Neural Machine Translation

Shusen Wang

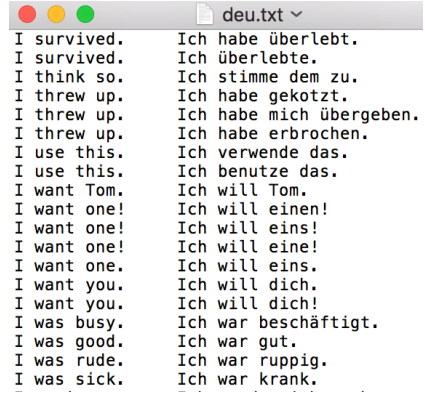
Sequence-to-Sequence Model (Seq2Seq)

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

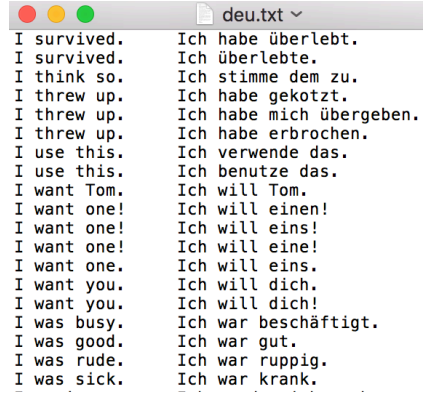
Datasets

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



Processing the Data

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



Processing the Data

- **Preprocessing**: to lower case, remove punctuation, remove non-printable chars.
- Get a list of English-German pairs.

```
for i in range(3000, 3010):
    print('[' + clean_pairs[i, 0] + '] => [' + clean_pairs[i, 1] + ']')
```

```
[my feet hurt] => [meine fue tun weh]
[my feet hurt] => [meine fue taten weh]
[my feet hurt] => [mir tun die fue weh]
[my hip hurts] => [mir tut die hufte weh]
[my jaw hurts] => [mir tut der kiefer weh]
[no one cares] => [niemanden interessierts]
[no one cares] => [niemand kummert sich darum]
[no one cares] => [interessiert niemanden]
[no one knows] => [das wei niemand]
[nobody asked] => [niemand fragte]
```

Processing the Data

- **`input_texts`** : a list of English sentences.
- **`target_texts`**: a list of German sentences (begin with `'\t'` and end with `'\n'`.

```
input_texts = clean_pairs[:, 0]
target_texts = ['\t' + text + '\n' for text in clean_pairs[:, 1]]
```

```
input_texts[3000]
```

```
'my feet hurt'
```

```
target_texts[3000]
```

```
'\tmeine fue tun weh\n'
```

Tokenize the Texts in the Character Level

- `input_texts => [Eng_Tokenizer] => encoder_input_seq`
- `target_texts => [Deu_Tokenizer] => decoder_input_seq`

Use 2 different tokenizers for the 2 languages

Tokenize the Texts in the Character Level

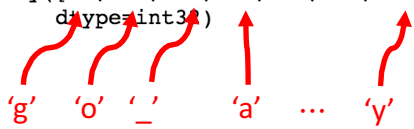
- `input_texts => [Eng_Tokenizer] => encoder_input_seq`
- `target_texts => [Deu_Tokenizer] => decoder_input_seq`

```
input_texts[100]
```

```
'go away'
```

```
encoder_input_seq[100]
```

```
array([17,  4,  1,  7, 16,  7, 15,  0,  0,  0,  0,  0,  0,  0,  0],
      dtype=int32)
```



Zero-padding: make all the sequences the same length.

Tokenize the Texts in the Character Level

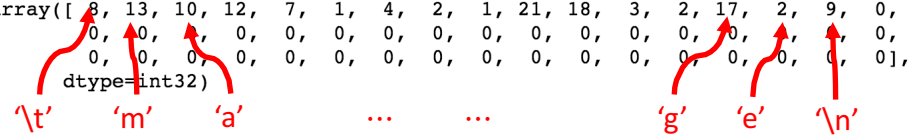
- input_texts => [**Eng_Tokenizer**] => encoder_input_seq
- target_texts => [**Deu_Tokenizer**] => decoder_input_seq

```
target_texts[100]
```

```
'\tmach ne fliege\n'
```

```
decoder_input_seq[100]
```

```
array([ 8, 13, 10, 12,  7,  1,  4,  2,  1, 21, 18,  3,  2, 17,  2,  9,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0],
      dtype=int32)
```



Tokenize the Texts in the Character Level

- `input_texts => [Eng_Tokenizer] => encoder_input_seq`
- `target_texts => [Deu_Tokenizer] => decoder_input_seq`

28: 26 letters, blank, and zero-padding

15-dim vector

15×28 matrix

- One-hot encode the sequences:
- `encoder_input_seq => [one_hot] => encoder_input_data`
- `decoder_input_seq => [one_hot] => decoder_input_data`

51-dim vector

51×30 matrix

30: 26 letters, '\t', '\n', blank, and zero-padding

Summary of the Data Processing

- Raw data: lists of English and German sentences.

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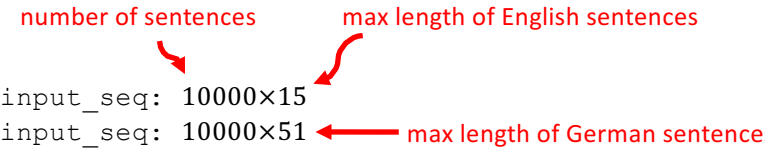
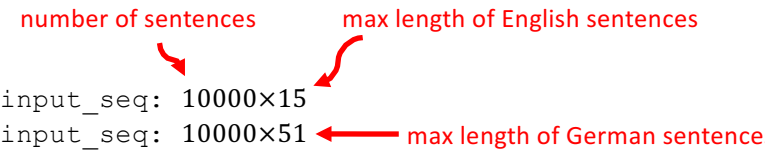


Summary of the Data Processing

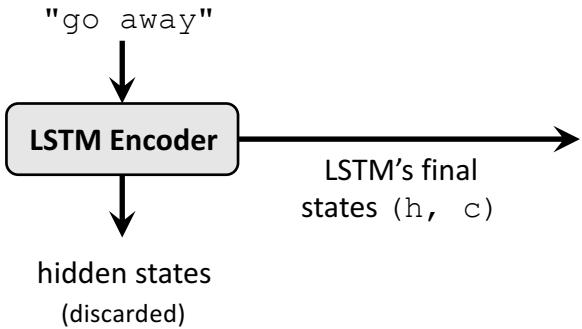
- Raw data: lists of English and German sentences.



- Sequences:
  - `encoder_input_seq`: 10000×15
  - `decoder_input_seq`: 10000×51
- One-hot encode:
  - `encoder_input_data`: 10000×15×28
  - `decoder_input_data`: 10000×51×30

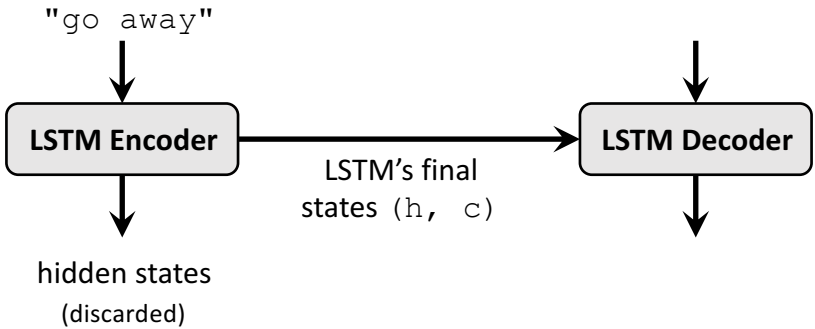
Seq2Seq Model

Training of the Seq2Seq Model

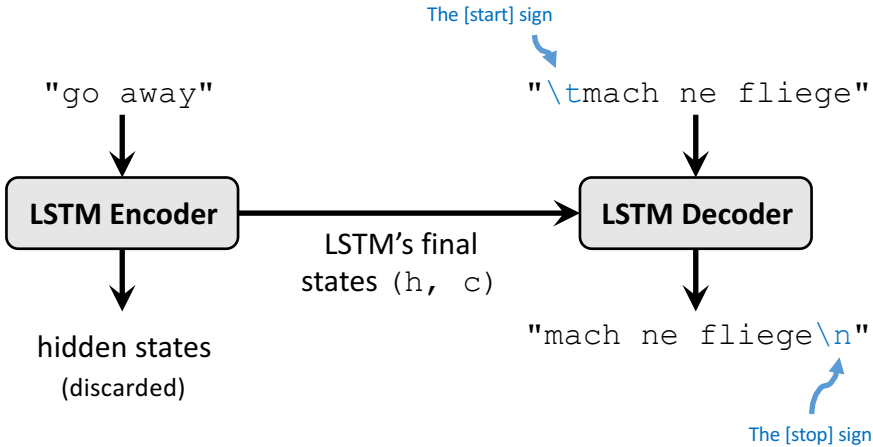


Training of the Seq2Seq Model

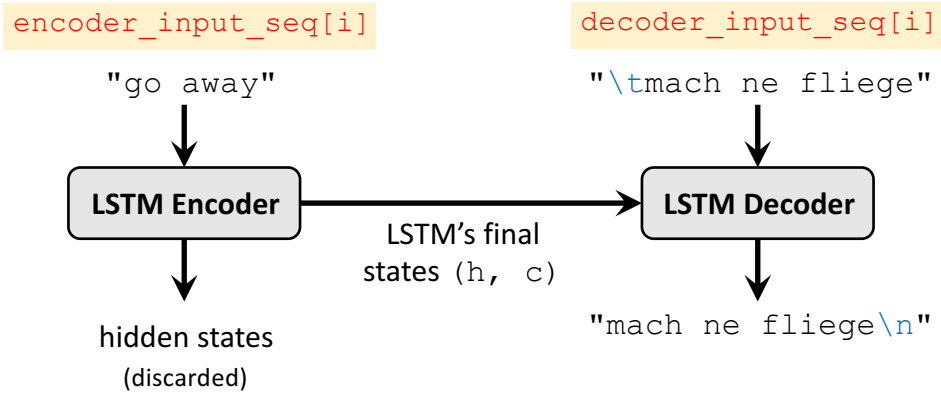
The [start] sign



Training of the Seq2Seq Model



Training of the Seq2Seq Model



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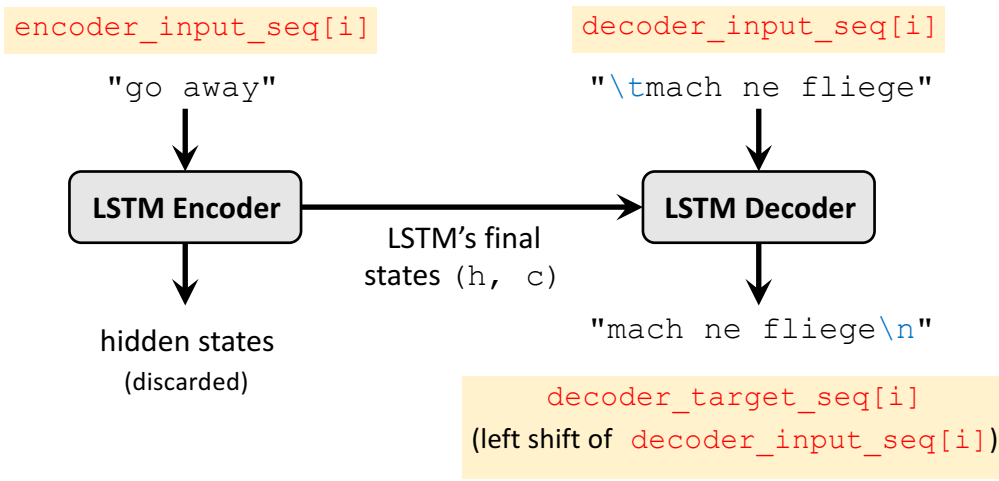
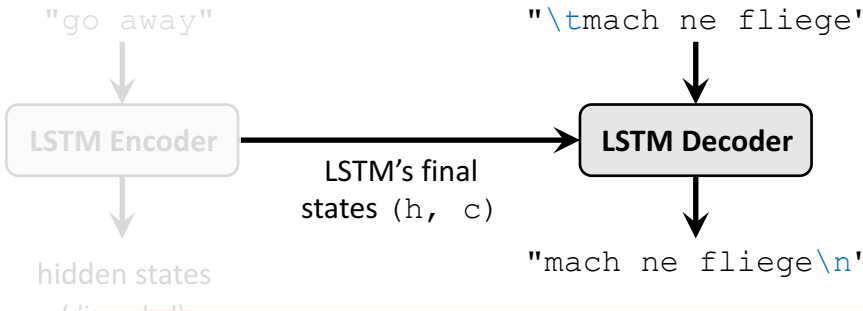


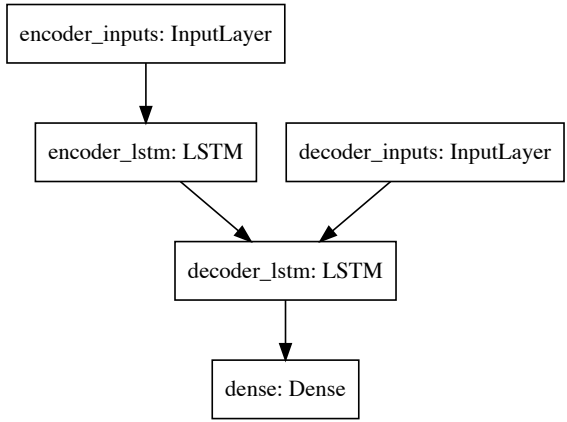
Training of the Seq2Seq Model



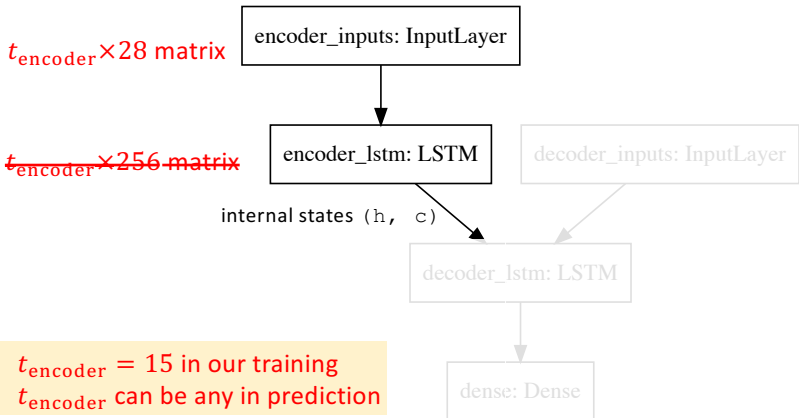
- The decoder is a text generator (in the previous lecture).
- Difference from the simple text generator: the initial states are determined by the encoder.

Seq2Seq Model in Keras

Implementation Using Keras



Encoder Network



- $t_{encoder} = 15$ in our training
- $t_{encoder}$ can be any in prediction

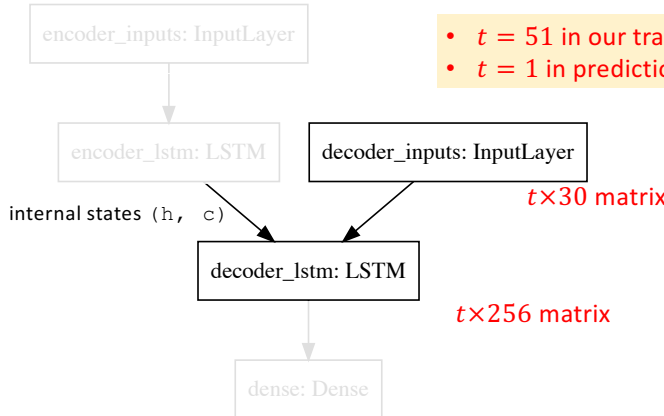
Encoder Network

```
from keras.layers import Input, LSTM


latent_dim = 256
                                                    num_encoder_tokens = 28 in our experiment
encoder_inputs = Input(shape=(None, num_encoder_tokens), name='encoder_inputs')

encoder_lstm = LSTM(latent_dim, return_state=True,
                    dropout=0.5, name='encoder_lstm')
_, state_h, state_c = encoder_lstm(encoder_inputs)
 discarded
encoder_states = [state_h, state_c]
```

Decoder Network



- $t = 51$ in our training
- $t = 1$ in prediction

$t \times 30$ matrix

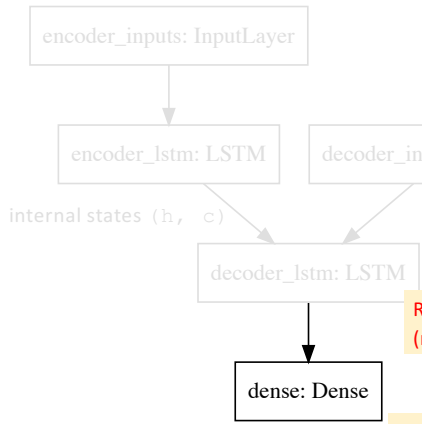
$t \times 256$ matrix

Decoder Network

```
from keras.layers import Input, LSTM


latent_dim = 256
                                                    num_decoder_tokens = 30 in our experiment
decoder_inputs = Input(shape=(None, num_decoder_tokens), name='decoder_inputs')
                                                    Return h_1, ..., h_t
decoder_lstm = LSTM(latent_dim, return_sequences=True,
        Return h_t and c_t return_state=True, dropout=0.5, name='decoder_lstm')
decoder_outputs, _, _ = decoder_lstm(decoder_inputs, initial_state=encoder_states)
                                                                  From the encoder network
```

The Dense Output Layer (Softmax Classifier)



- $t = 51$ in our training
- $t = 1$ in prediction

Return all the hidden states $\mathbf{h}_1, \cdots, \mathbf{h}_t \in \mathbb{R}^{256}$ (make a $t \times 256$ matrix)

Return probability distributions $\mathbf{p}_1, \cdots, \mathbf{p}_t \in \mathbb{R}^{30}$ (make a $t \times 30$ matrix)

The Dense Output Layer (Softmax Classifier)

```
from keras.layers import Input, LSTM, Dense
from keras.models import Model

latent_dim = 256

decoder_inputs = Input(shape=(None, num_decoder_tokens), name='decoder_inputs')

decoder_lstm = LSTM(latent_dim, return_sequences=True,
                    return_state=True, dropout=0.5, name='decoder_lstm')
decoder_outputs, _, _ = decoder_lstm(decoder_inputs, initial_state=encoder_states)
                        num_decoder_tokens = 30 in our experiment
decoder_dense = Dense(num_decoder_tokens, activation='softmax', name='dense')
decoder_outputs = decoder_dense(decoder_outputs)


model = Model([encoder_inputs, decoder_inputs], decoder_outputs)
```

The Dense Output Layer (Softmax Classifier)

```
from keras.layers import Input, LSTM, Dense
from keras.models import Model

latent_dim = 256

decoder_inputs = Input(shape=(None, num_decoder_tokens), name='decoder_inputs')

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decoder_dense = Dense(num_decoder_tokens, activation='softmax', name='dense')
decoder_outputs = decoder_dense(decoder_outputs)


model = Model([encoder_inputs, decoder_inputs], decoder_outputs)
```

Connect the Whole Network

```
from keras.layers import Input, LSTM, Dense
from keras.models import Model

latent_dim = 256

decoder_inputs = Input(shape=(None, num_decoder_tokens), name='decoder_inputs')
decoder_lstm = LSTM(latent_dim, return_sequences=True,
                    return_state=True, dropout=0.5, name='decoder_lstm')
decoder_outputs, _, _ = decoder_lstm(decoder_inputs, initial_state=encoder_states)

decoder_dense = Dense(num_decoder_tokens, activation='softmax', name='dense')
decoder_outputs = decoder_dense(decoder_outputs)

model = Model([encoder_inputs, decoder_inputs], decoder_outputs)
```

One-hot encode of a German sentence.

Probability distributions. (Predictions for the next chars.)

One-hot encode of an English sentence.

Training

```
model.compile(optimizer='rmsprop', loss='categorical_crossentropy')

model.fit([encoder_input_data, decoder_input_data], decoder_target_data,
          batch_size=64, epochs=50, validation_split=0.2)
```

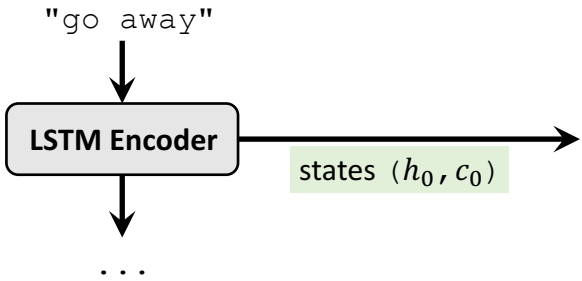
```
Train on 8000 samples, validate on 2000 samples
Epoch 1/50
8000/8000 [==============================] - 17s 2ms/step - loss: 1.2445 - val_loss: 1.2276
Epoch 2/50
8000/8000 [==============================] - 18s 2ms/step - loss: 0.9616 - val_loss: 0.9512
```



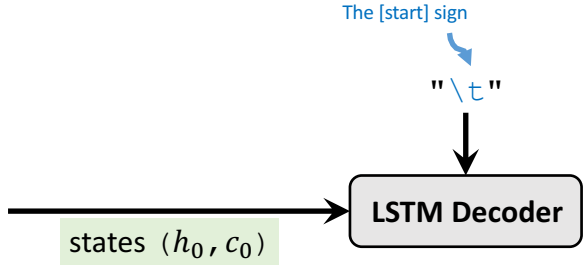
```
Epoch 49/50
8000/8000 [==============================] - 22s 3ms/step - loss: 0.3637 - val_loss: 0.4842
Epoch 50/50
8000/8000 [==============================] - 22s 3ms/step - loss: 0.3609 - val_loss: 0.4806
```

Inference Using the Seq2Seq Model

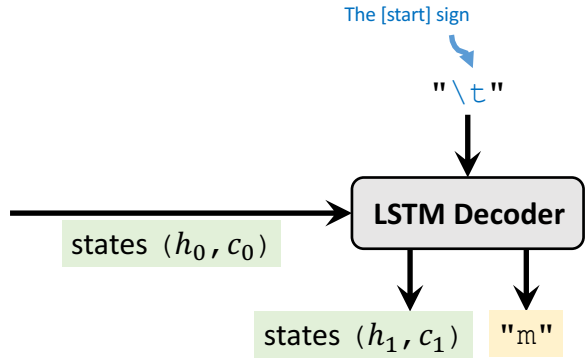
Inference



Inference

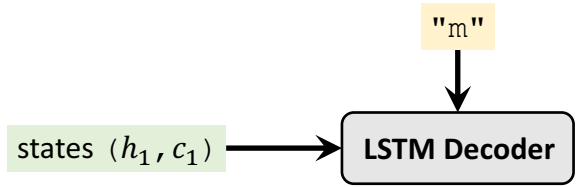


Inference



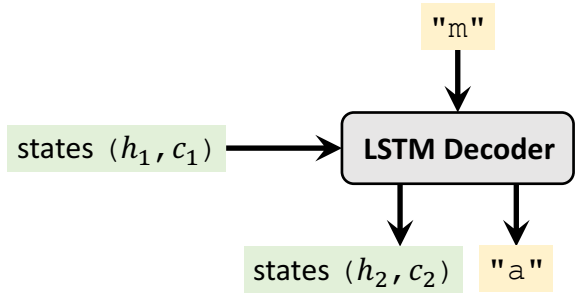
Record: "m"

Inference



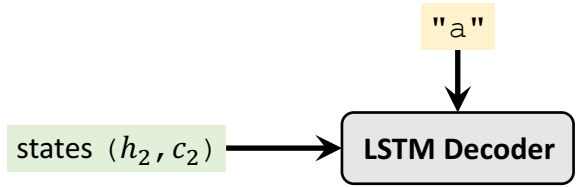
Record: "m"

Inference



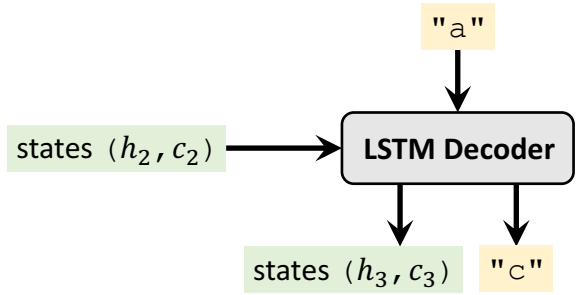
Record: "ma"

Inference



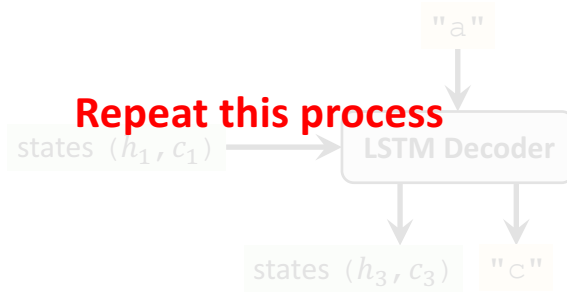
Record: "ma"

Inference

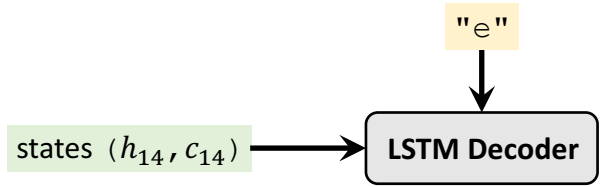


Record: "mac"

Inference

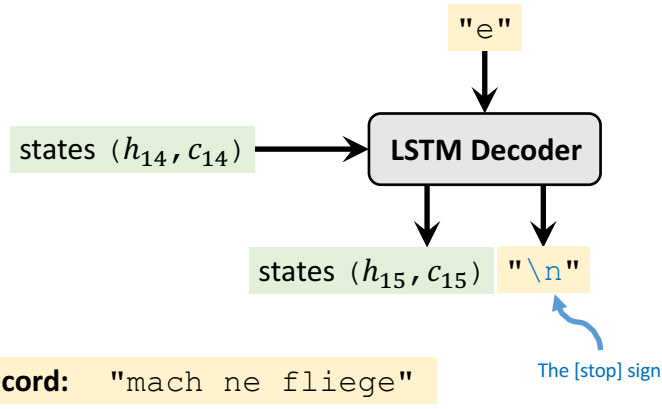

"a"
Repeat this process
states (h_1, c_1)
LSTM Decoder
states (h_3, c_3)
"c"
Record: "mac"

Inference



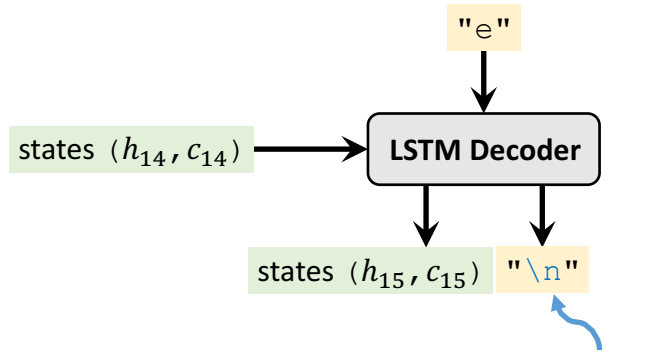
Record: `"mach ne fliege"`

Inference



Record: "mach ne fliege"

Inference



Return: "mach ne fliege"

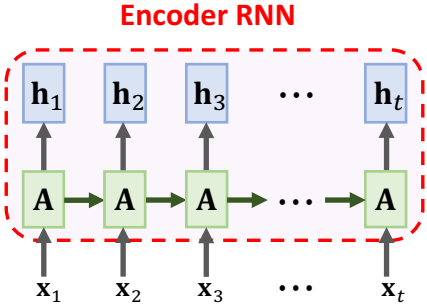
Examples

```
-
English:         go away
German (true):   scher dich weg
German (pred):   verpiss dich
-
English:         go away
German (true):   scher dich fort
German (pred):   verpiss dich
-
English:         go away
German (true):   geh weg
German (pred):   verpiss dich
-
English:         go away
German (true):   verpiss dich
German (pred):   verpiss dich
```

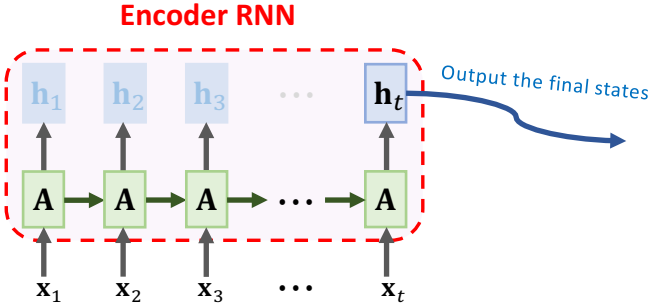
```
-
English:         wait up
German (true):   warten sie mal
German (pred):   warten sie auf
-
English:         wait up
German (true):   wartet mal
German (pred):   warten sie auf
-
English:         wake up
German (true):   wach auf
German (pred):   wachen sie auf
-
English:         wake up
German (true):   wachen sie auf
German (pred):   wachen sie auf
```

Summary

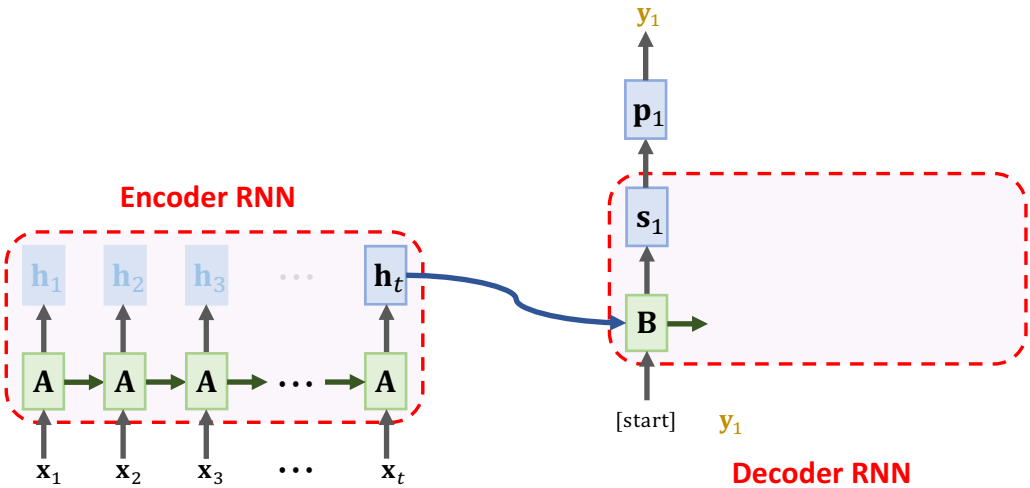
Seq2Seq Model



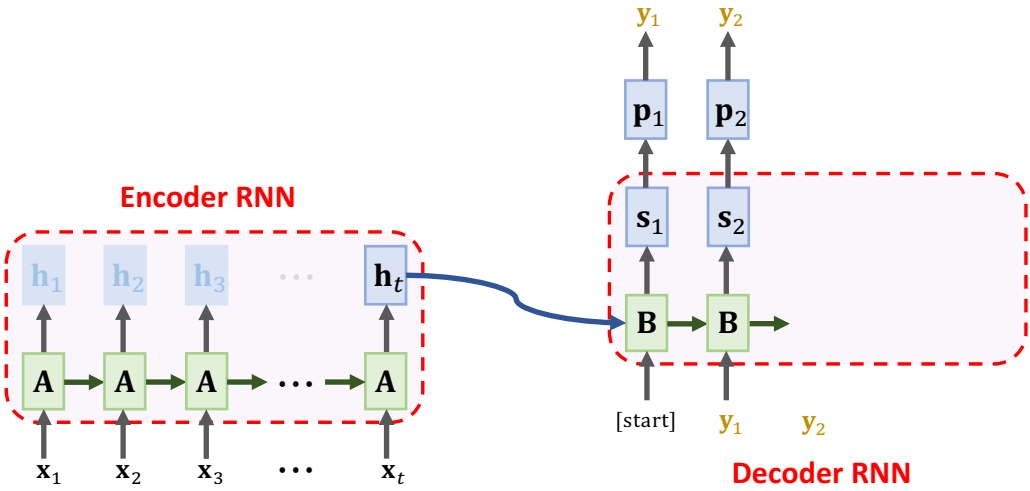
Seq2Seq Model



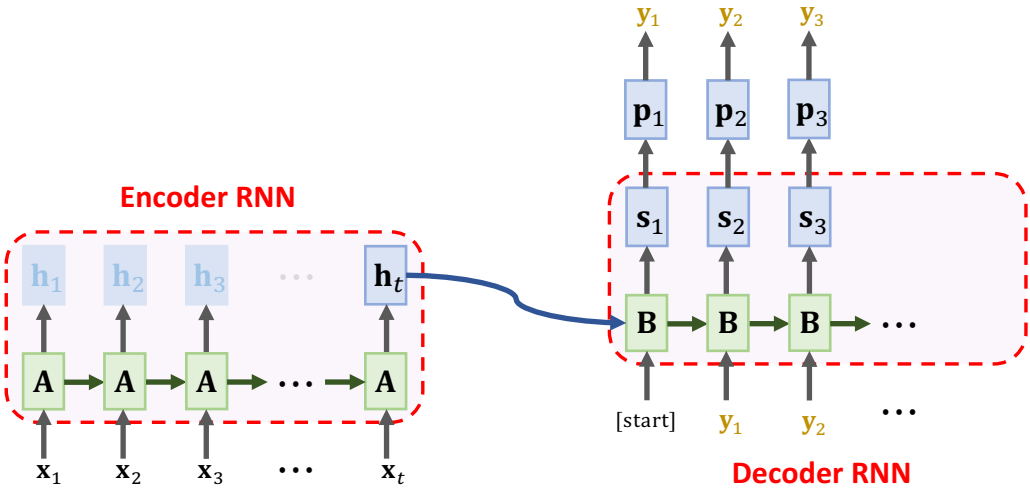
Seq2Seq Model



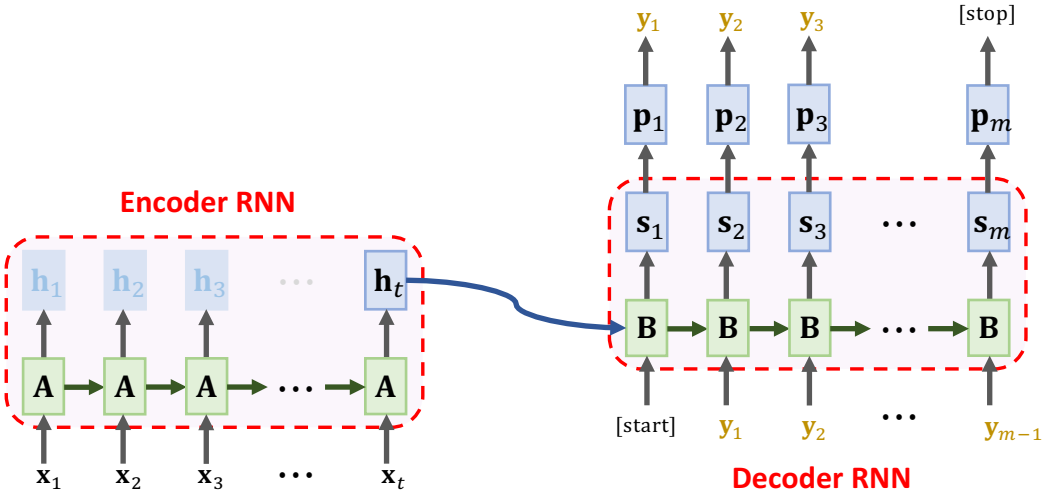
Seq2Seq Model



Seq2Seq Model



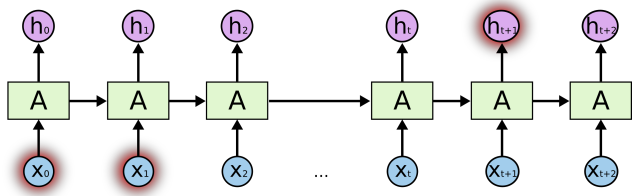
Seq2Seq Model



How to Improve?

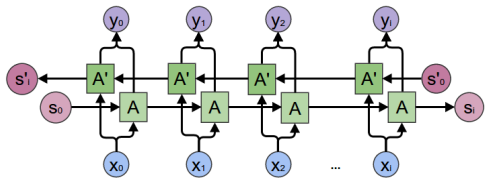
1. Bi-LSTM instead of LSTM

- 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.



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.
- 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.
- But you will need a large dataset!
  - # of (frequently used) chars is ~10^2.
  - # of (frequently used) words is ~10^4.
  - Word Embedding Layer has many parameters ➔ overfitting!

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)

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- 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

- Even if you want to translate English to German, you can use all the datasets.
- [English ==> German], [English ==> French], [English ==> Spanish] …
  - The same Encoder Network.
  - Different Decoder Network.
  - Build 100 seq2seq models sharing the Encoder Network.
  - Train the 100 seq2seq models on the 100 datasets.
- 100x more datasets ➔ better trained Encoder Network.

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! (Next lecture.)

Homework

- Build a seq2seq model for machine translation.
  - Anything languages except for [English ==> German].
  - Data processing, tokenization, build networks, training, and prediction.
  - 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/