

Deep Learning

RNN-based Models (Lab)

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In This Lecture

- RNN-based Models
 - Autocomplete Model
 - Seq2Seq Model
- Word embedding
- Batch generation
- Autoencoder structure



Outline

- Overview
 - ☐ Autocomplete Model
 - ☐ Seq2Seq Model



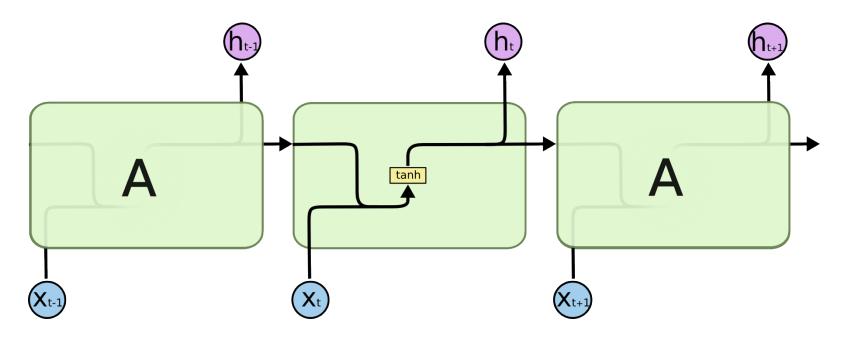
Overview

- There exist various RNN-based models
- Autocomplete model
 - Problem: to finish an incomplete sentence
 - Basic RNN application for sequential data
- Seq2Seq Model
 - Problem: to convert a sequence into another
 - Mixture of an autoencoder and RNN cells



Recurrent Neural Network (RNN)

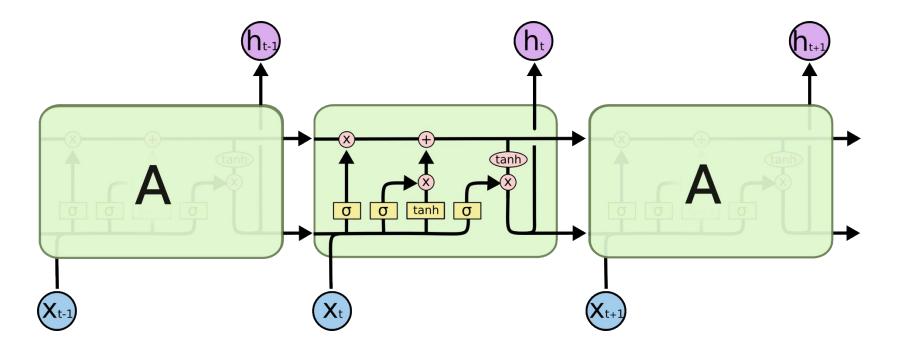
- A deep learning structure for sequential data
- Contains a cell, which is a repeated structure
- Stores and passes states through a sequence





Long Short-term Memory (LSTM)

- An advanced RNN structure
- It avoids the long-term dependency problem





Outline

- Overview
- **→** □ Autocomplete Model
 - ☐ Seq2Seq Model



Autocomplete Model (1)

- We'll implement a simple autocomplete model
- It learns a sequence of four words
- Given the first three words, it predicts the last one
- It is called "autocomplete" because it completes the given incomplete sentence

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Autocomplete Model (2)

- For example, it solves the following problem
- Given "I went to," which word will come?

■ School: 95%

□ John: 3%

□ Me: 1%

■ Monitor: 1%

- In our model, we use letters instead of words
 - □ For example, given "lov" which letter will come next?



Import Statements

Let's import tensorflow keras packages and numpy

```
import numpy as np
from tensorflow.keras import layers, Sequential, losses, optimizers
```



Word Embedding (1)

- We want to implement a language model
- But, a computer cannot take word inputs
 - It prefers numerical values, not strings
- We need to convert words into vectors



Word Embedding (2)

We generate a character pool as follows:

- These are all the letters we should consider
- We build a simple dictionary for conversion



Training Data

We generate the following training data:

- Each string is a sequence of four letters
- Thus, it contains both features and the label
- We have 10 training instances



Batch Generation

We define a function to generate batches:

```
def make_batch(seq_data):
    input_batch, target_batch = [], []

for seq in seq_data:
    input = [num_dic[n] for n in seq[:-1]]
    target = num_dic[seq[-1]]
    input_batch.append(np.eye(dic_len)[input])
    target_batch.append(target)

return np.array(input_batch, dtype=np.float32), np.array(target_batch, dtype=np.int32)
```

target_batch contains the last letters



Hyperparameters

We set hyperparameters of the model:

```
learning_rate = 0.01
n_hidden = 128
total_epoch = 30
n_step = 3
n_input = n_class = dic_len
```



Outline

- Overview
- Autocomplete Model
- **→** □ Seq2Seq Model



Seq2Seq Model (1)

- We'll implement a simple seq2seq model
- It is basically an autoencoder model
 - We use the outputs from the middle layer
- We solve the **machine translation** problem
- It is to translate an English word into Korean



Seq2Seq Model (2)

- For example, our model learned "love"
- Then, what would be the meaning of "lovely?"
- Our model should be able to translate words
 - That do not appear in the training set
 - That have variable lengths ("love" and "lovely")



Word Embedding

We generate a character pool as follows:

- char_arr contains all ENG & KOR characters
- num_dic maps a character into an integer



Training Data

We generate the following training data:

- Each instance is a pair of words
 - One is English and the other is Korean
 - Korean words correspond to the labels
- We set the maximum length of a word



Batch Generation (1)

- We use all training data as a single batch
- We need four kinds of data:
 - □ Input data (batch_e) to the encoder
 - Input data (batch_d) to the decoder
 - Target data (batch_y) as ground truth
 - Length (len_y) of the target data
- The last three are needed only for training
 - batch_d, batch_y, len_y



Batch Generation (2)

The input and output of the batch function:

```
def make_batch(seq_data):
   batch_e, batch_d, batch_y, len_y = [], [], [], []

for seq in seq_data:
    pass

return np.array(batch_e), np.array(batch_d), np.array(batch_y), np.array(len_y)
```



Batch Generation (3)

What we actually do at the pass statement

```
input = np.zeros((max_length, dic_len))
output = np.zeros((max_length, dic_len))
target = np.zeros(max_length, dtype=int)
for i, n in enumerate(seq[0]):
    input[i, num_dic[n]] = 1
for i, n in enumerate('S' + seq[1]):
    output[i, num\_dic[n]] = 1
for i, n in enumerate(seq[1] + 'E'):
    target[i] = num_dic[n]
batch e.append(input)
batch_d.append(output)
batch_y.append(target)
len_y.append(len(seq[1]) + 1)
```



Batch Generation (4)

- Each word is represented as a one-hot vector
 - \Box Thus, the shape of *input* and *output* is (n, d)
 - n is the maximum length of a sequence
 - lack d is the number of unique (possible) words
 - It is not necessary for the target sequence

- We add zero vectors to the end of each seq.
 - Because the sequences have variable lengths



Hyperparameters

We set hyperparameters of the model:

```
learning_rate = 0.01
n_hidden = 128
total_epoch = 100
n_class = n_input = dic_len
```



Questions?