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/

Datasets

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

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. 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

```
"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]
```

2. One-Hot Encoding

"Es geht mir gut”

Deu_Tokenizer

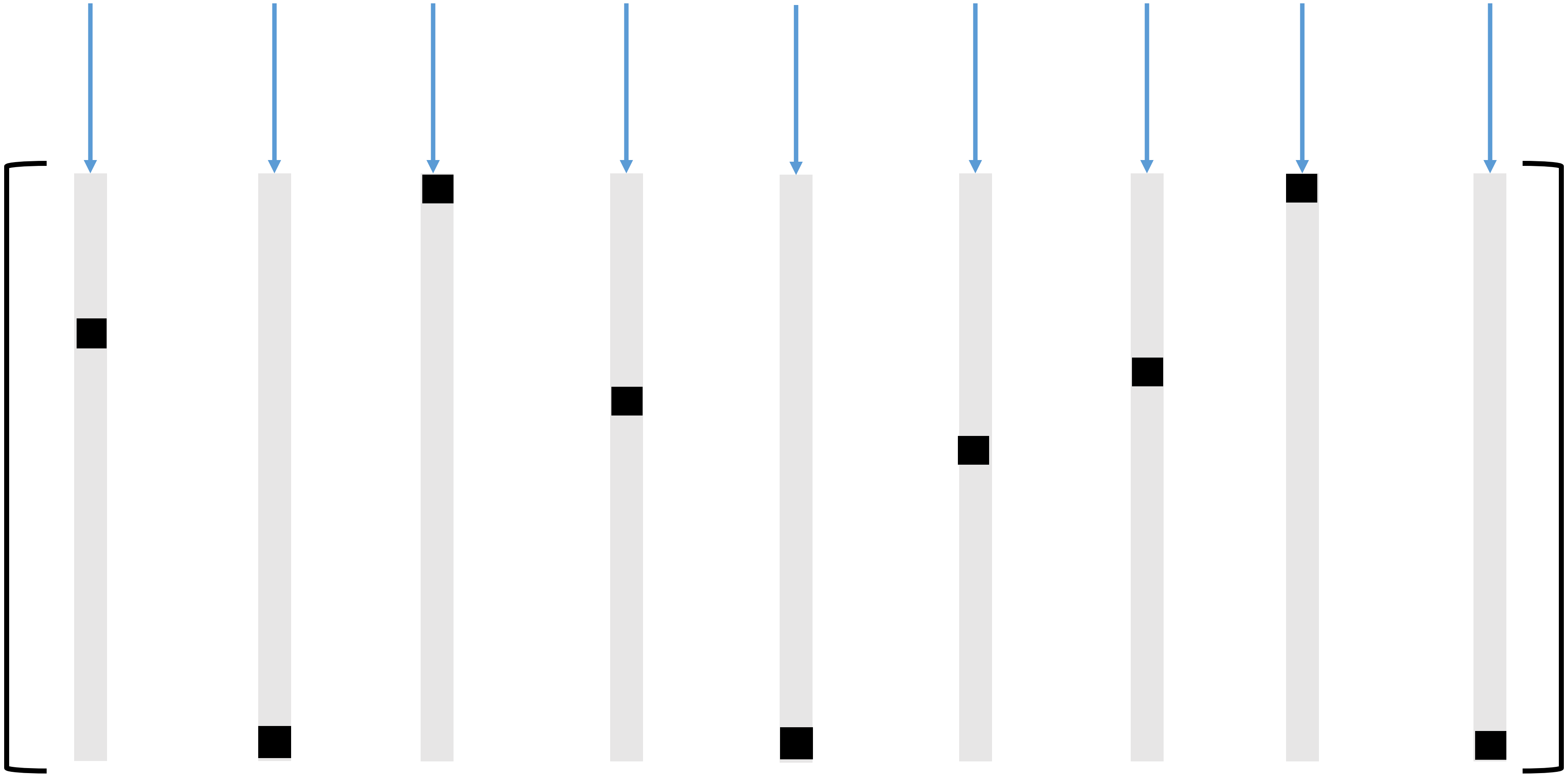
['e', 's', '_', 'g', 'e', ..., 'g', 'u', 't']

Encoding using Deu_Dictionary

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

2. One-Hot Encoding

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



Why not using embedding?

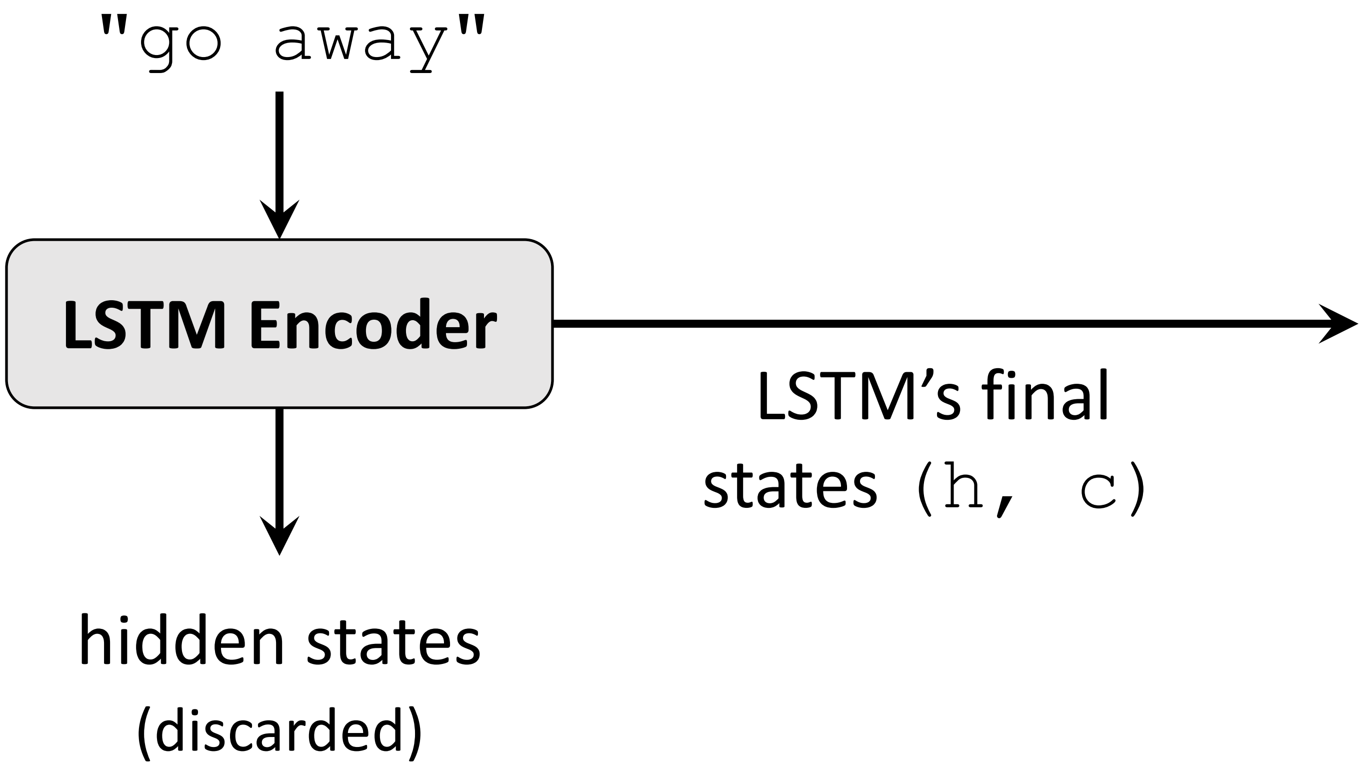
- There are around 100 frequent characters. (Vocabulary $\approx$ 100.)
- One-hot converts a character to 100-dim vector.

- There are around $10K$ frequent English words. (Vocabulary $\approx 10K$.)
- One-hot converts a word to $10K$-dim vector. (Too big.)

- Conclusion:
  - For char-level tokenization, do not use embedding layer.
  - For word-level tokenization, use an embedding layer.

Training the Seq2Seq Model

Training of the Seq2Seq Model



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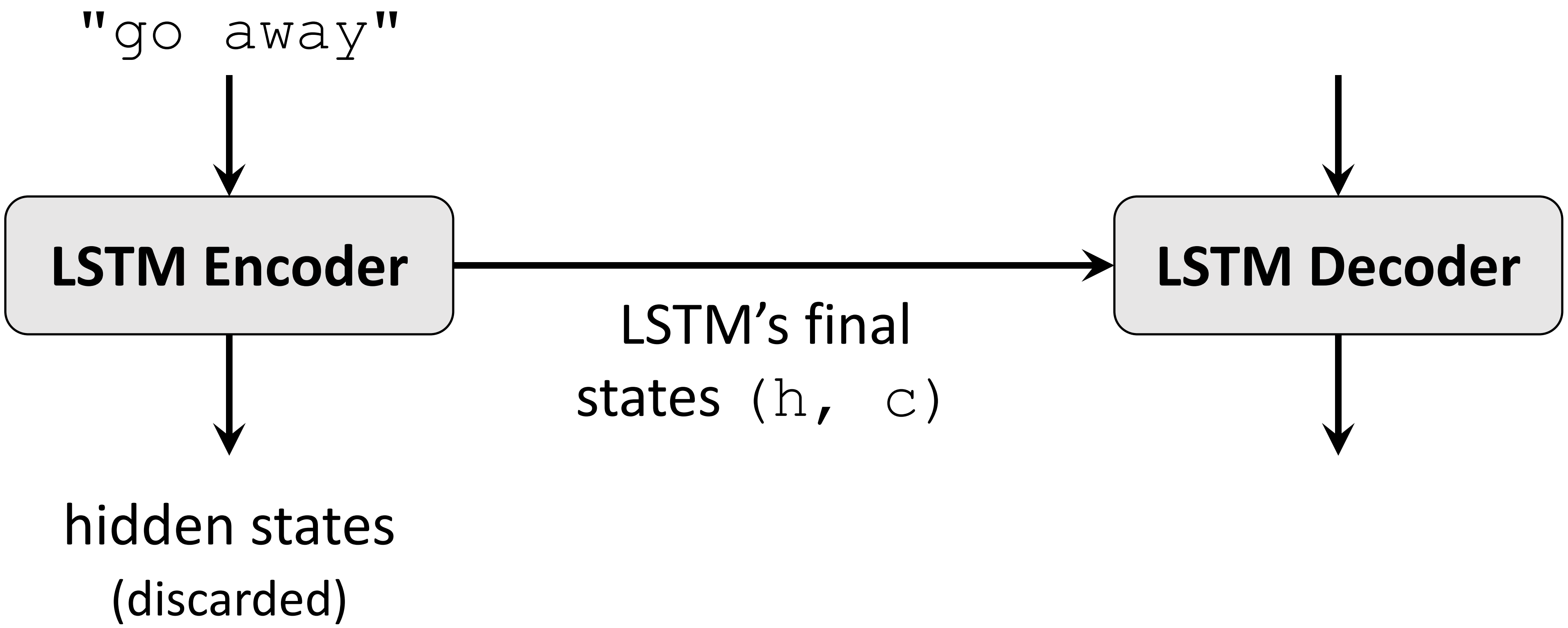

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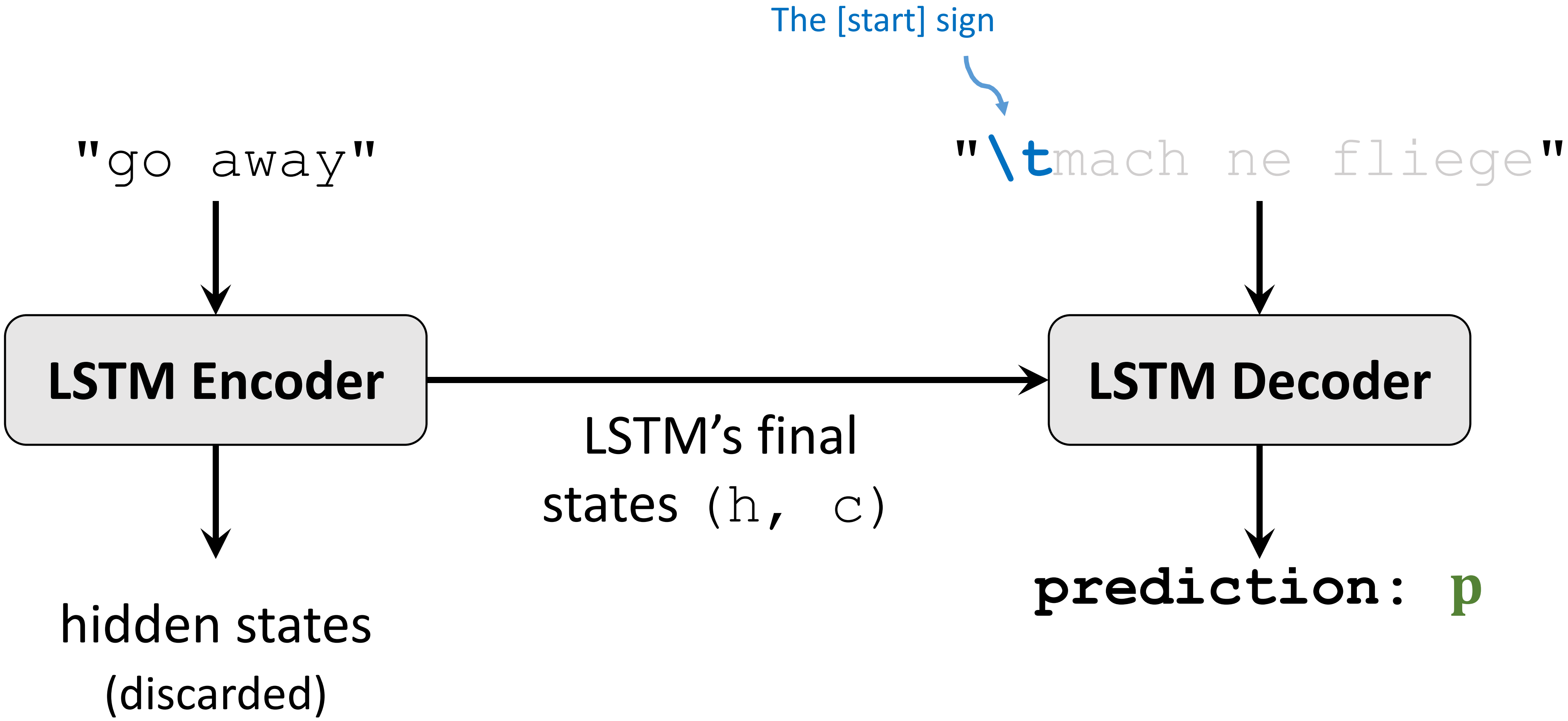

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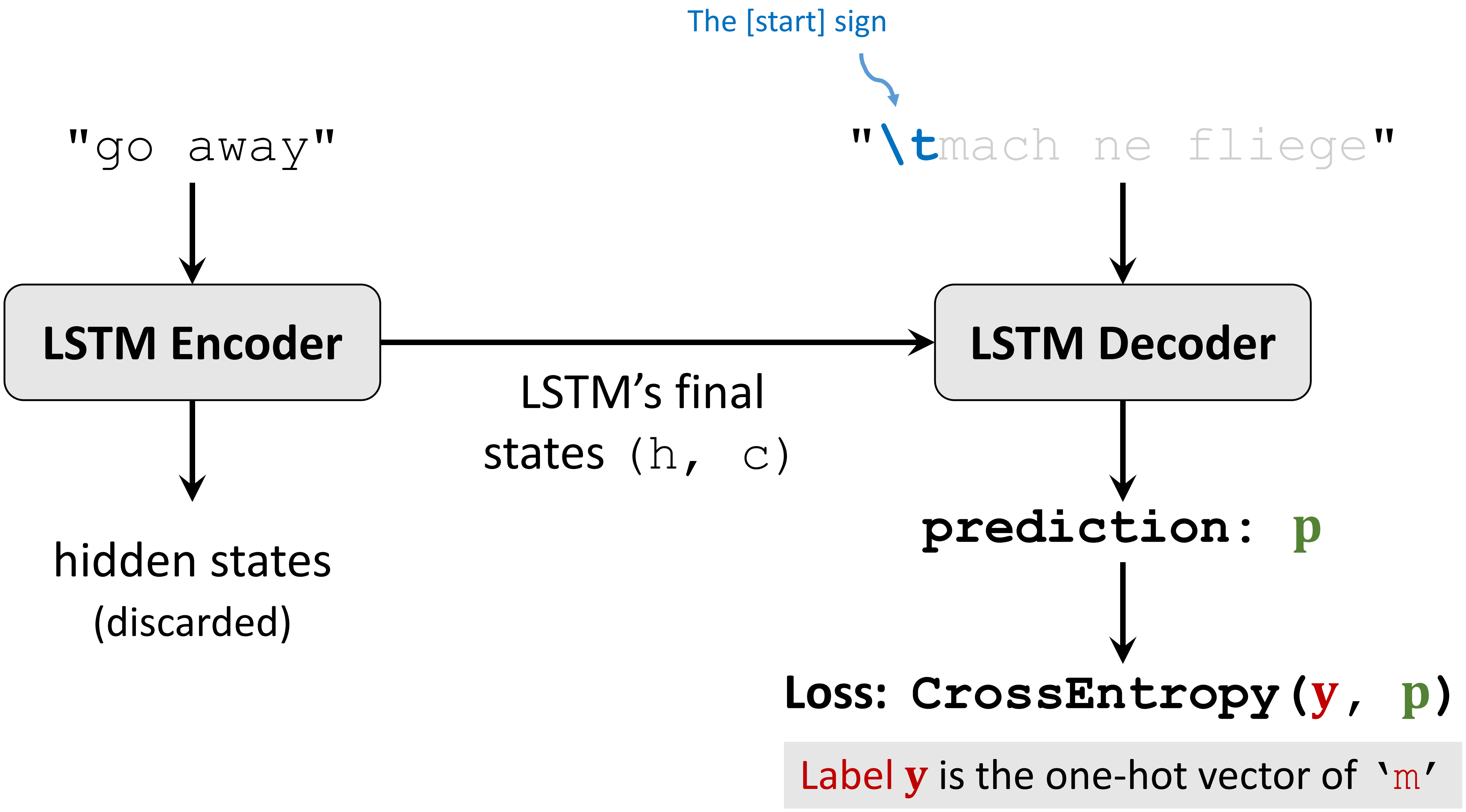

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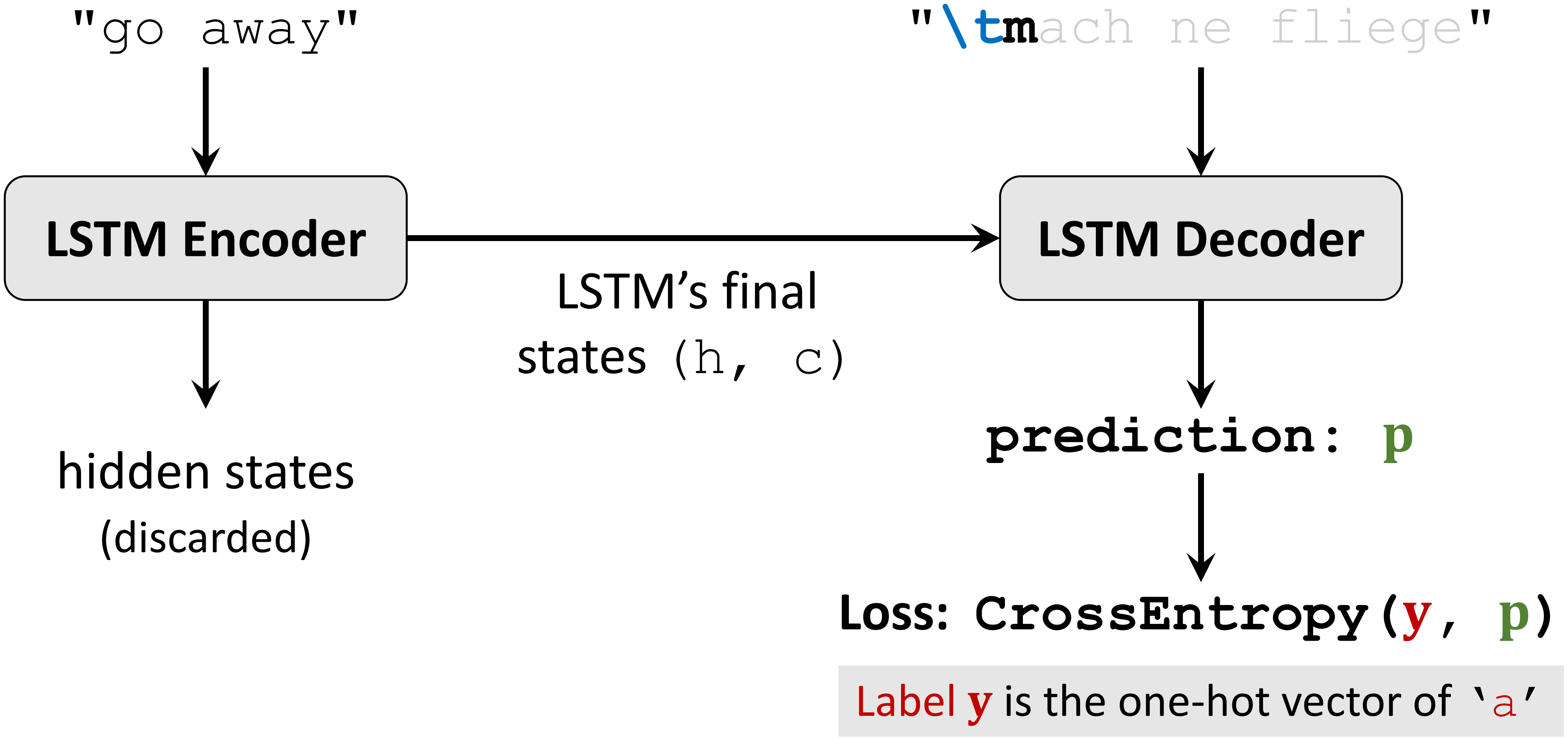

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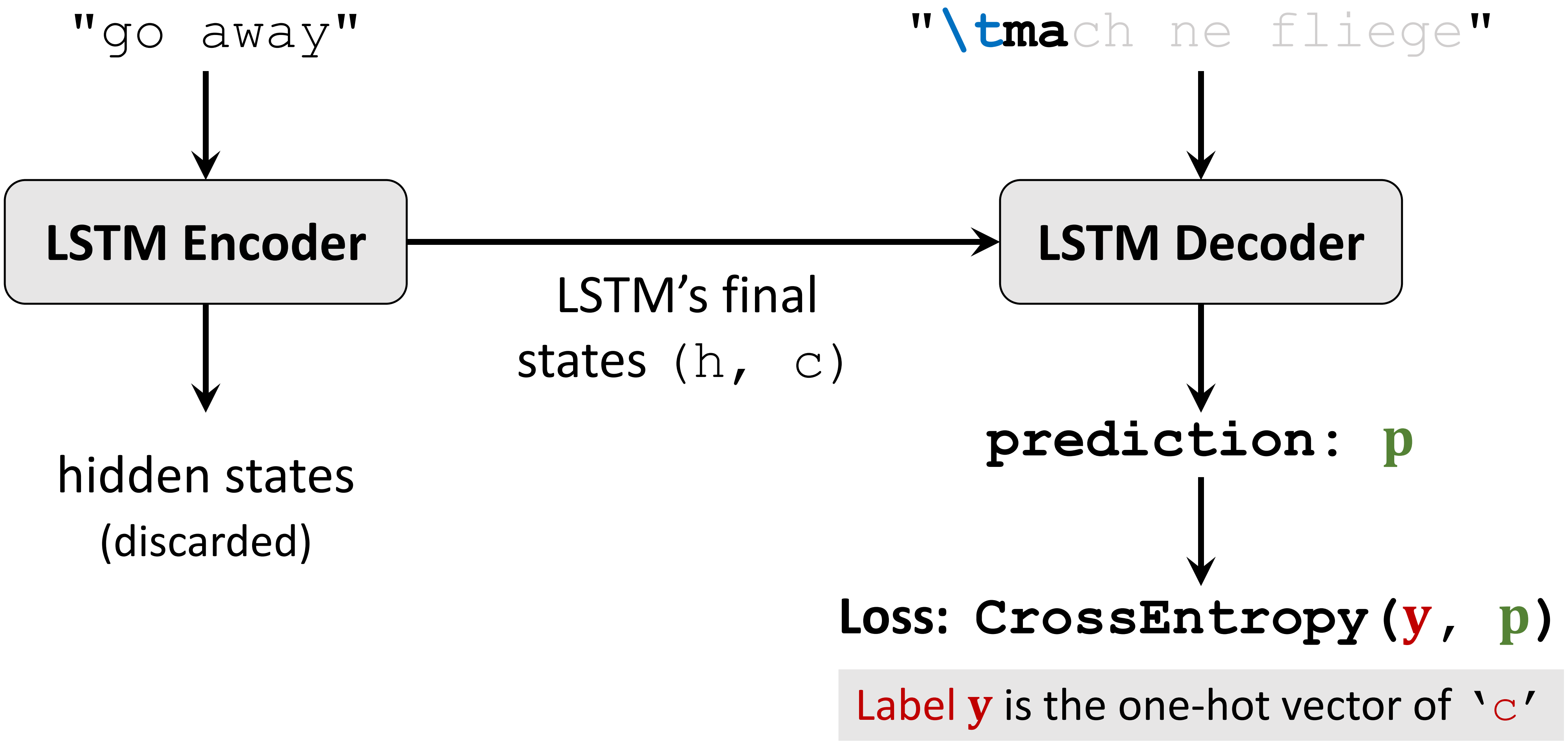

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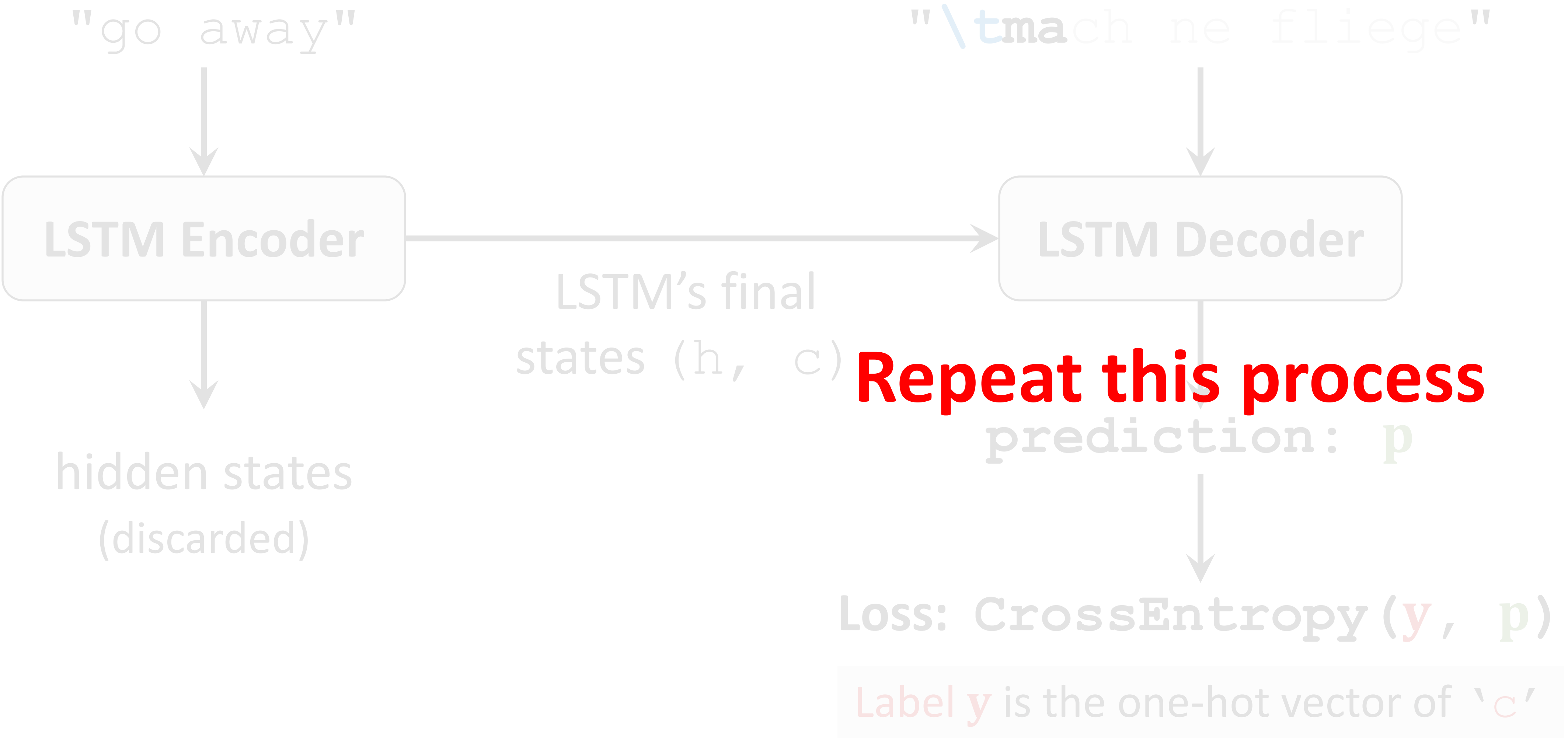

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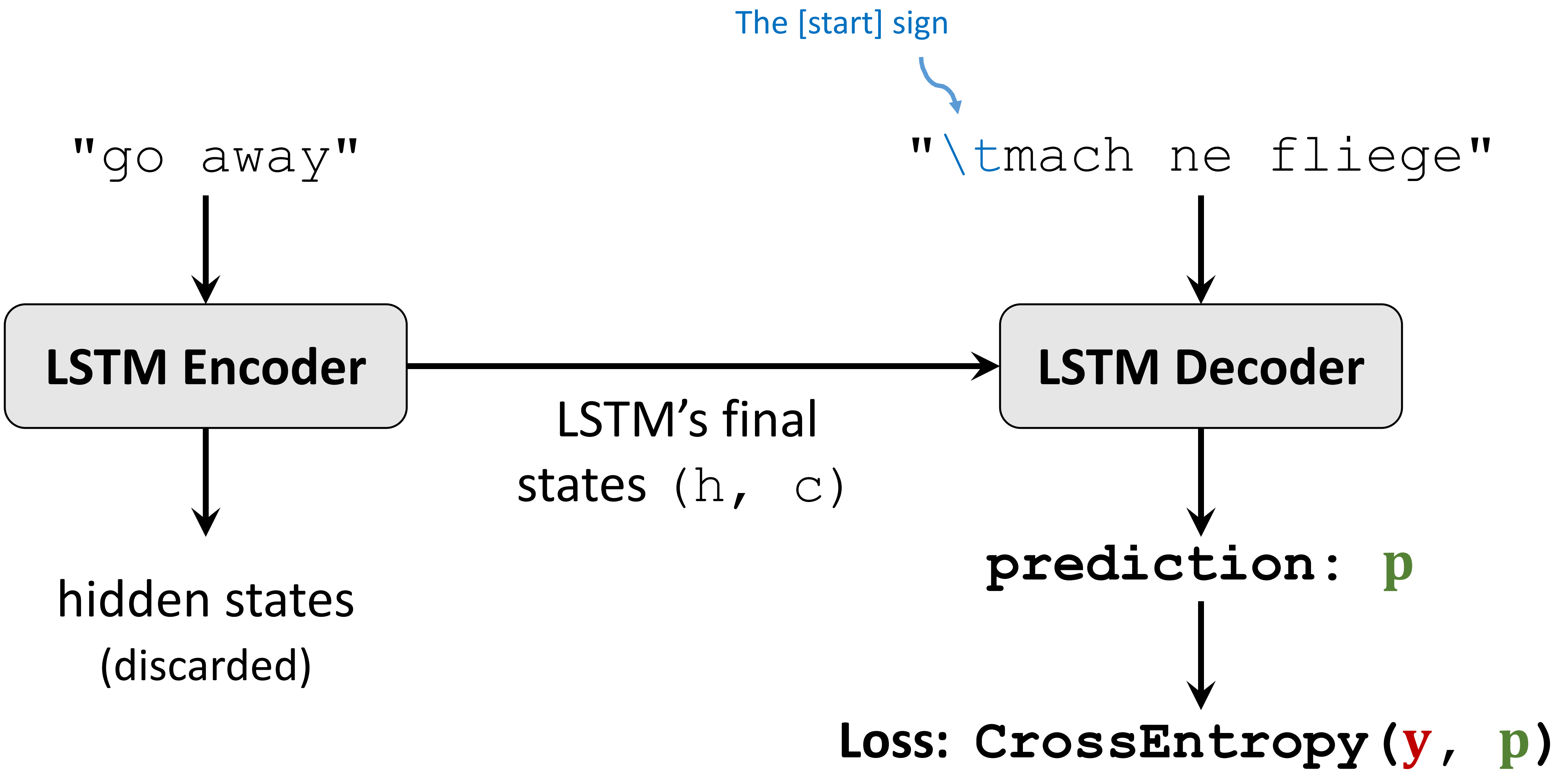
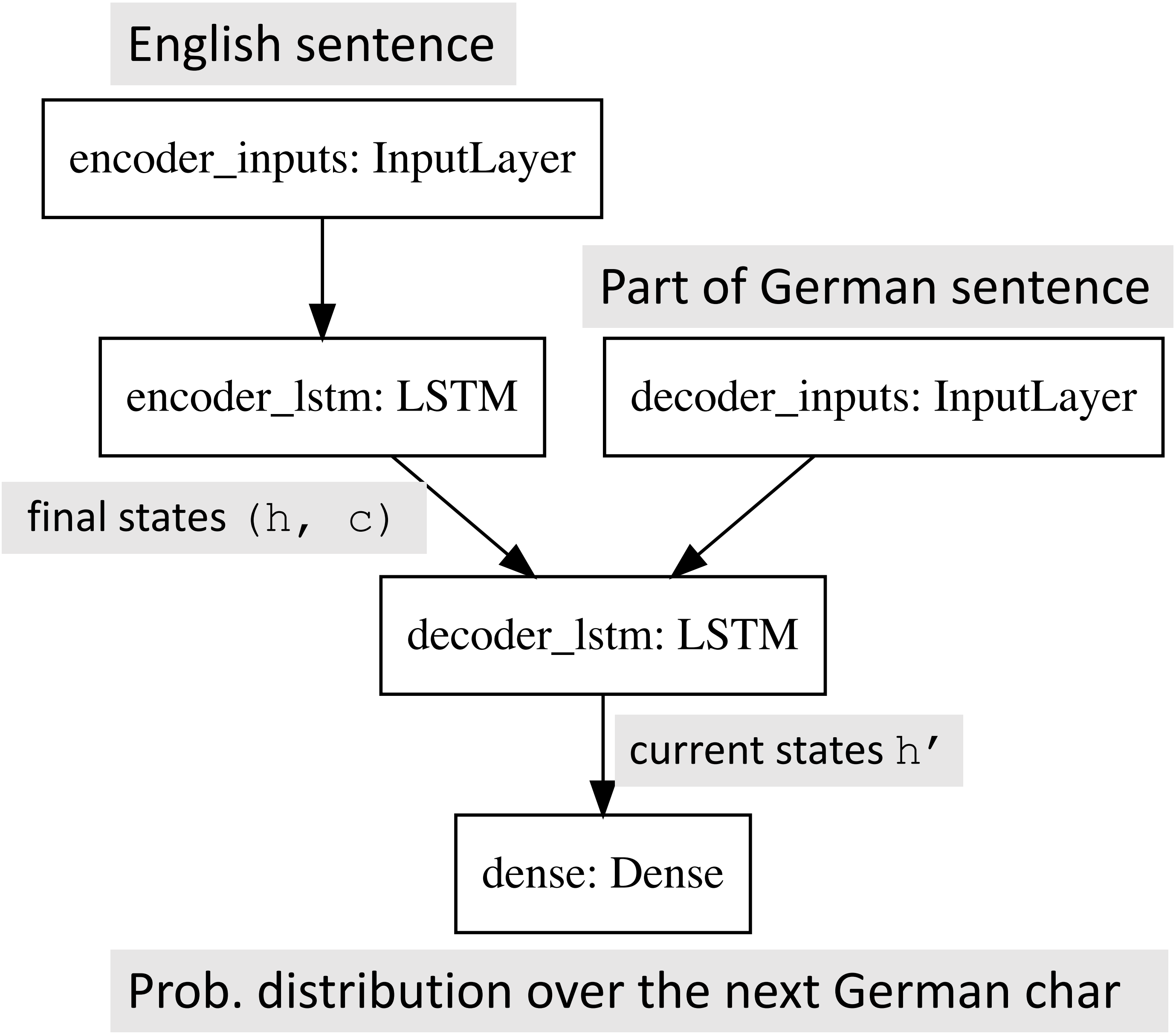


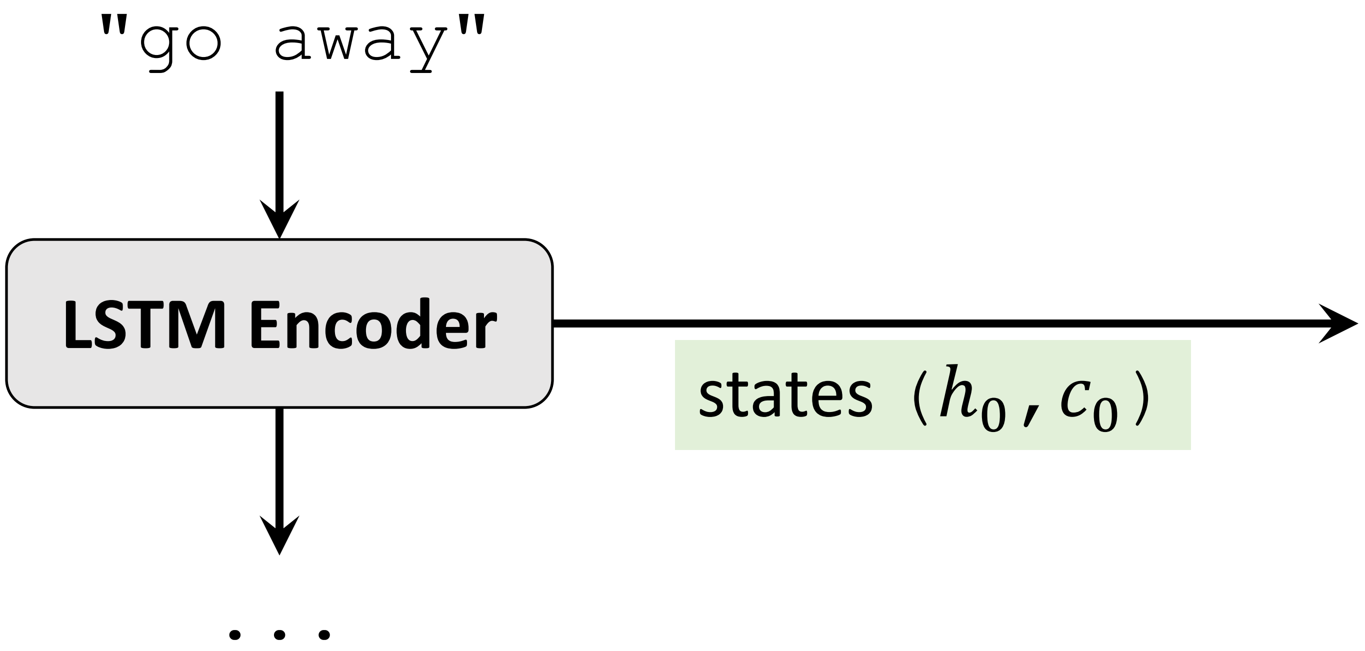
Label **y** is the one-hot vector of the [stop] sign.

Seq2Seq Model in Keras



Inference Using the Seq2Seq Model

Inference



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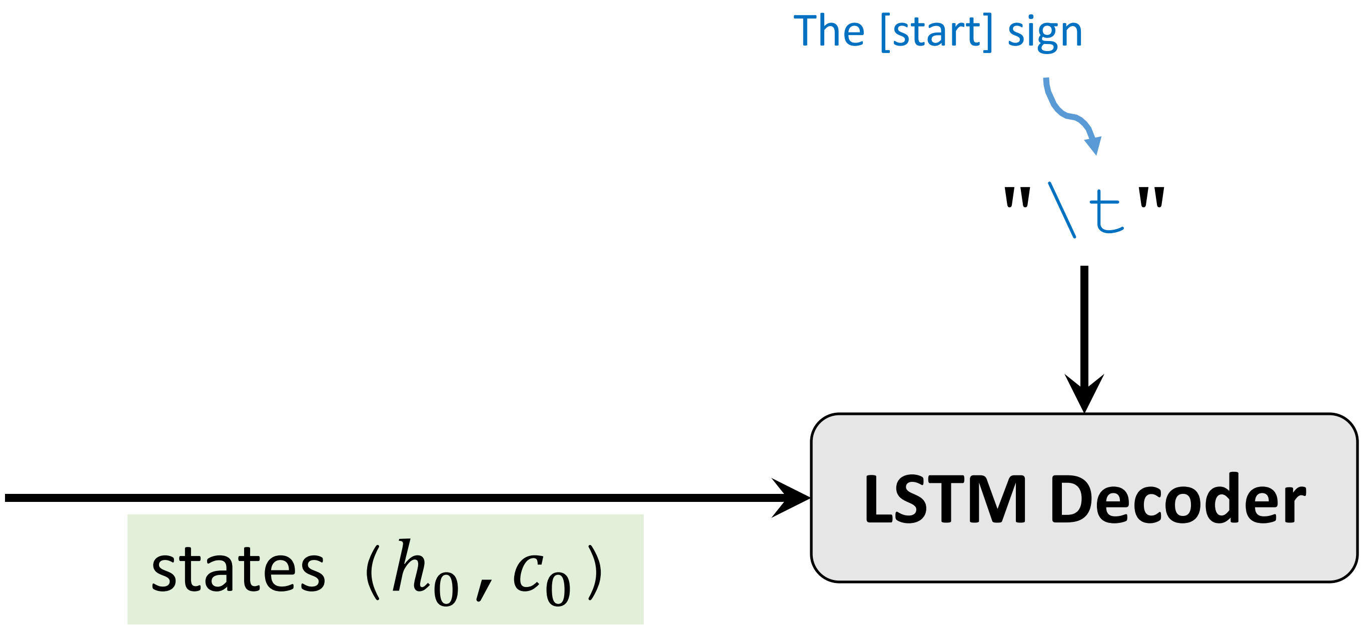

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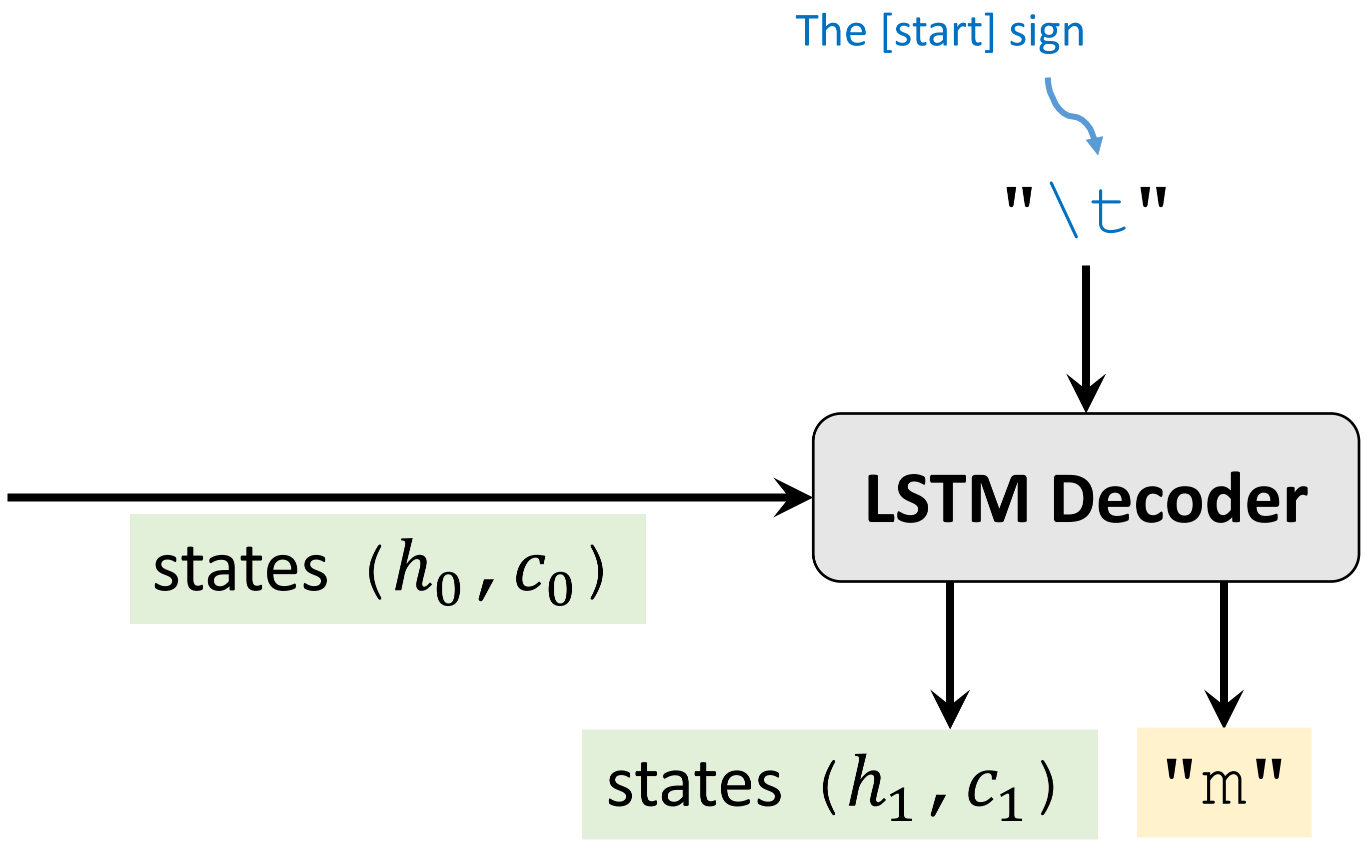
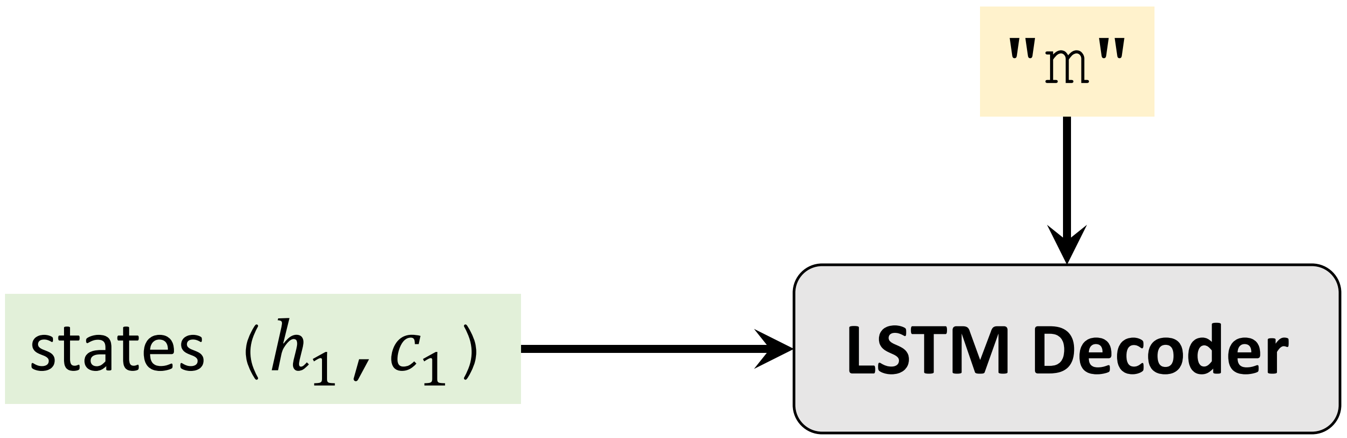


Record: "m"

Inference



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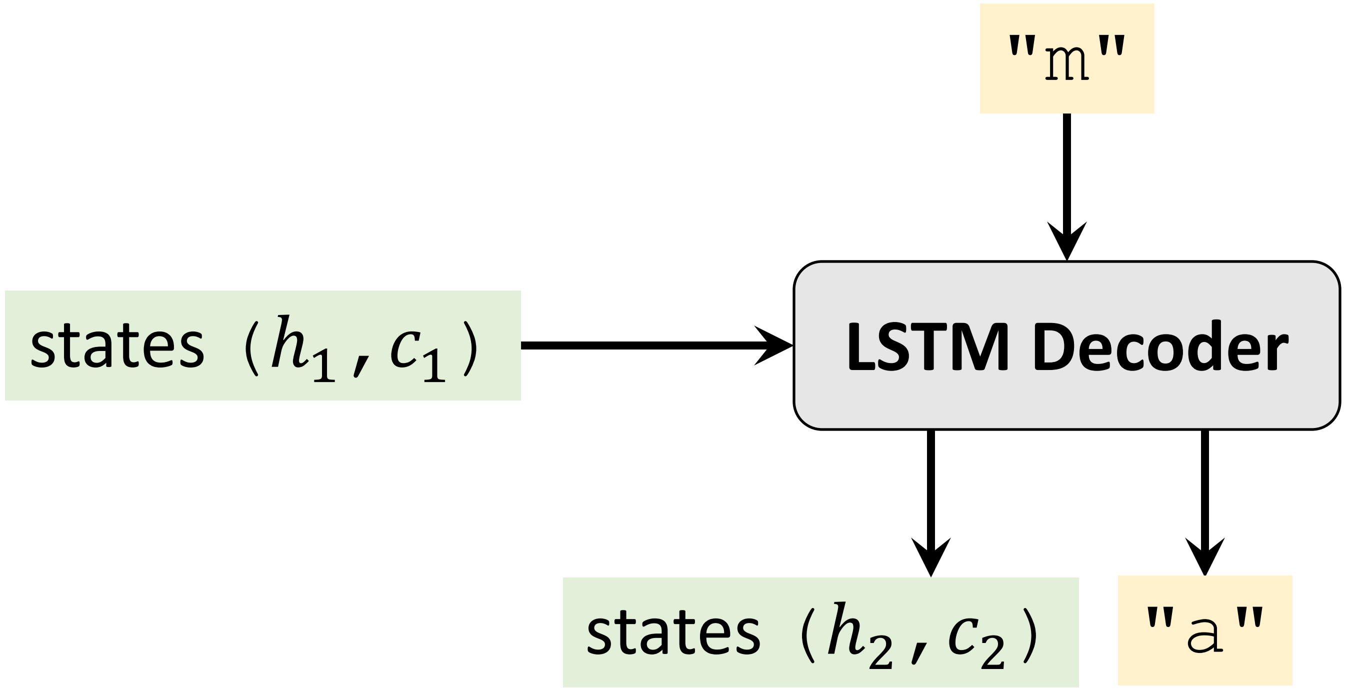

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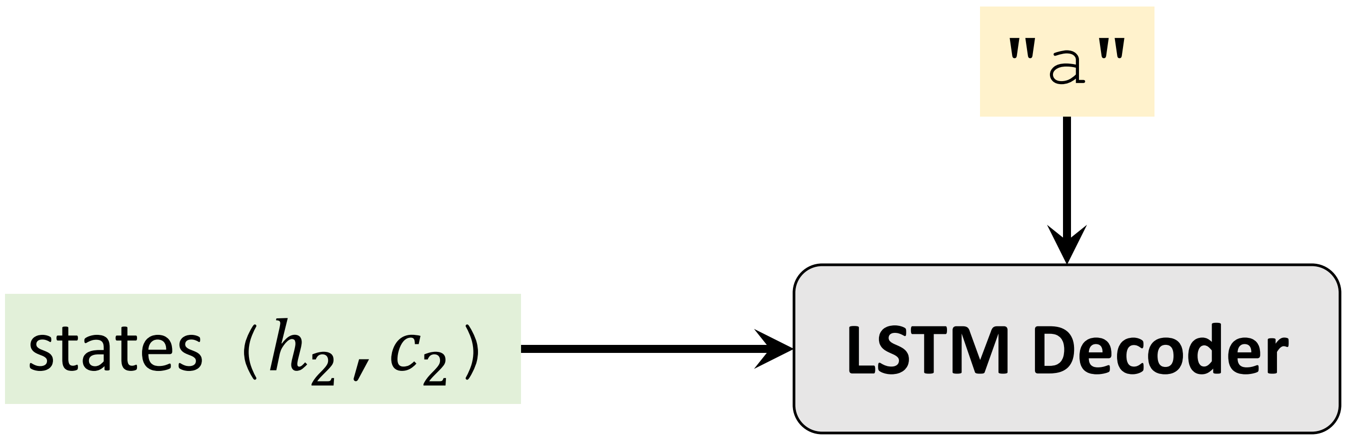

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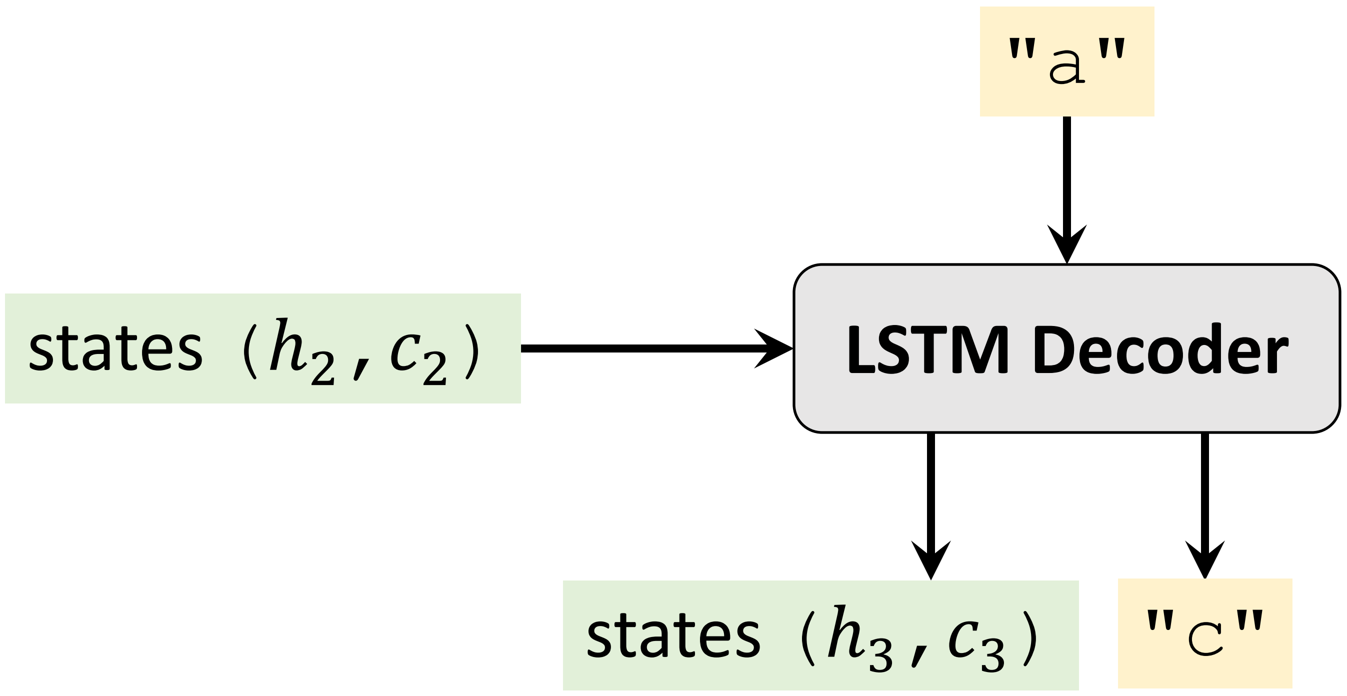
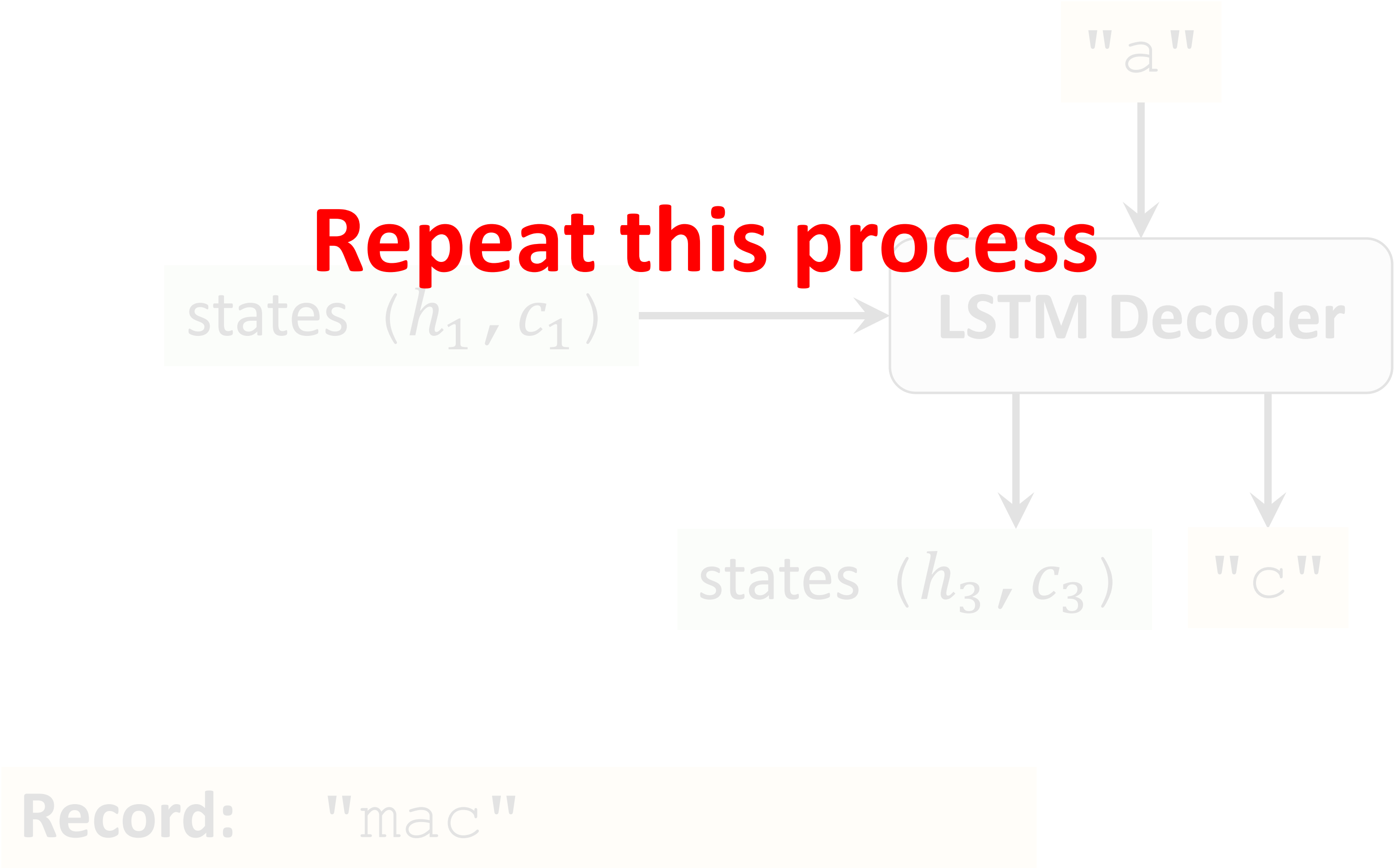


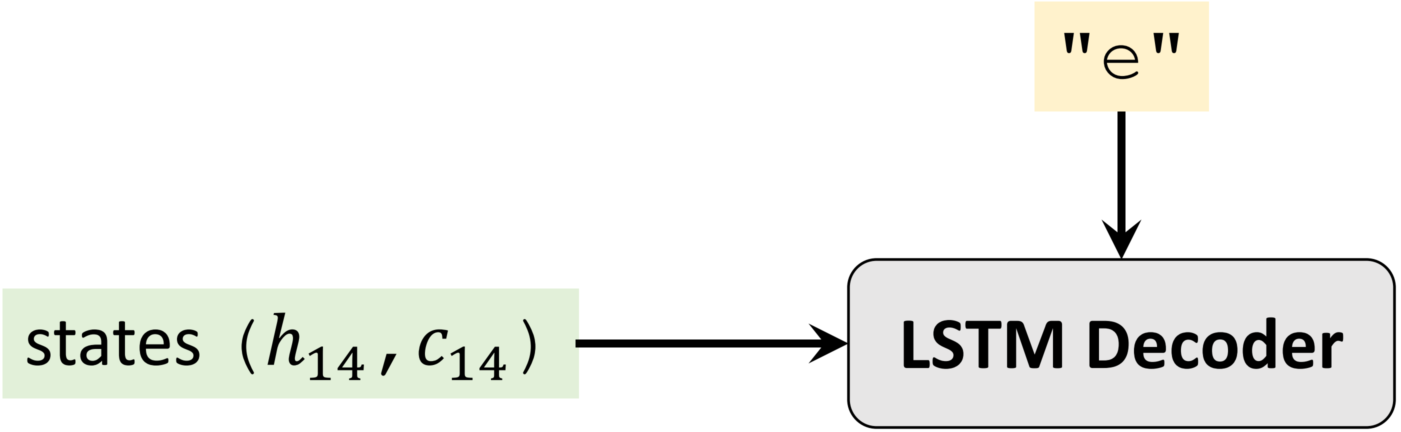
Record: "mac"

Inference

Repeat this process

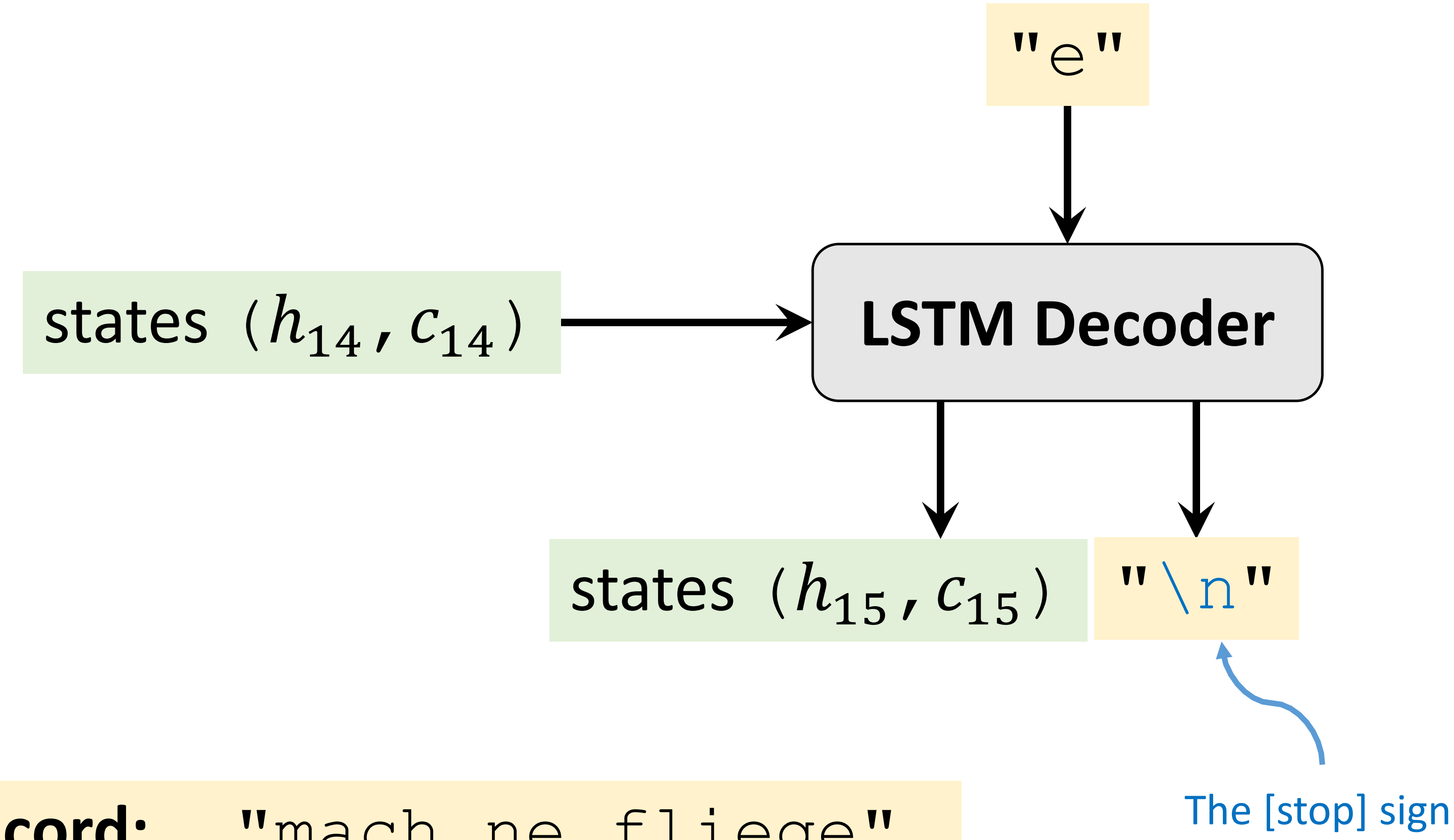


Inference



Record: `"mach ne fliege"`

Inference



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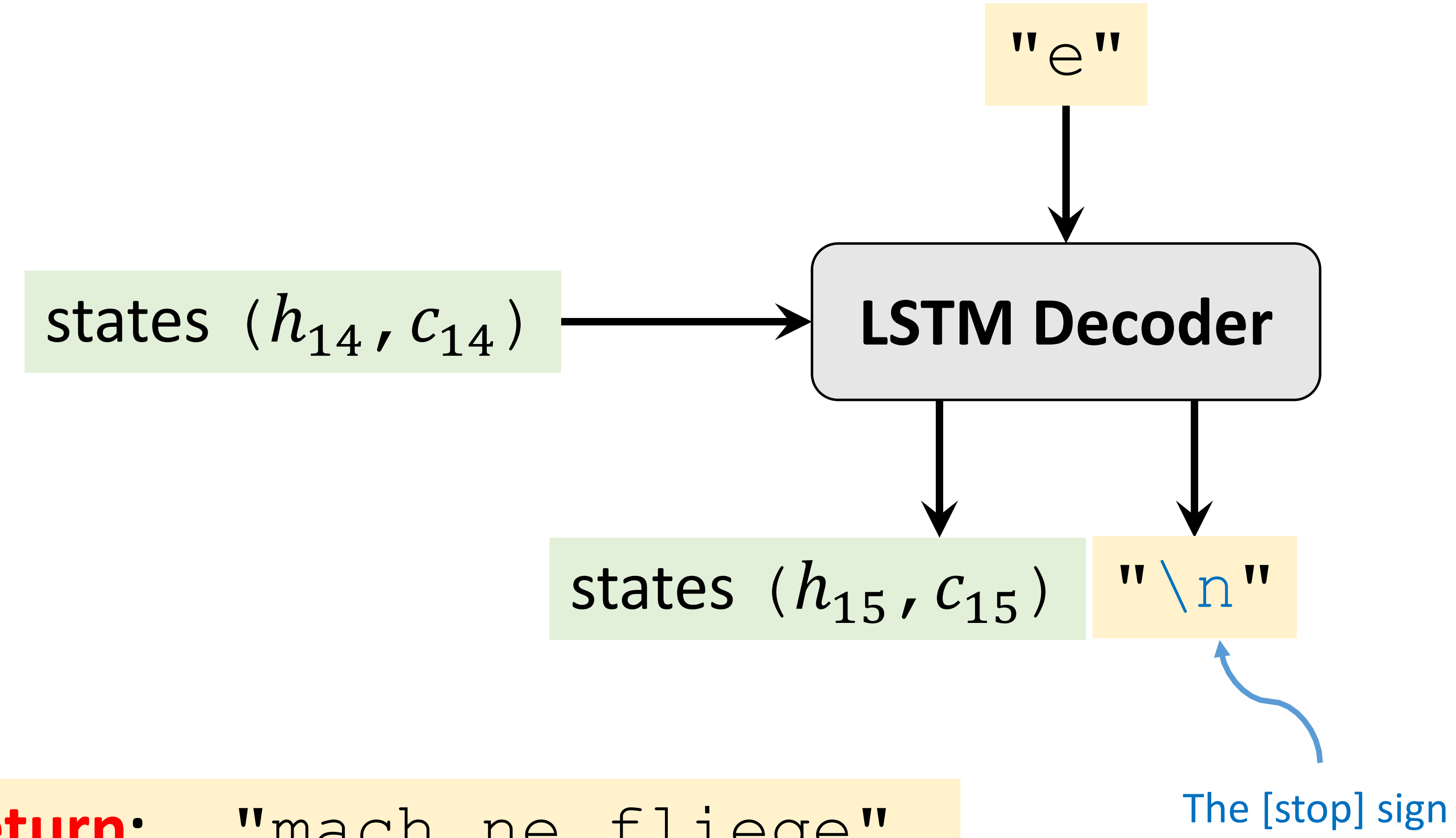
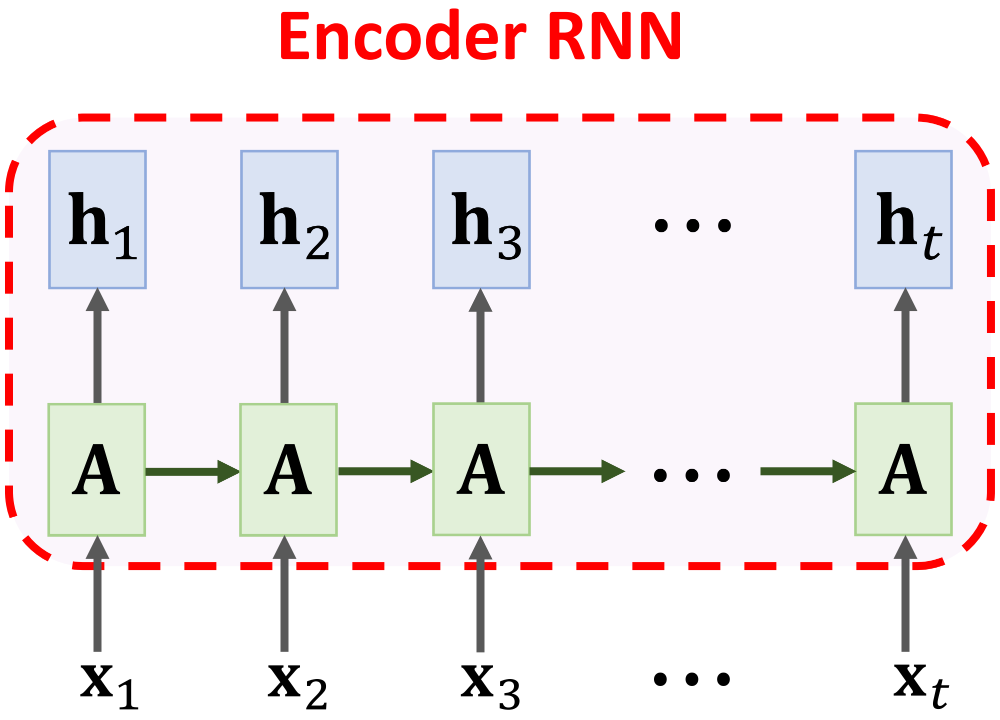


Return: `"mach ne fliege"`

Summary

Seq2Seq Model



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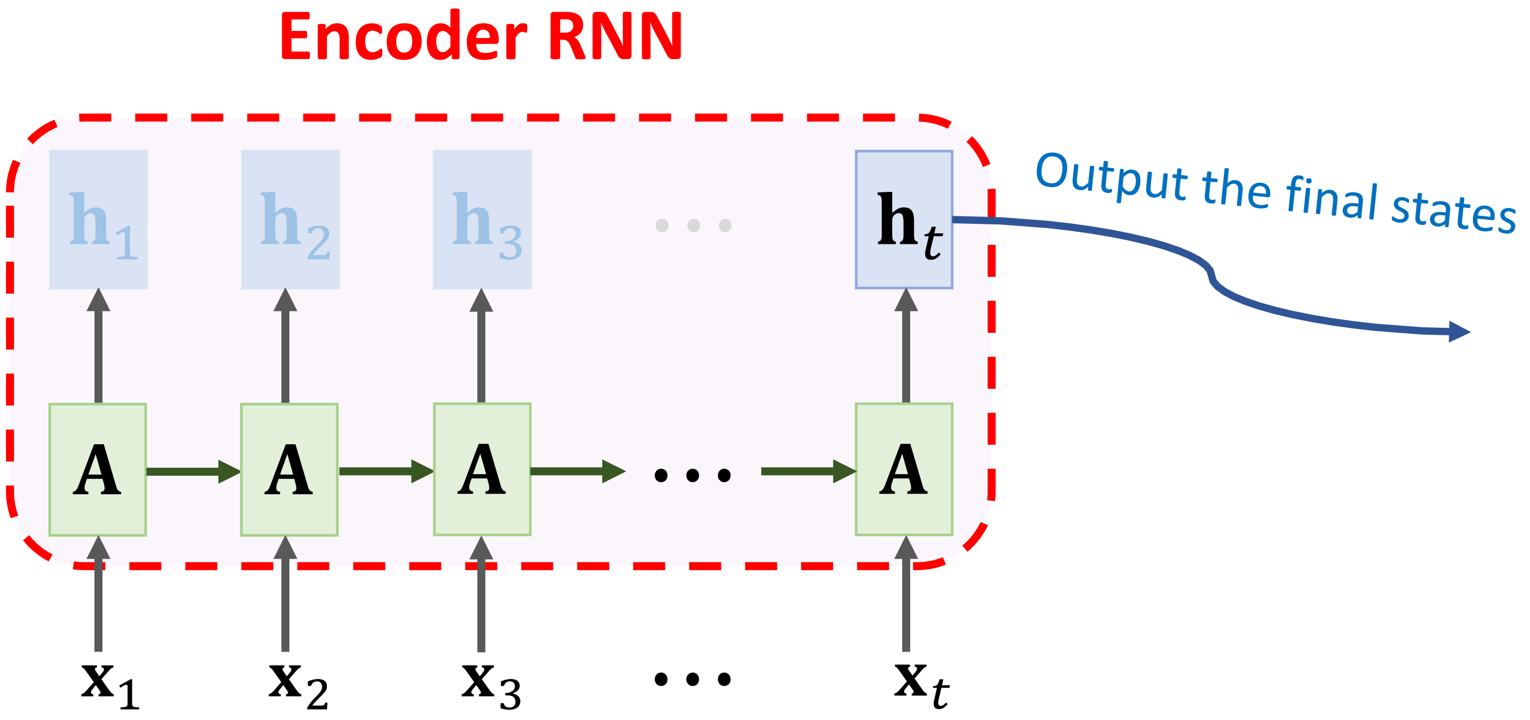

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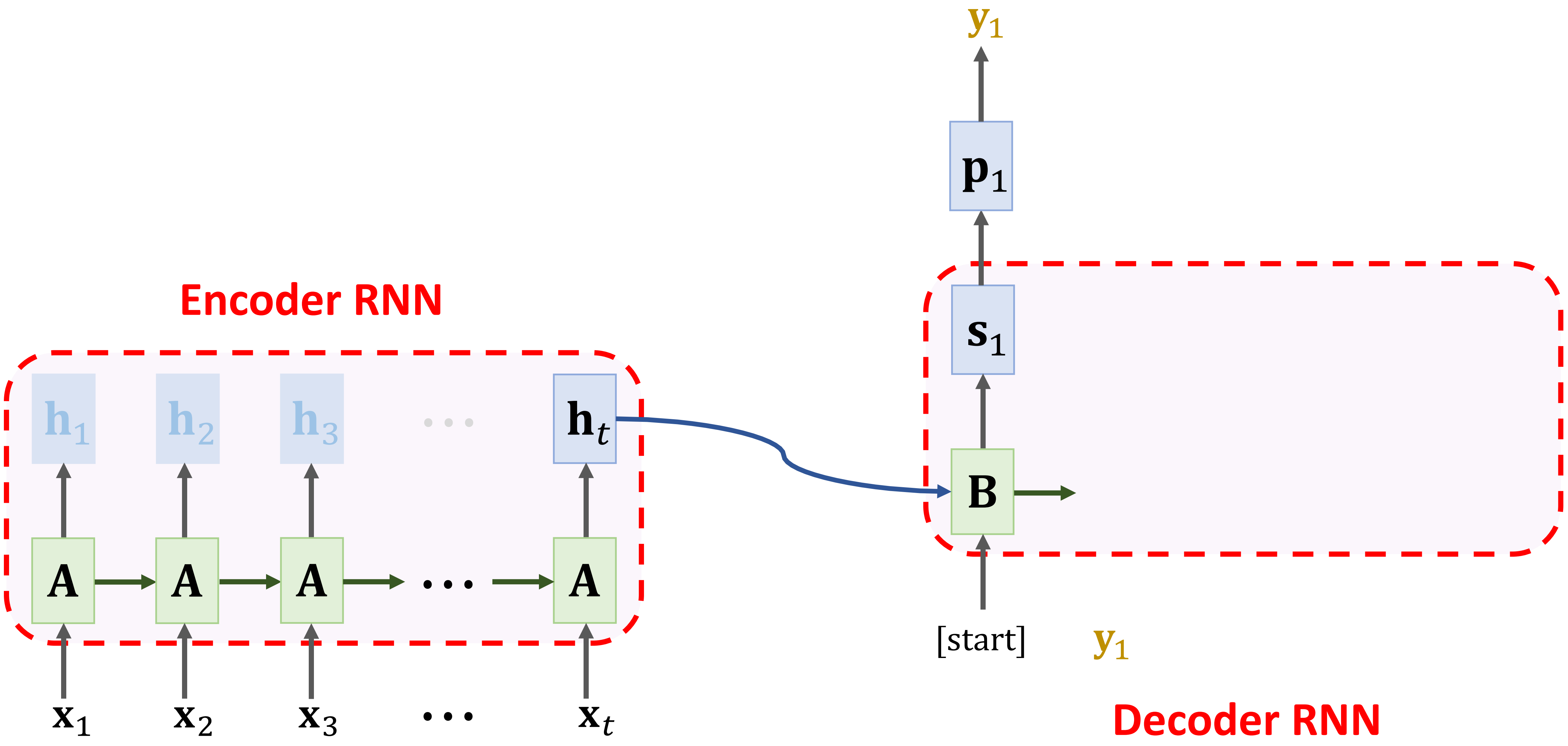

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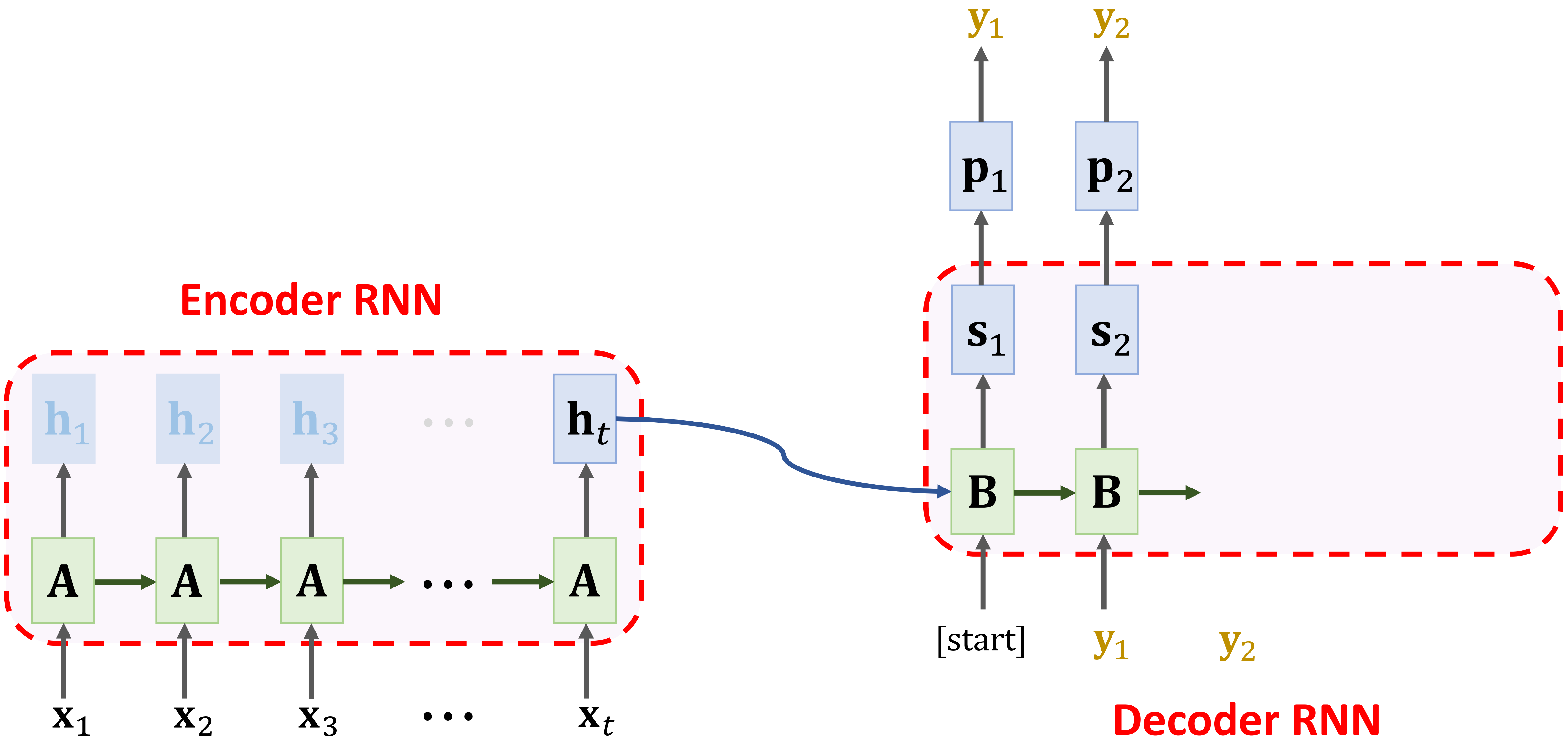

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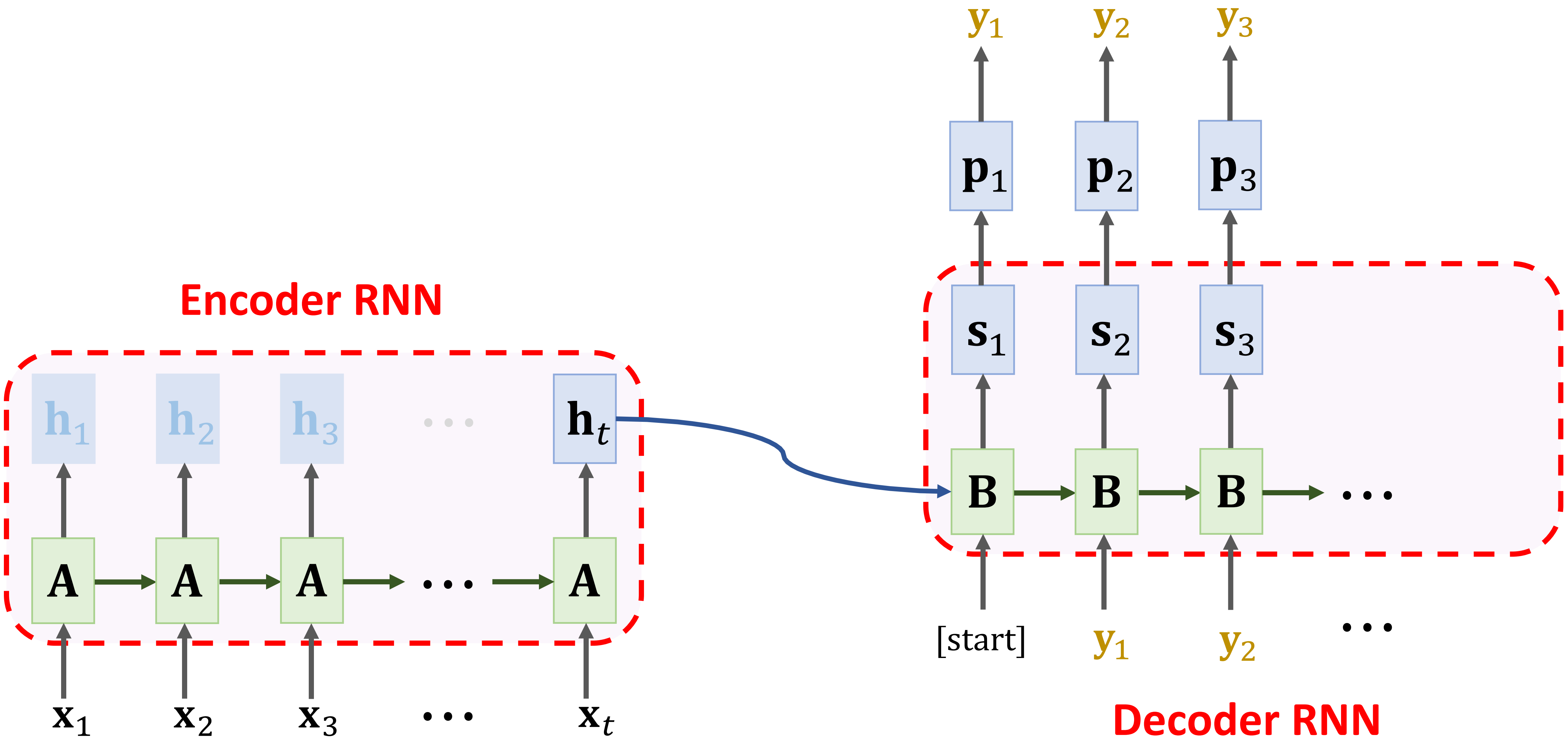

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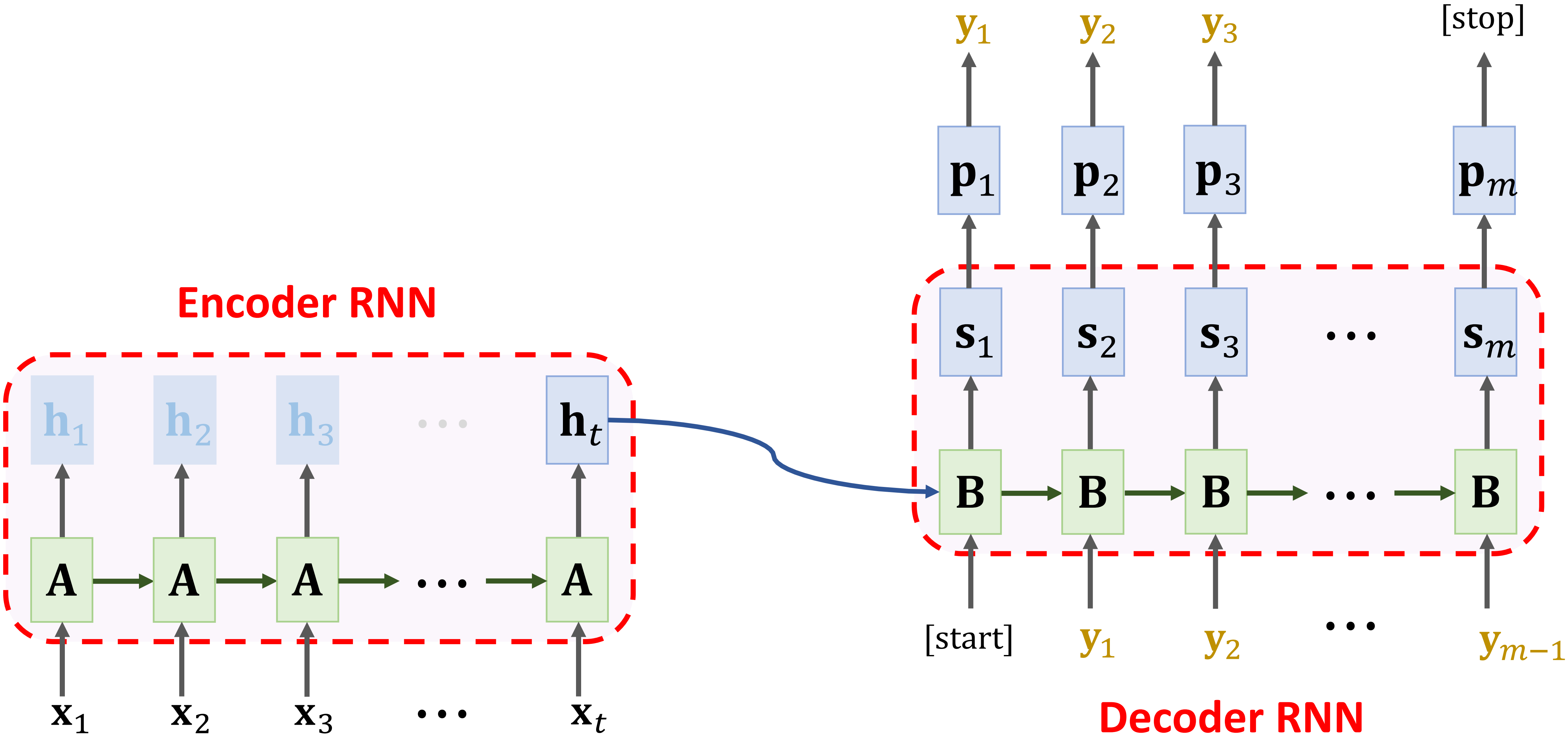
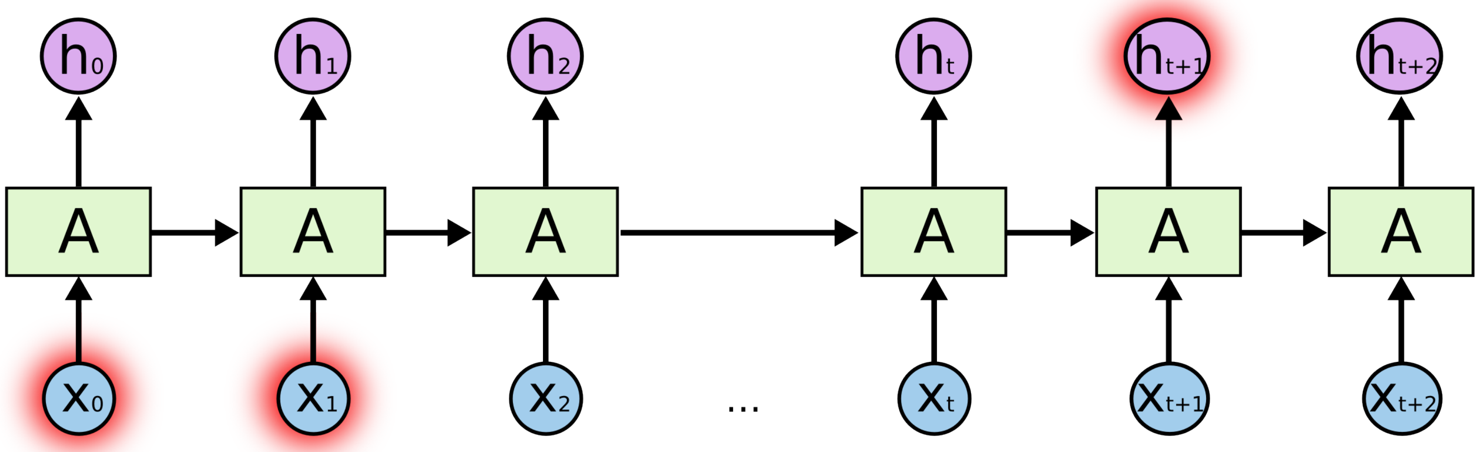


How to Improve?

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

- 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, the final states have forgotten the first tokens.



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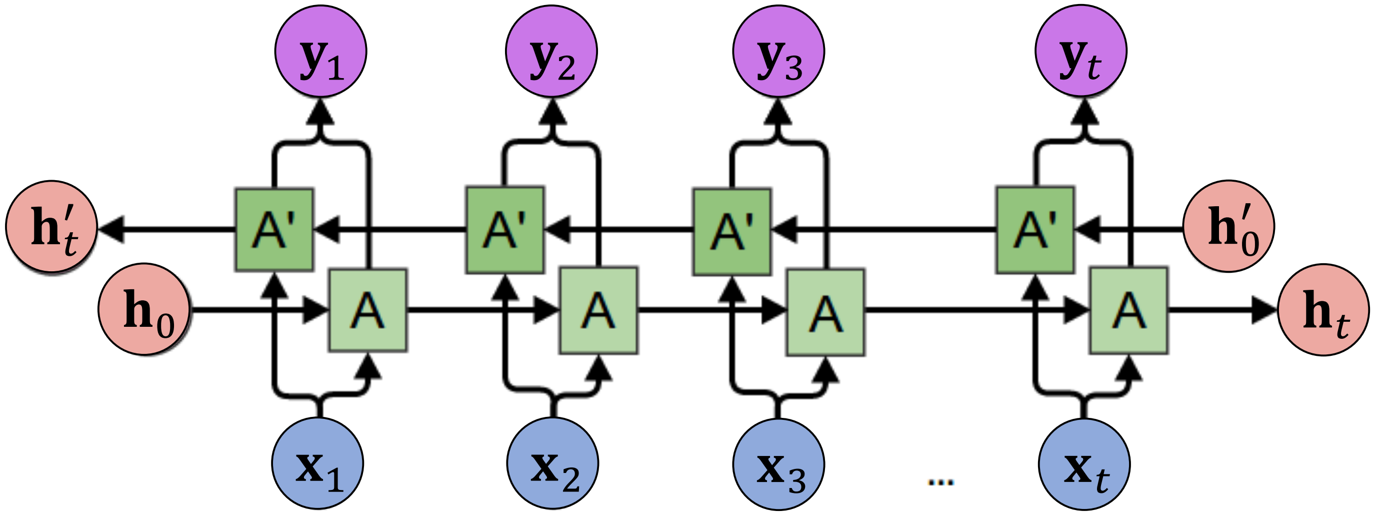

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- The final states ($\mathbf{h}_t$ and $\mathbf{c}_t$) of the Encoder have all the information of the English sentence.
- Really?
  - If the sentence is long, the final states have forgotten the first tokens.
- Bi-LSTM (left-to-right and right-to-left)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

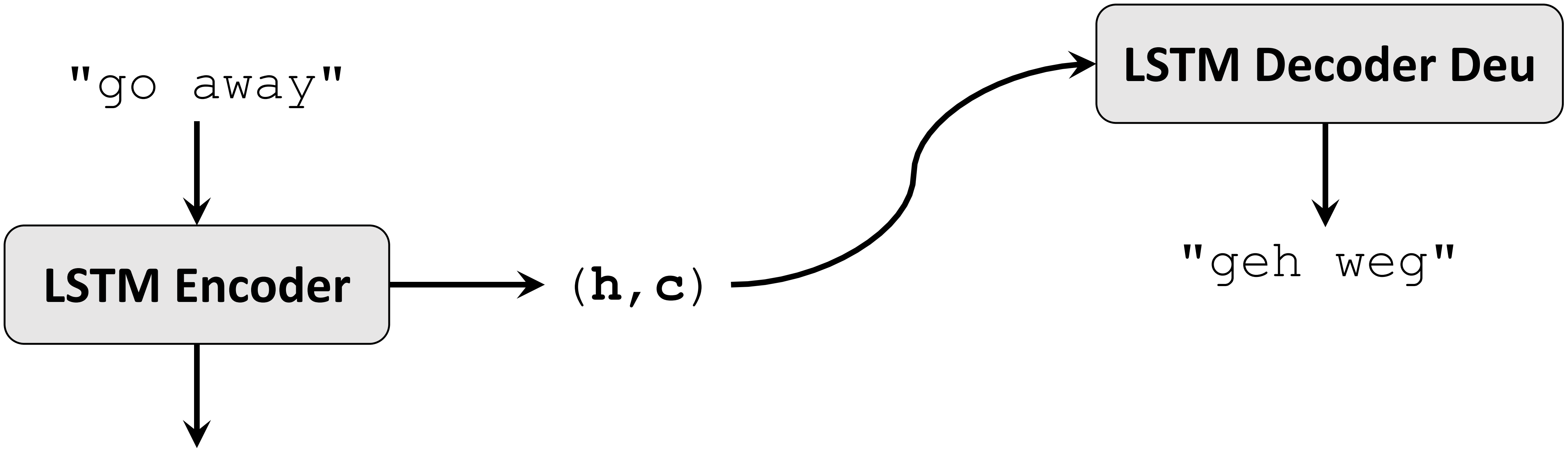
2. Word-Level Tokenization

- 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.
  - 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!

3. Multi-Task Learning



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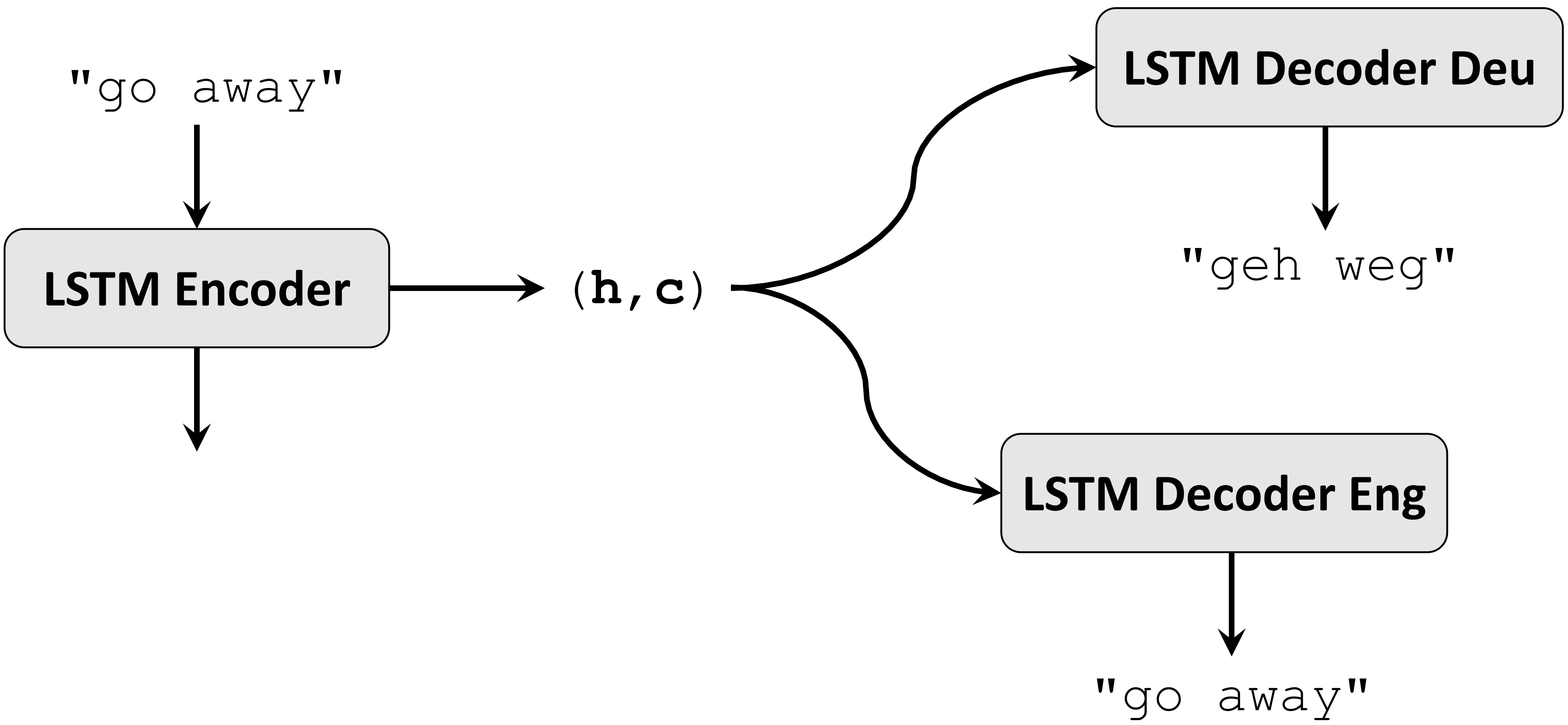


3. Multi-Task Learning

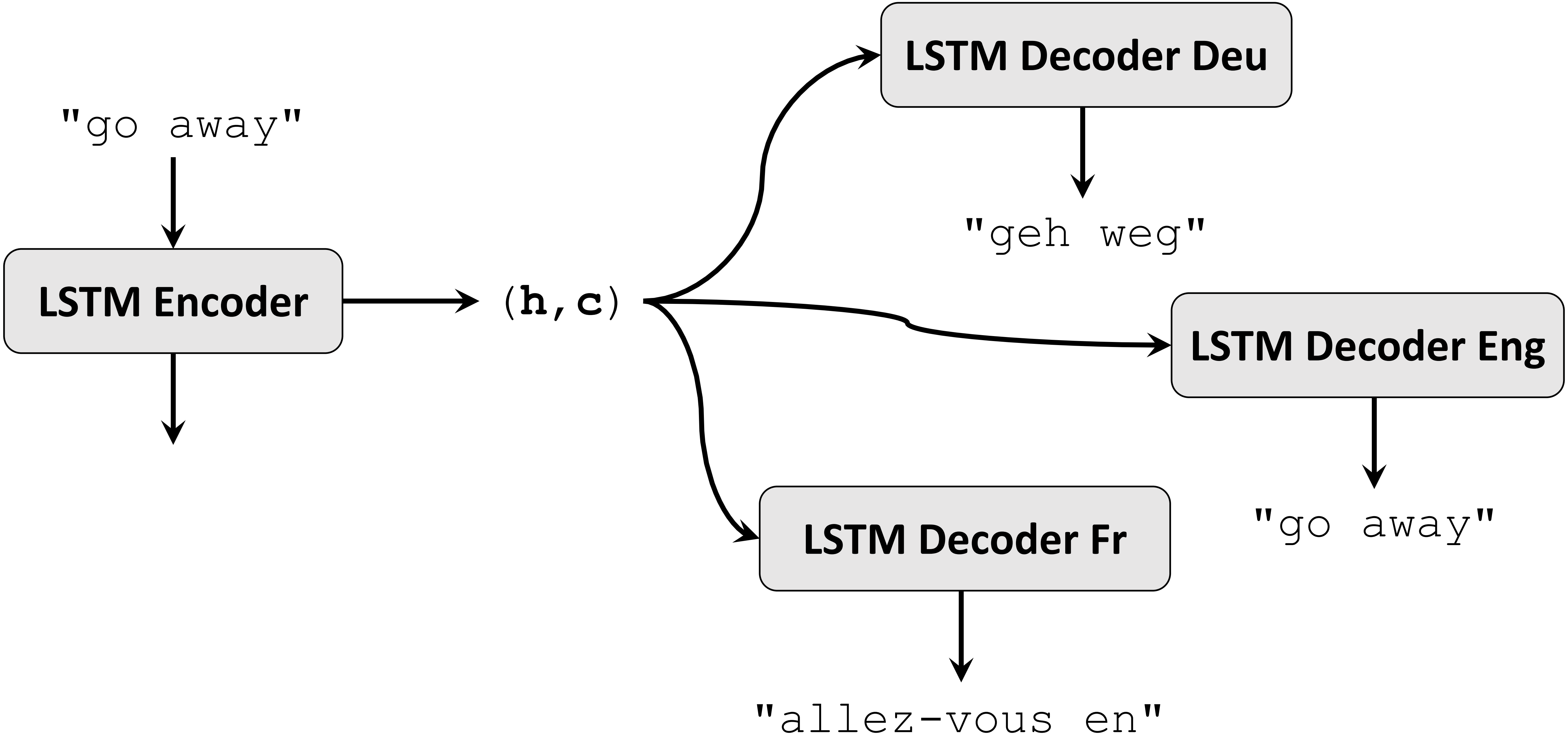
- Even if you want to translate English to German, you can use all the datasets:

- 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.)

Homework 5

- 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, 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/

Homework 5

- You can get up to 2 bonus scores:
  - 1pt: attention
  - 1pt: BLEU score

- You will get a bonus score only if you do it right.
  - E.g., BLEU score should be around 0.1~0.5; over-high or over-low means something is wrong.
  - If your result looks obviously wrong, don't submit; it would be a waste of everyone's time.

Thank you!