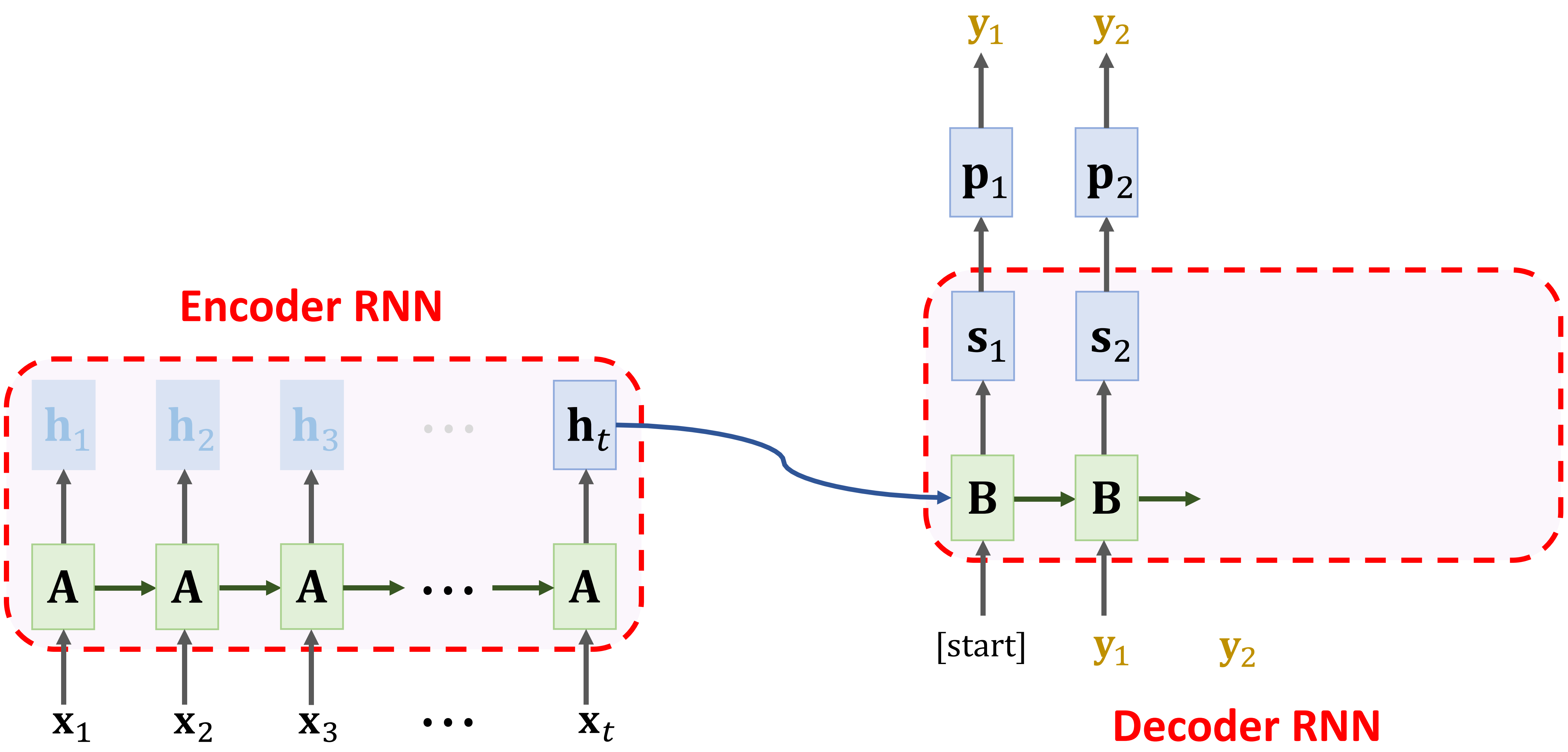

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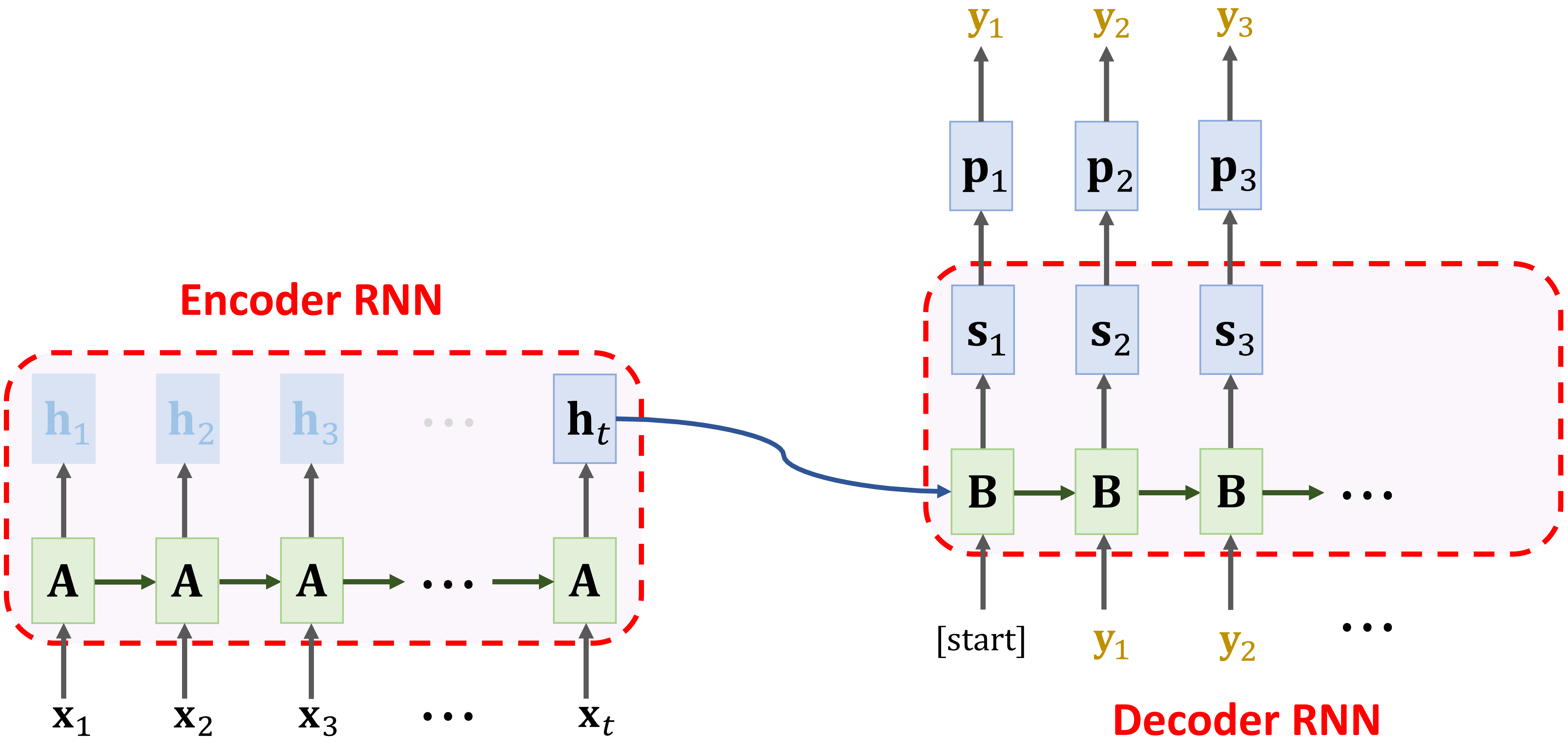

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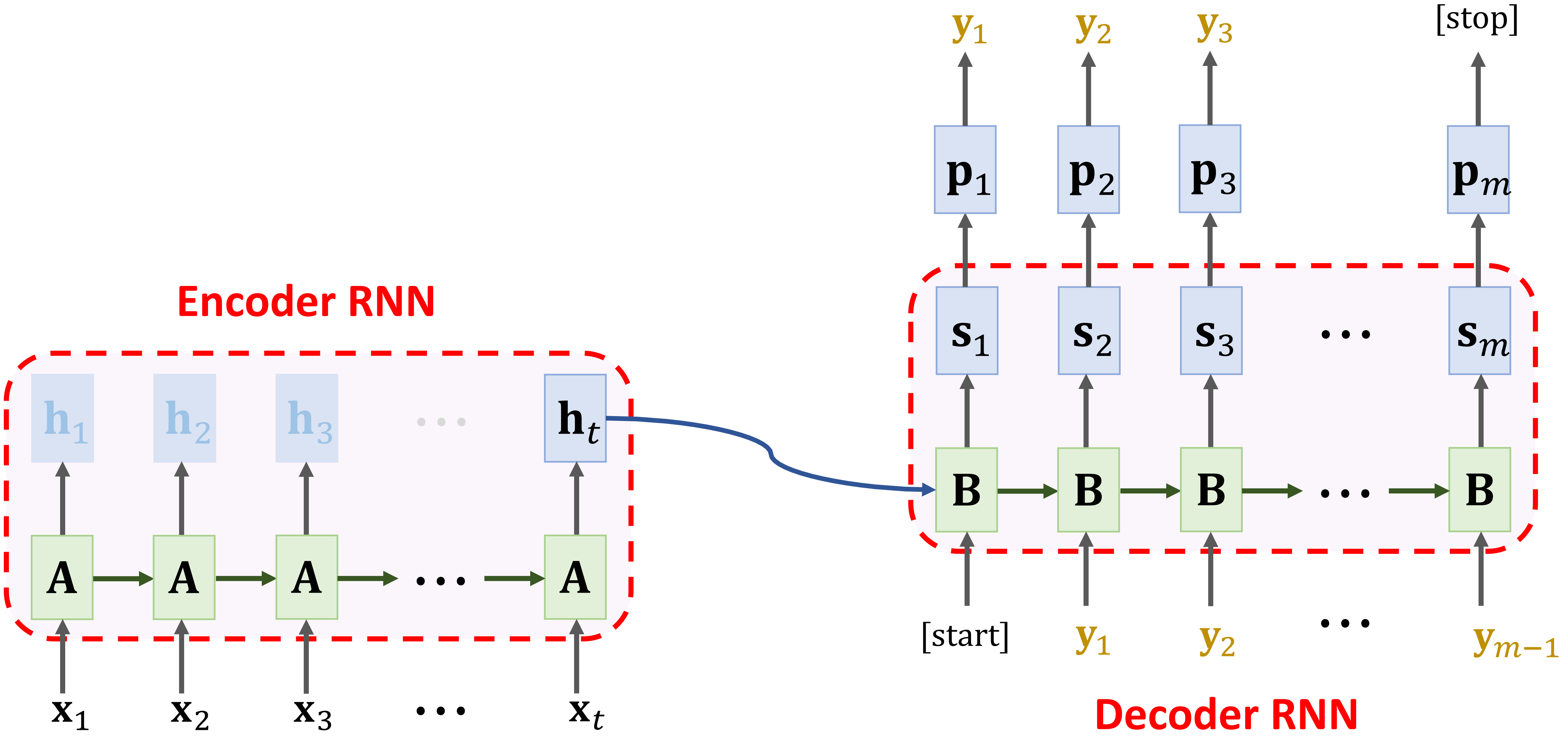
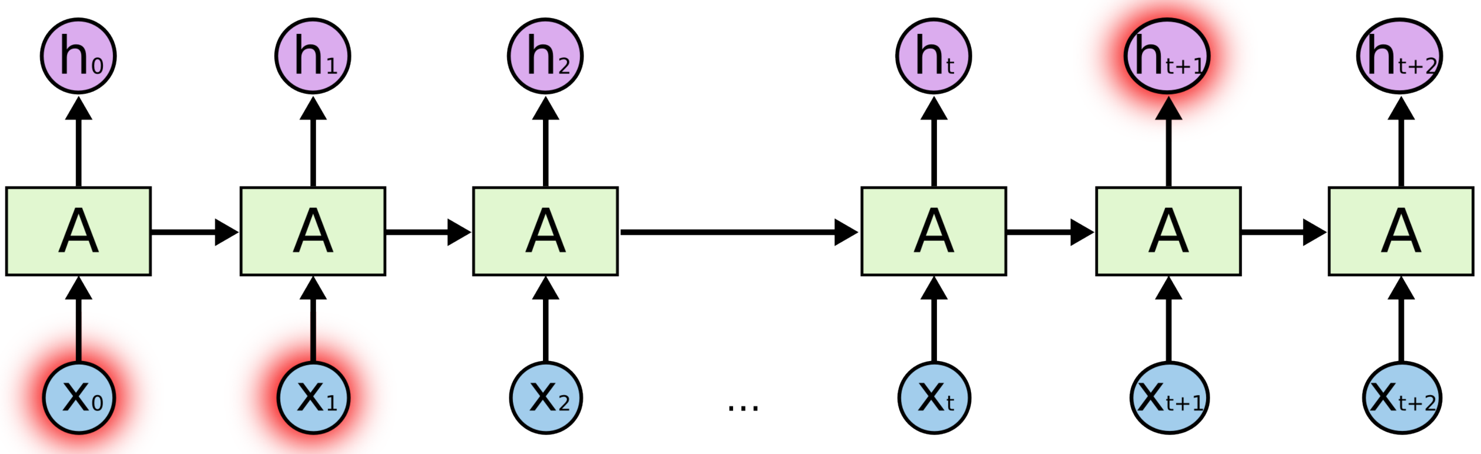


How to Improve?

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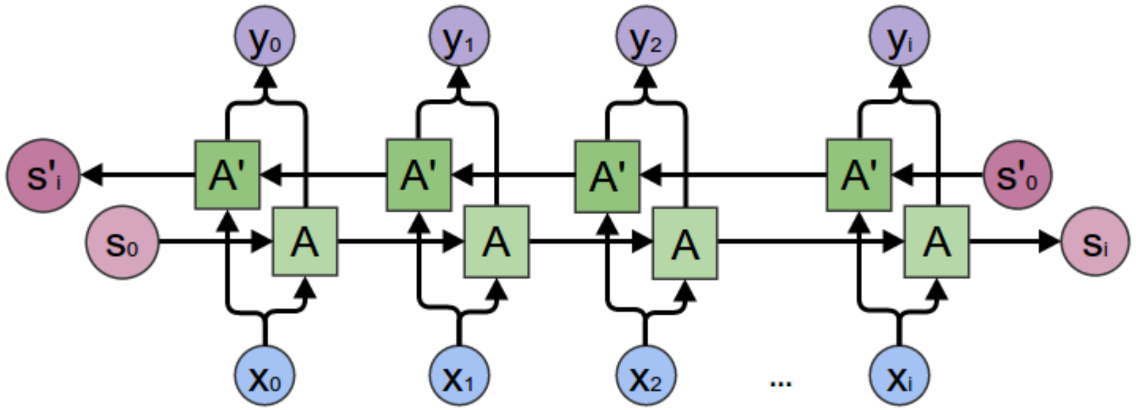
- The final states ($\mathbf{h}_t$ and $\mathbf{c}_t$) of the Encoder have all the information of the English sentence.
- Really?
  - If the sentence is long (hundreds of tokens), the final states have forgotten the first tokens.
- Bi-LSTM (left-to-right and right-to-left) remembers the first tokens.



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 ~10^2 ➔ one-hot suffices.
  - # of (frequently used) words is ~10^4 ➔ must use embedding.
  - Embedding Layer has many parameters ➔ overfitting!