Deep Learning II

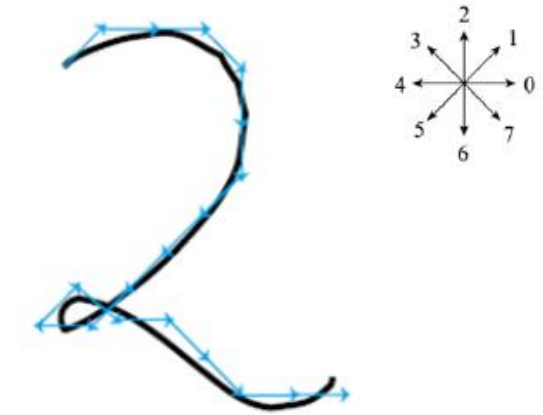
(Recurrent Neural Network, Long Short-term Memory)

Time-series Data

- Applications
  - Prediction or forecasting
    - Stock price forecast for tomorrow
    - Weather forecast for tomorrow
    - Prediction of machine failure
    - Wind speed and wind direction prediction
    - Agricultural price/demand forecast, etc.
  - Apply to language translation
  - Apply to speech recognition
  - Apply to neural engineering (e.g., digital healthcare)
  - Apply to generative models (e.g., view pictures and generate descriptive sentences)

Representation of Time-series Data

- Examples
  - Number and electrocardiogram



x=100766555541707700

(a) 온라인 숫자

(b) 심전도 신호(3채널)

Representation of Time-series Data

❖ Characteristics

- The order of the elements is important
  - e. g., “세상에는 시계열 데이터가 참 많다 " 를 “시계열 참 데이터가 많다 세상에는 " 으로 바꾸면 의미 훼손
- Sample length is different
  - e. g., 짧은 발음 “인공지능 " 과 긴 발음 “인~공~~지~능 "
- Context dependence
  - e. g., “시계열은 앞에서 말한 바와 … 특성이 있다 " 에서 “시계열은 " 과 “특성이 있다 " 는 밀접한 관련성
- Seasonality
  - e. g., 상추 판매량, 미세먼지 수치, 항공권 판매량 등

Representation of Time-series Data

- Notation
  - Vector of vector

$$\mathbf{x} = \left(\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, \cdots, \mathbf{x}^{(T)}\right)^{\mathrm{T}}$$

  - E.g., , electroencephalogram signals:

    (If the data were recorded for 100 times per second and were measure it for 2 minutes, the length is T=12,000)

$$\mathbf{x} = \left(\begin{pmatrix}0.3\\0.1\\0.2\end{pmatrix}, \begin{pmatrix}0.5\\0.6\\0.4\end{pmatrix}, \cdots \cdots\right)^{\mathrm{T}}$$

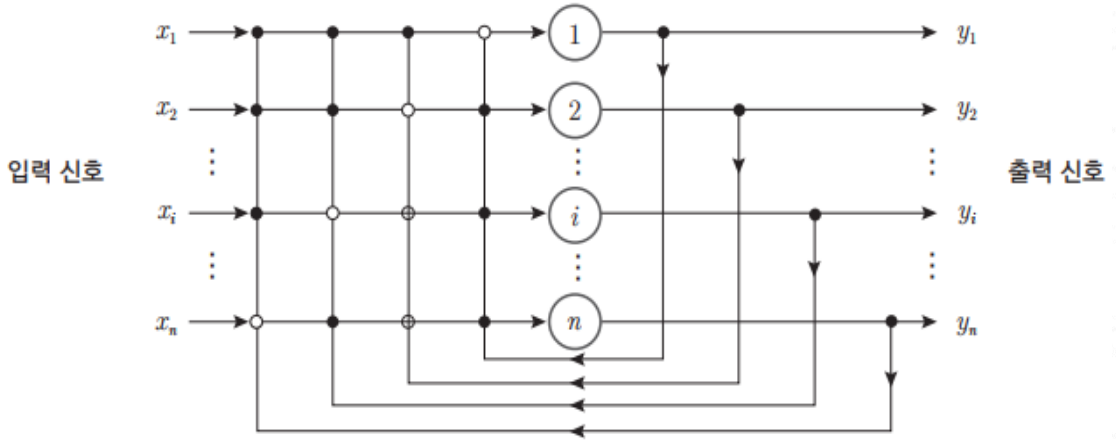
- Training set

$$\mathbf{x} = \left(\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, \cdots, \mathbf{x}^{(T)}\right)^{\mathrm{T}}, \quad \mathbf{y} = \left(\mathbf{y}^{(1)}, \mathbf{y}^{(2)}, \cdots, \mathbf{y}^{(L)}\right)^{\mathrm{T}}$$

Recurrent Neural Network

- Neural network model with memory
  - Associated with Hopfield network
    - John Hopfield proposed a Hopfield network in 1982 with memory storage and associated memory
    - Hopfield network with feedback structure

John Hopfield

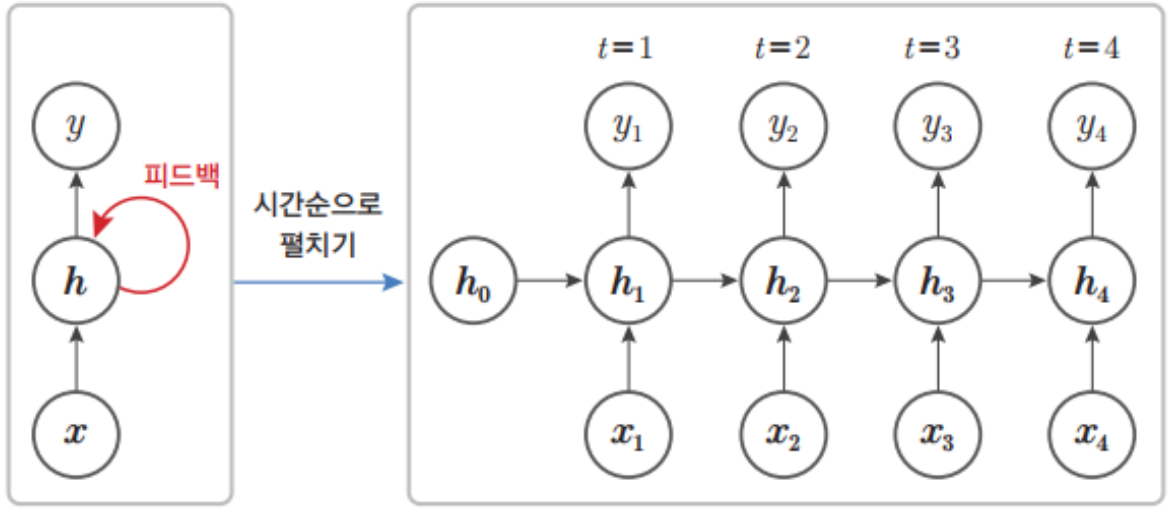


Hopfield Network

Recurrent Neural Network

❖ Essential features of a recurrent neural network (RNN)

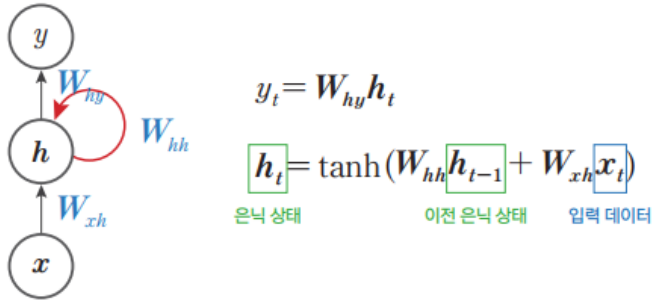
- 시간성: 특징을 순서대로 한 번에 하나씩 입력해야 한다.
- 가변 길이: 길이가 T인 샘플을 처리하려면 은닉층이 T번 나타나야 한다. T는 가변적이다.
- 문맥 의존성: 이전 특징 내용을 기억하고 있다가 적절한 순간에 활용해야 한다.

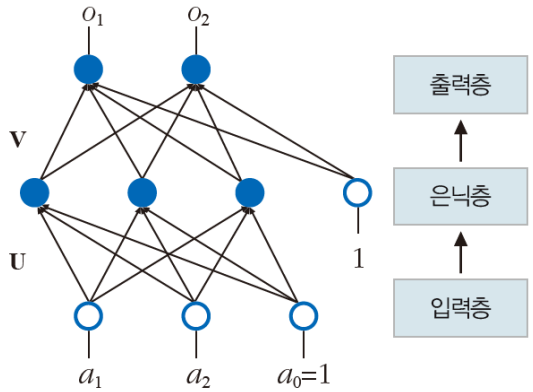


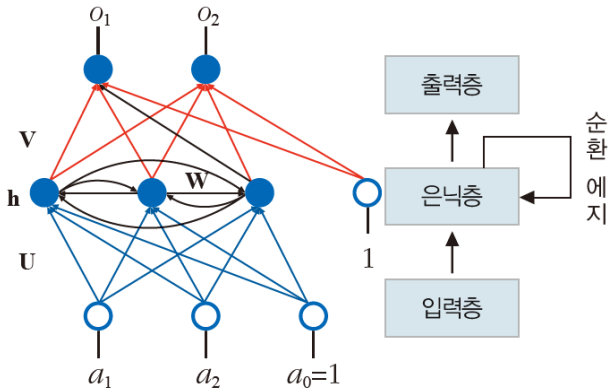
Recurrent Neural Network

❖ Structures

- Structure of MLP
  - Input, hidden, output layers
- The hidden layer has a recurrent edge
  - Handle all timeliness, variable length, and context dependencies
  - Recurrent edges are responsible for transmitting information that occurs at the t-1 moment to the t moment







Recurrent Neural Network

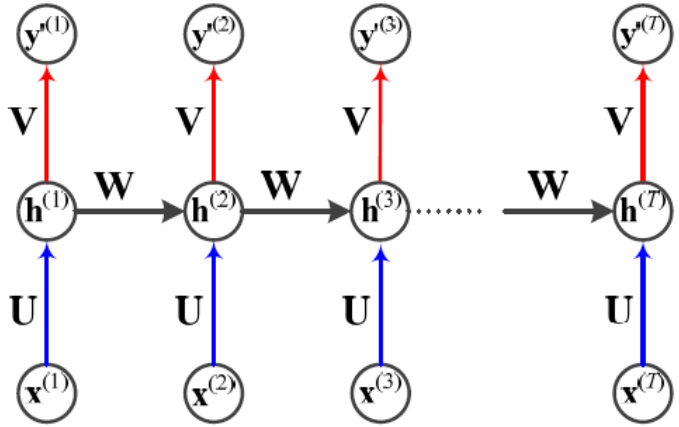
❖ Equation is,

$$\mathbf{h}^{(t)} = f\left(\mathbf{h}^{(t-1)}, \mathbf{x}^{(t)}; \Theta\right)$$

- Calculate at t = 1 moment, calculate at t = 2 moment with the result, calculate at t = 3 moment with the result, …, t = repeat until n moment
- At the t moment, the hidden layer value (state) $\mathbf{h}^{(t-1)}$ at the t-1 moment and the input $\mathbf{x}^{(t)}$ at the t moment are received and switched to $\mathbf{h}^{(t)}$
- Θ는 a parameter of a recurrent neural network
- The learning algorithm of is called backpropagation through time (BRTT)

Recurrent Neural Network

- Overall flow,

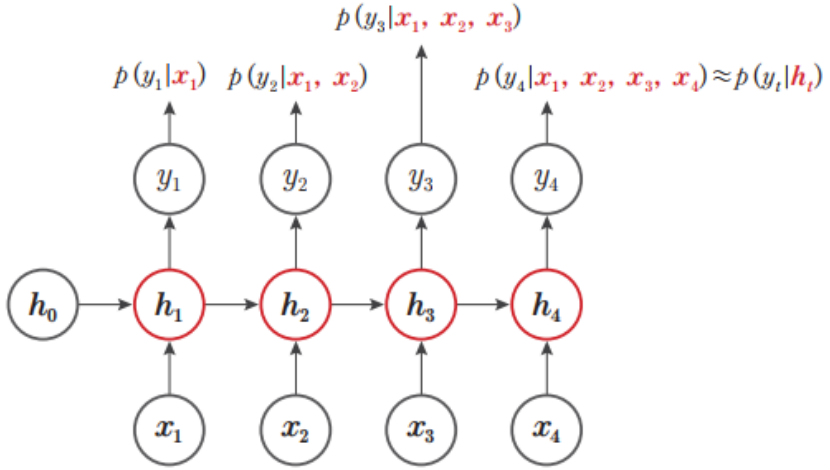


To find out the optimal {**U**, **V**, **W**} in training

$$
\begin{aligned}
\mathbf{h}^{(T)} &= f(\mathbf{h}^{(T-1)}, \mathbf{x}^{(T)}; \Theta) \\
&= f(f(\mathbf{h}^{(T-2)}, \mathbf{x}^{(T-1)}; \Theta), \mathbf{x}^{(T)}; \Theta) \\
&\quad \vdots \\
&= f(f(\cdots f(\mathbf{h}^{(1)}, \mathbf{x}^{(2)}; \Theta), \cdots, \mathbf{x}^{(T-1)}; \Theta), \mathbf{x}^{(T)}; \Theta) \\
&= f(f(\cdots f(f(\mathbf{h}^{(0)}, \mathbf{x}^{(1)}; \Theta), \mathbf{x}^{(2)}; \Theta), \cdots, \mathbf{x}^{(T-1)}; \Theta), \mathbf{x}^{(T)}; \Theta)
\end{aligned}
$$

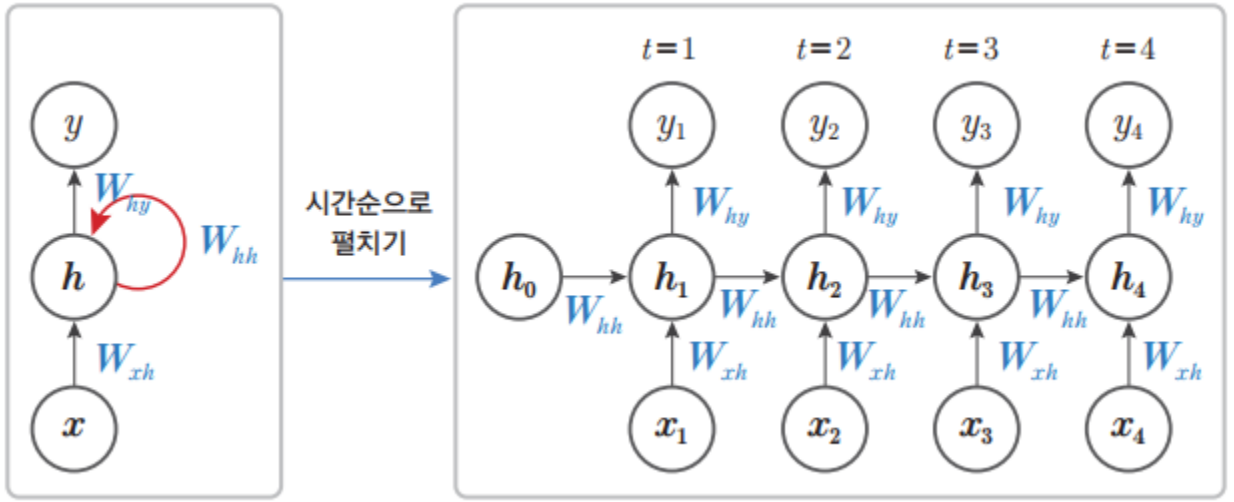
Recurrent Neural Network

- Output representation
  - If x_1 is given, the conditional probability $p(y_1|x_1)$ of y_1
  - Express the conditional probability $p(y_2|x_1, x_2)$ of y_2 given the inputs x_1 and x_2 because x_1 was passed to h_2 through h_1
  - Therefore, the output of step t expresses the conditional $p(y_2|x_1, x_2, \ldots, x_t)$ of y_t given x_1, x_2 , …, x_t



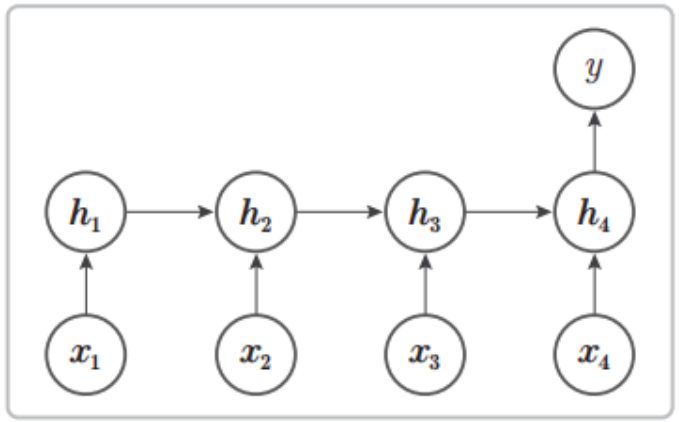
Recurrent Neural Network

- Weight sharing effects of RNN
  - Allows capturing sequential structures
  - Easy to process variable length data
  - Number of parameters saved and normalized

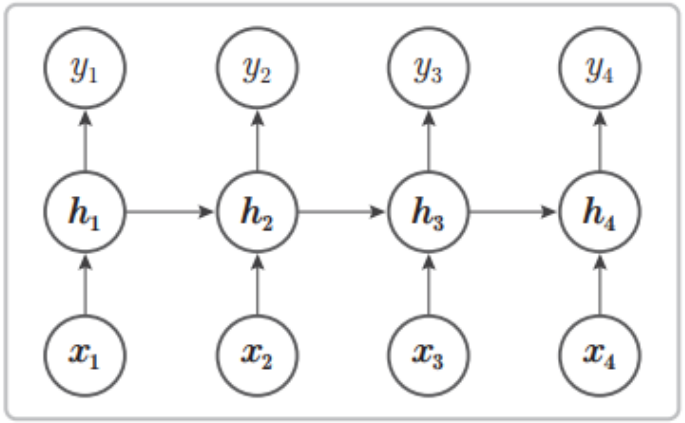


Recurrent Neural Network

- A variety of architecture
  - Many-to-One model
    - he input is a sequential column but the output is not a sequential column; all steps receive the input but only the output is in the last step
  - Many-to-Many model
    - Used when input and output are sequential columns of the same length, receives input at all stages and outputs at all stages



Many-to-One model

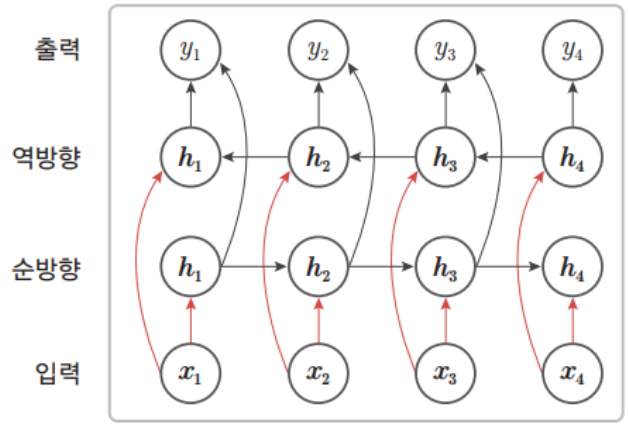


Many-to-Many model

Recurrent Neural Network

❖ A variety of architecture

- Bidirectional model
  - Both ways at the input
  - Data generated in chronological order depends only on the past in the present, depending on the causal relationship, viewed only in the direction of the passage of time
  - Relative order is important for data with spatial order relationships, so it is more accurate to examine and judge in both directions

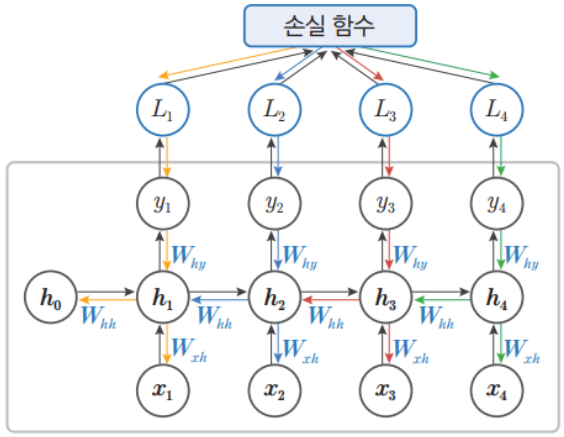


양방향 모델

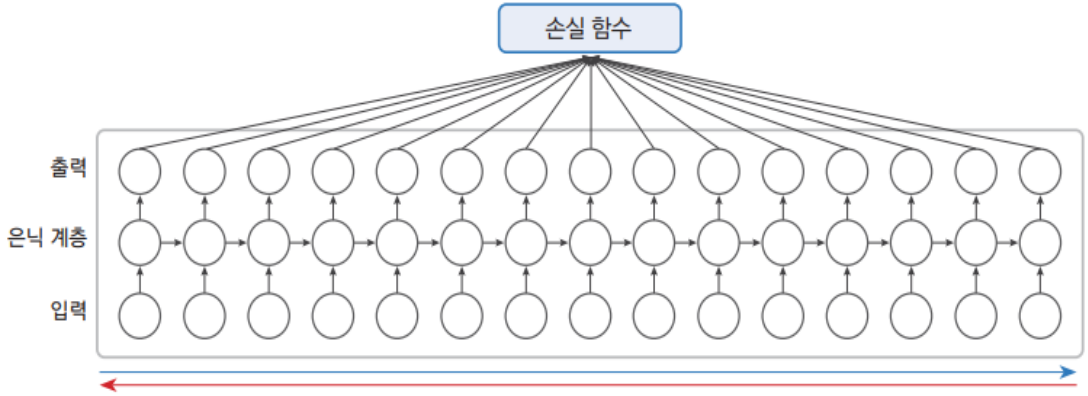
Recurrent Neural Network

❖ Limitation of Backpropagation

- Backpropagation starts in the loss function and proceeds to all stages simultaneously in order
- Reverse propagation after running the last step, so it cannot be applied to an endless or very long sequential column



Principle of BRTT

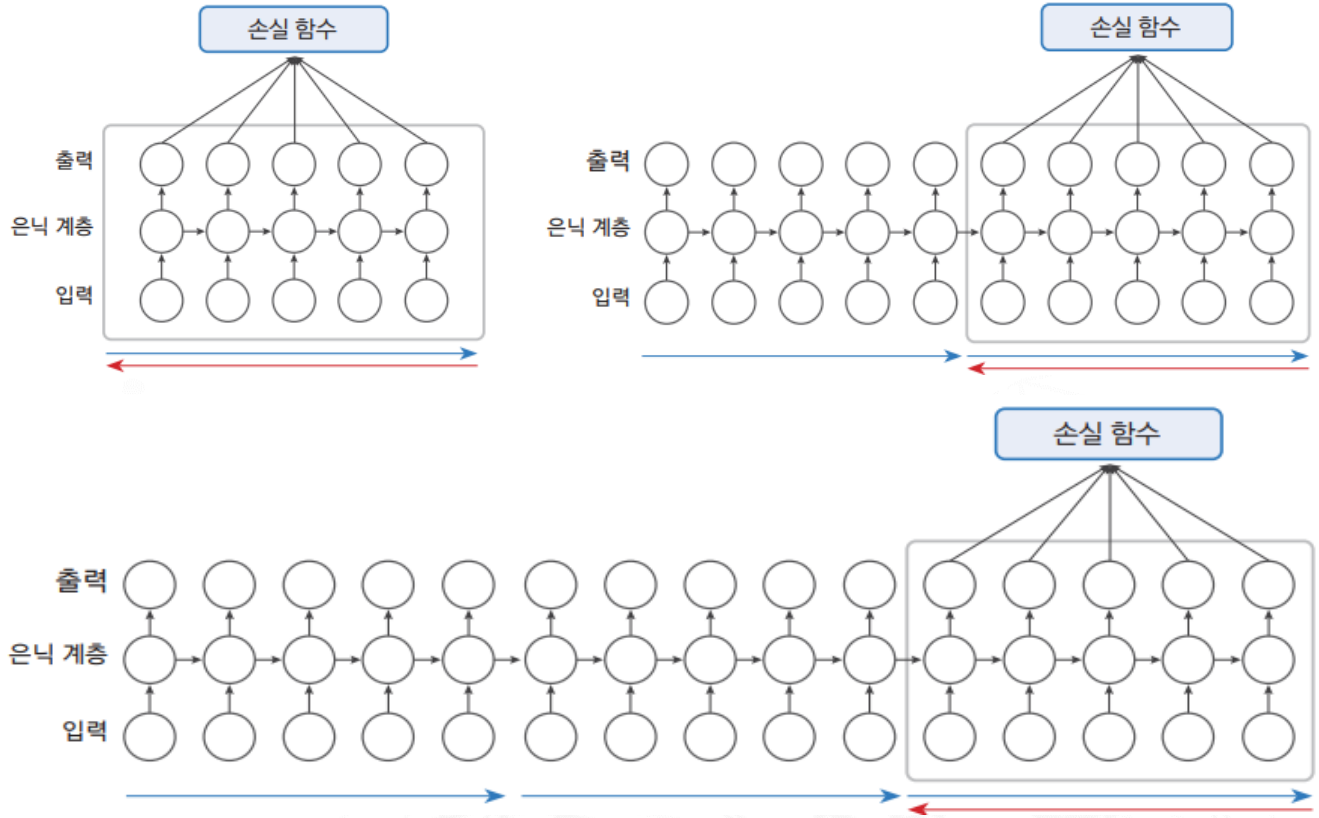


Limitation of BRTT

Recurrent Neural Network

❖ Answer of backpropagation problem

- To perform forward training and reverse training by grouping certain steps

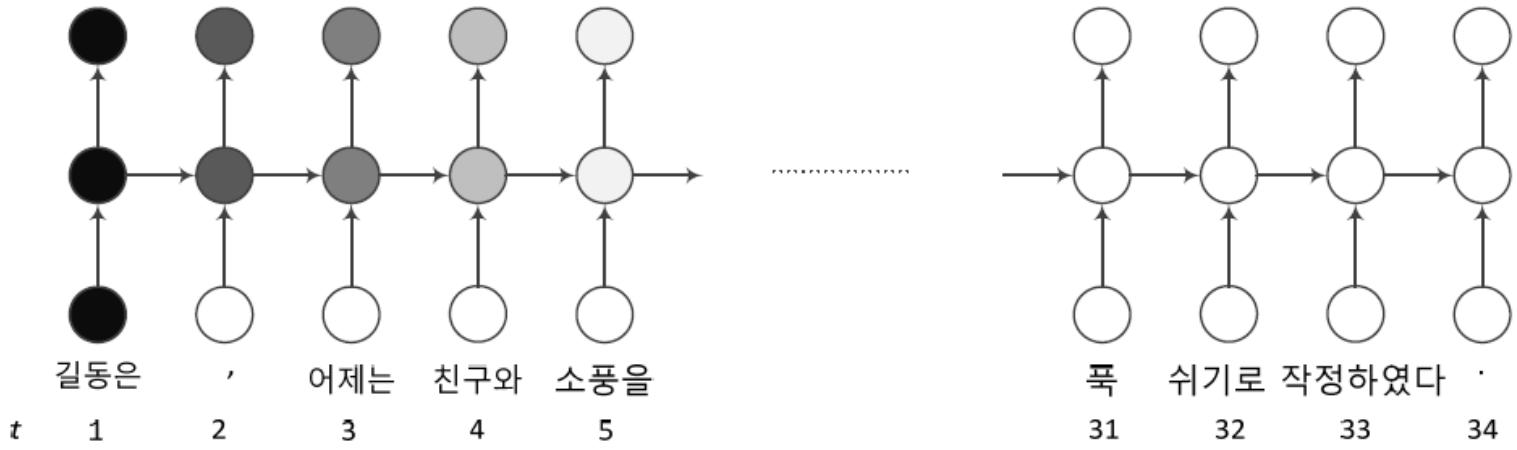


Long Term Dependency

❖ Problem

- A phenomenon in which the influence of input is increasingly lost despite the dependence on distant input when the context is wide
  - e.g., 아래 문장에서 t=1의 '길동은'과 t=32의 '쉬기로'는 아주 밀접한 관련

"길동은, 어제는 친구와 소풍을 다녀왔고, 글피는 엄마를 따라 시장에 가서 반찬거리를 사 오고, 그글피는 여자 친구와 함께 비가 옴에도 불구하고 놀이동산에서 재미있게 놀고 왔기 때문에 오늘은 집에서 푹 쉬기로 작정하였다."

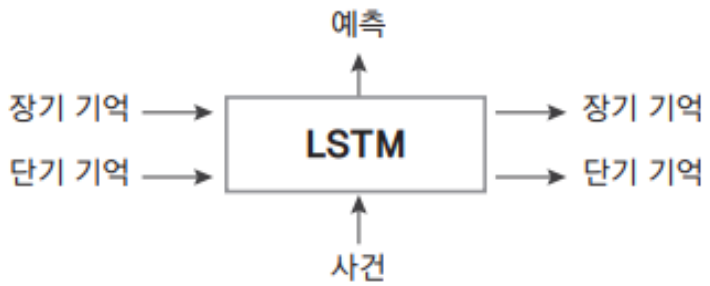


Long term dependency

Long Short-Term Memory(LSTM)

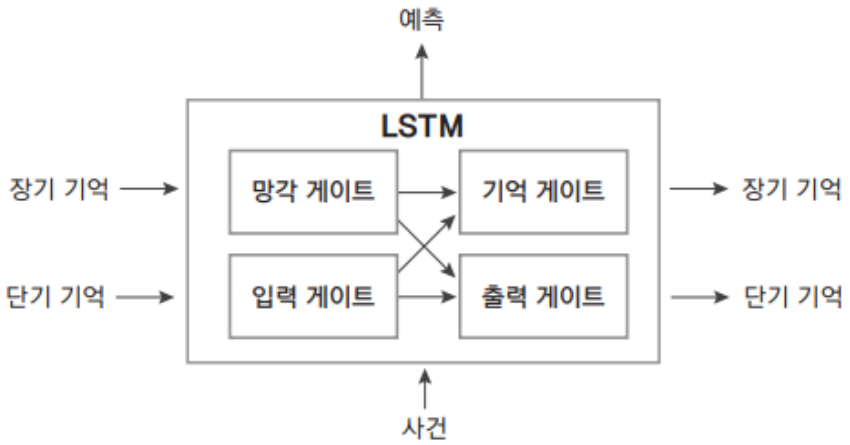
❖ Modeling of long-term and short-term memory

- Remember the past with the ability to pass the hidden layer state to the next moment
- However, the limitations of not properly dealing with long-term context dependencies (a phenomenon where distant elements interact closely)
- Memory loss due to the influence of continuous incoming input
- People retain their memories of a long time ago with selective memory

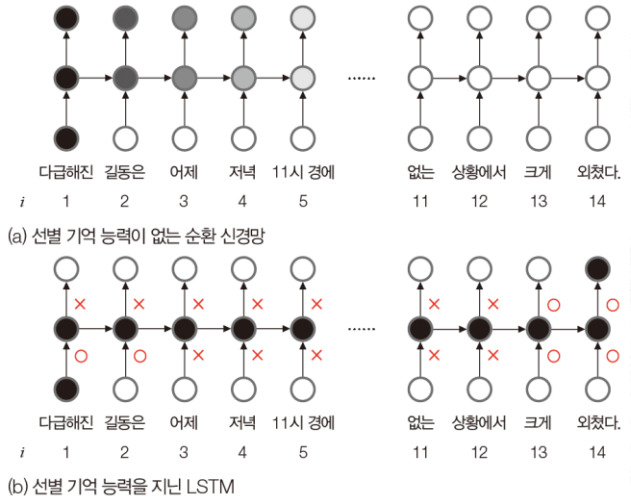


Structure of LSTM

- Gate structure for selecting memory
  - Four types of gates in the LSTM that are involved in shaping memory
  - Gate is the role of choosing whether to keep or forget memories
    - Remember to keep up with the current context and frequently used memories, but forget those that don't.
  - Forget gate, input gate, memory gate, output gate in LSTM cell



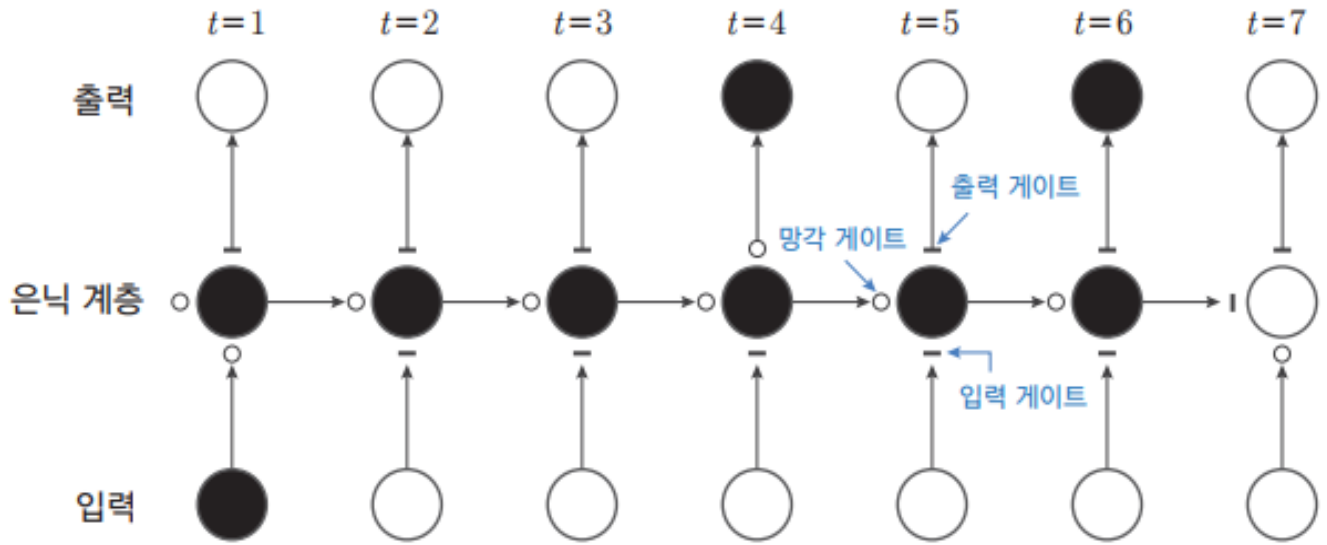
LSTM의 장기기억과 단기기억



Structure of LSTM

❖ Flow of memory and the input, output, and forget gates

- LSTM maintains or eliminates newly formed memory through gate

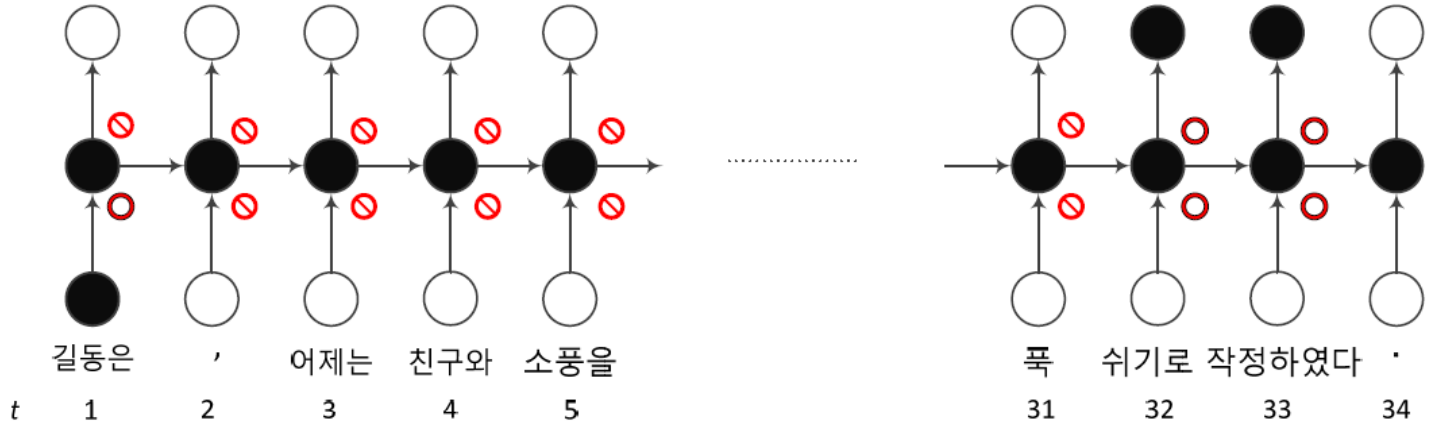


장기 기억의 전달

Structure of LSTM

❖ Input gate and output gate

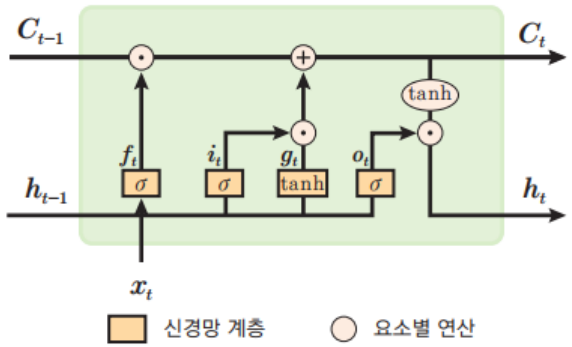
- A signal flows when the gate is opened (⊘) and is blocked when the gate is closed (○)
  - Only input was opened at *t*=1, and both input and output were opened at *t* =32 and *t* =33



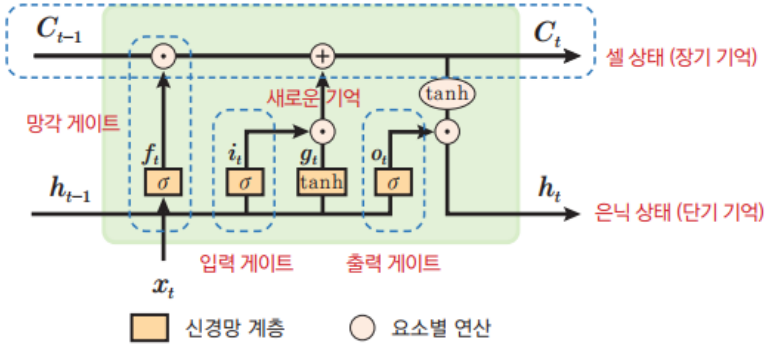
입력 게이트와 출력 게이트를 이용한 입출력 제어

Training of LSTM

❖ LSTM Cell



LSTM Cell



LSTM 게이트 위치

❖ Gate values that depend on the gate location and context in the LSTM cell

- The complexity of the LSTM cell structure separates each gate from the memory area

Training of LSTM

❖ Calculate $\boldsymbol{i_t}$, $\boldsymbol{f_t}$, $\boldsymbol{o_t}$, $\boldsymbol{g_t}$

입력 게이트 / 망각 게이트 / 출력 게이트 / 새로운 기억

$$\begin{pmatrix} i_t \\ f_t \\ o_t \\ g_t \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}, \quad W = \begin{bmatrix} W_{hi} & W_{xi} \\ W_{hf} & W_{xf} \\ W_{ho} & W_{xo} \\ W_{hg} & W_{xg} \end{bmatrix}$$

이전 단기 기억 / 새로운 사건

❖ Calculate $\boldsymbol{C_t}$ with respect to long term memory

이전 장기 기억 / 새로운 기억 / 망각 게이트 / 입력 게이트 / 장기 기억

$$C_t = f_t \odot C_{t-1} + i_t \odot g_t$$

$$\begin{aligned} \mathbf{f}_t &= \sigma\left(\mathbf{W}_{xf}^T \cdot \mathbf{x}_t + \mathbf{W}_{hf}^T \cdot \mathbf{h}_{t-1} + \mathbf{b}_f\right) \\ \mathbf{i}_t &= \sigma\left(\mathbf{W}_{xi}^T \cdot \mathbf{x}_t + \mathbf{W}_{hi}^T \cdot \mathbf{h}_{t-1} + \mathbf{b}_i\right) \\ \mathbf{o}_t &= \sigma\left(\mathbf{W}_{xo}^T \cdot \mathbf{x}_t + \mathbf{W}_{ho}^T \cdot \mathbf{h}_{t-1} + \mathbf{b}_o\right) \\ \mathbf{g}_t &= \tanh\left(\mathbf{W}_{xg}^T \cdot \mathbf{x}_t + \mathbf{W}_{hg}^T \cdot \mathbf{h}_{t-1} + \mathbf{b}_g\right) \\ \mathbf{c}_t &= \mathbf{f}_t \otimes \mathbf{c}_{t-1} + \mathbf{i}_t \otimes \mathbf{g}_t \end{aligned}$$

Training of LSTM

❖ Calculate $\boldsymbol{i_t}$, $\boldsymbol{f_t}$, $\boldsymbol{o_t}$, $\boldsymbol{g_t}$

입력 게이트
망각 게이트
출력 게이트
새로운 기억

$$\begin{pmatrix} i_t \\ f_t \\ o_t \\ g_t \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}, \quad W = \begin{bmatrix} W_{hi} & W_{xi} \\ W_{hf} & W_{xf} \\ W_{ho} & W_{xo} \\ W_{hg} & W_{xg} \end{bmatrix}$$

이전 단기 기억
새로운 사건

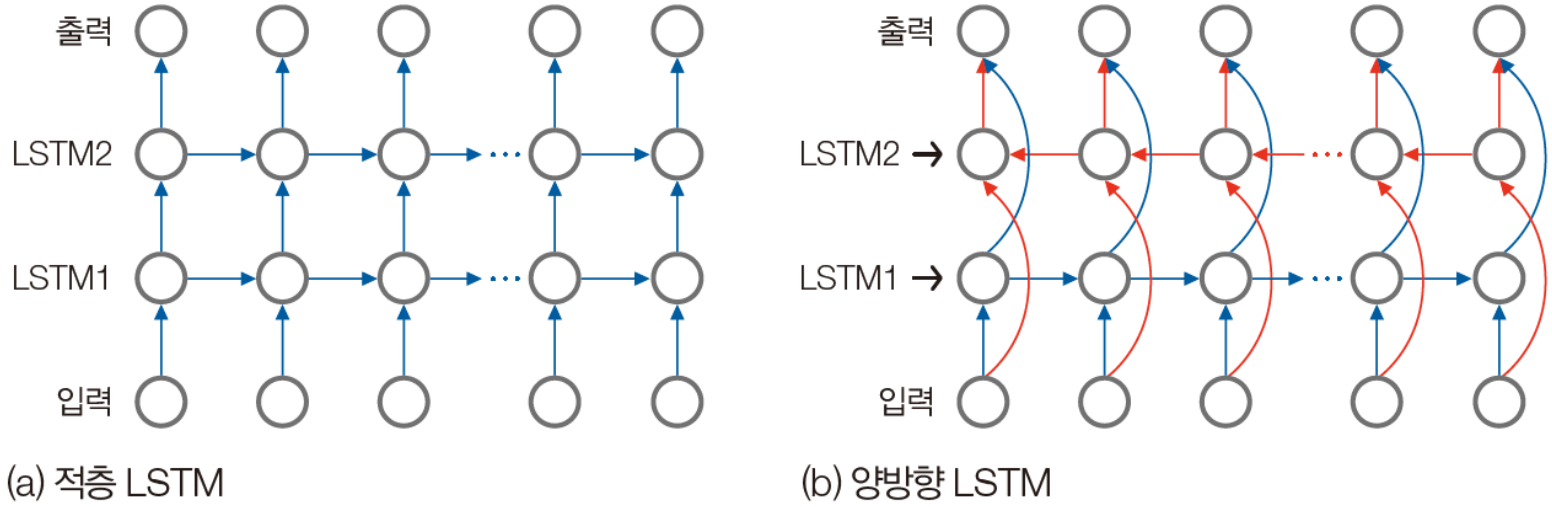
❖ Calculate $\boldsymbol{h_t}$ with respect to short term memory

$$h_t = o_t \odot \tanh(C_t)$$

출력 게이트
장기 기억

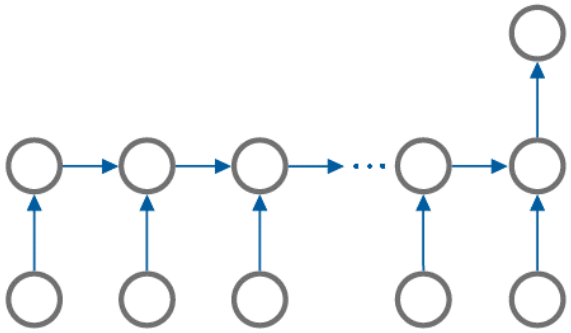
LSTM Model

- A variety structure
  - Use bi-directional LSTM if context needs to be examined in both directions

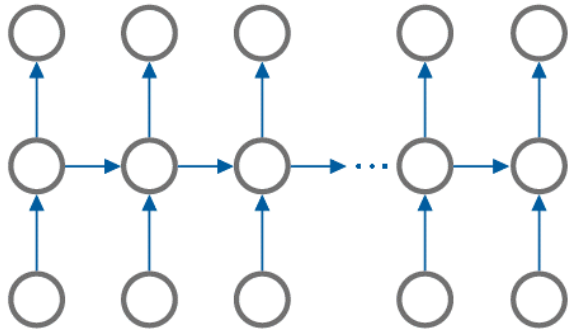


LSTM Model

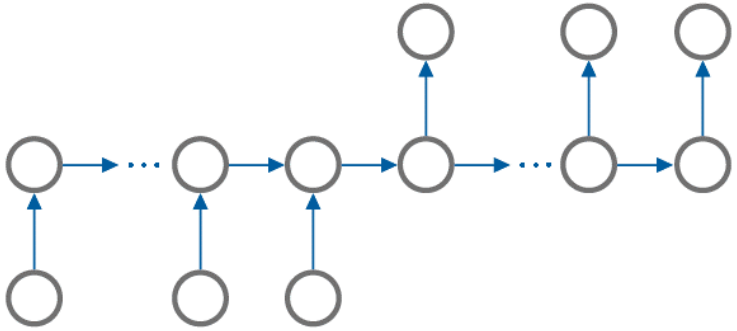
❖ A variety structure according to each problem



(a) 분류 또는 예측 문제



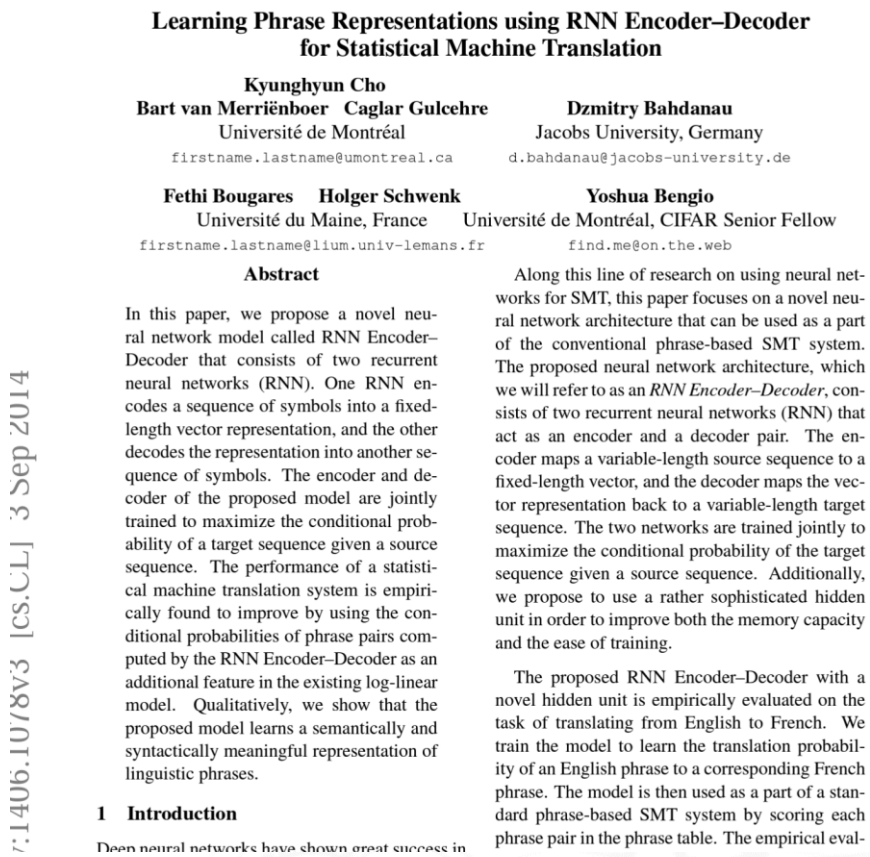
(b) 비디오 프레임 분류



(c) 언어 번역

Gated Recurrent Unit

- Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation



Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation

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Abstract

In this paper, we propose a novel neural network model called RNN Encoder–Decoder that consists of two recurrent neural networks (RNN). One RNN encodes a sequence of symbols into a fixed-length vector representation, and the other decodes the representation into another sequence of symbols. The encoder and decoder of the proposed model are jointly trained to maximize the conditional probability of a target sequence given a source sequence. The performance of a statistical machine translation system is empirically found to improve by using the conditional probabilities of phrase pairs computed by the RNN Encoder–Decoder as an additional feature in the existing log-linear model. Qualitatively, we show that the proposed model learns a semantically and syntactically meaningful representation of linguistic phrases.

1 Introduction

Deep neural networks have shown great success in

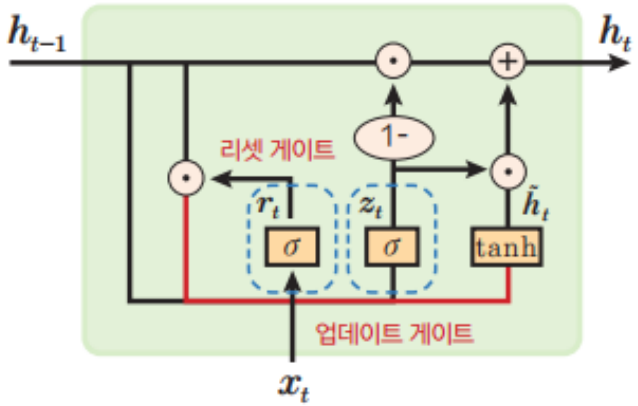
Along this line of research on using neural networks for SMT, this paper focuses on a novel neural network architecture that can be used as a part of the conventional phrase-based SMT system. The proposed neural network architecture, which we will refer to as an *RNN Encoder–Decoder*, consists of two recurrent neural networks (RNN) that act as an encoder and a decoder pair. The encoder maps a variable-length source sequence to a fixed-length vector, and the decoder maps the vector representation back to a variable-length target sequence. The two networks are trained jointly to maximize the conditional probability of the target sequence given a source sequence. Additionally, we propose to use a rather sophisticated hidden unit in order to improve both the memory capacity and the ease of training.

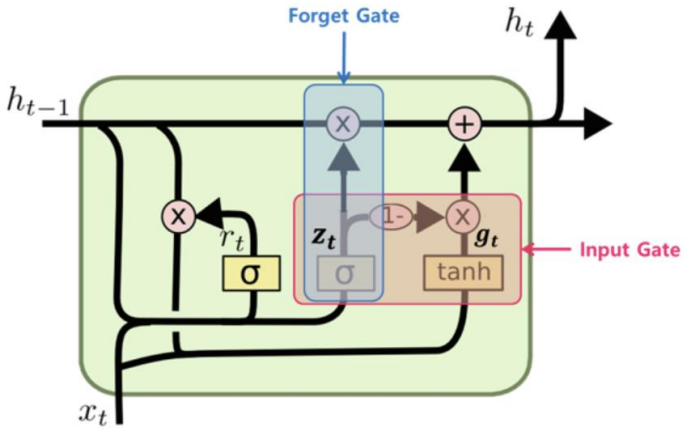
The proposed RNN Encoder–Decoder with a novel hidden unit is empirically evaluated on the task of translating from English to French. We train the model to learn the translation probability of an English phrase to a corresponding French phrase. The model is then used as a part of a standard phrase-based SMT system by scoring each phrase pair in the phrase table. The empirical eval-

Gated Recurrent Unit

❖ Structure of GRU

- Recurrent neural networks that simplify gate structure while maintaining the advantages of LSTM
- Remove cell state $\boldsymbol{C_t}$ and again hide state $\boldsymbol{h_t}$ remember both long-term and short-term memory
- How the path branches into two branches and then merges again within the GRU cell between $\boldsymbol{h_{t-1}}$ and $\boldsymbol{h_t}$





Training of GRU

❖ Calculate reset gate $\boldsymbol{r_t}$ and update gate $\boldsymbol{z_t}$

- Process for calculating each gate and hidden status inside the GRU

리셋 게이트
업데이트 게이트

$$\begin{pmatrix} r_t \\ z_t \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}, \quad W = \begin{bmatrix} W_{hr} & W_{xr} \\ W_{hz} & W_{xz} \end{bmatrix}$$

❖ Calculate a newborn memory $\widetilde{\boldsymbol{h}}_{\boldsymbol{t}}$

리셋 게이트 과거의 기억

새로운 기억 $\tilde{h}_t = \tanh\left((W_{hh} \;\; W_{xh}) \begin{pmatrix} r_t \odot h_{t-1} \\ x_t \end{pmatrix} \right)$

$$\begin{aligned}
\mathbf{r}_t &= \sigma\left(\mathbf{W}_{xr}^T \cdot \mathbf{x}_t + \mathbf{W}_{hr}^T \cdot \mathbf{h}_{t-1} + \mathbf{b}_r\right) \\
\mathbf{z}_t &= \sigma\left(\mathbf{W}_{xz}^T \cdot \mathbf{x}_t + \mathbf{W}_{hz}^T \cdot \mathbf{h}_{t-1} + \mathbf{b}_z\right) \\
\mathbf{g}_t &= \tanh\left(\mathbf{W}_{xg}^T \cdot \mathbf{x}_t + \mathbf{W}_{hg}^T \cdot (\mathbf{r}_t \otimes \mathbf{h}_{t-1}) + \mathbf{b}_g\right) \\
\mathbf{h}_t &= \mathbf{z}_t \otimes \mathbf{h}_{t-1} + (1 - \mathbf{z}_t) \otimes \mathbf{g}_t
\end{aligned}$$

❖ Calculate Update memory $\boldsymbol{n_t}$

- The updated memory, the hidden state $\boldsymbol{h_t}$, is calculated as the weighted average of the previous state $\boldsymbol{h_{t-1}}$ and the memory $\widetilde{\boldsymbol{h}}_{\boldsymbol{t}}$ formed by the new event

현재 기억 $h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t$

업데이트 기억 업데이트 기억

과거의 기억 새로운 기억

Applications

- Musical composition

Polyphonic music generation with style transitions using recurrent neural networks

Mathieu De Coster

Supervisors: Bart Dhoedt, Cedric De Boom, Steven Bohez, Sam Leroux

Abstract— **Computer aided music generation is a problem that has occupied researchers' minds for several decades. While composition is typically seen as a human skill or an art form, requiring creativity, having an algorithm generate music is something that has merit in certain situations. Consider for example a video game, in which scenes or player actions are often unpredictable. Having music that adapts to the situation could improve player immersion. This master dissertation is not solely about music generation, however. It also considers style transitions, where style is represented as the composer of a piano piece, in this case Bach, Haydn, Beethoven or Chopin. The proposed methods can also be applied to other interpretations of style, such as musical genres or the mood of the music.**

A novel data representation is presented. A recurrent neural network is trained on such data and conditioned on composer information. The quality of the compositions created by the neural network is rated closely to the quality of real compositions by a panel of volunteers. The accuracy of composer classifications by this panel is also similar to that of real compositions.

A method for generating polyphonic music with style transitions is presented and forms a basis for future work.

Keywords— **Music generation, Style transitions, Recurrent neural networks**

I. Introduction

TO be able to compose new music solely with a computer is an interesting and challenging goal. Such a composer algorithm could be used to create new music on the fly, or to

However, traditional RNNs are unable to learn very long time dependencies due to the vanishing and exploding gradient problem [1]. For this reason, the Long-Short Term Memory (LSTM) unit is often used instead of the hyperbolic tangent activation function found in traditional RNNs. Another alternative is the Gated Recurrent Unit (GRU). Both have been shown to perform better than traditional RNNs [2].

Previous research has used both text based methods and methods based on piano rolls. A piano roll is a binary matrix $\mathbf{P} = [P_{i,j}]$, where $P_{i,j}$ is 1 if the note with pitch i is to be played at time j and 0 otherwise. A text based approach was taken by Choi et al. to generate jazz chord progressions [3]. Eck and Schmidhuber have used piano rolls to generate chord progressions from a limited set of chords [4]. Liu et al. also used piano rolls, to generate Bach chorales [5]. Both Liu et al. and Eck and Schmidhuber reported that in piano rolls, it is not possible to distinguish between held notes and repeated notes and that this is a drawback of this data representation.

Style transitions for music generation have not yet been considered in literature. WaveNet however performs conditioning on speaker identity for a text to speech model [6], which is

TABLE I
NETWORK HYPER-PARAMETERS.

Hyper-parameter	Value
Batch size	64
Sequence length	100
Optimiser	Adam
Learning rate	10^{-5}

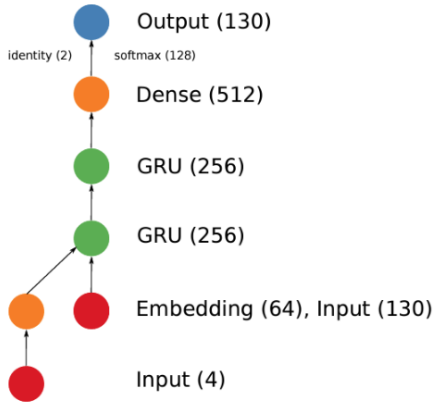


Fig. 1. The network architecture.

https://www.youtube.com/watch?v=j60J1cGINX4

Applications

- To restore the sound of a video

Visually Indicated Sounds

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Antonio Torralba[1] Edward H. Adelson[1] William T. Freeman[1,3]

[1]MIT [2]U.C. Berkeley [3]Google Research

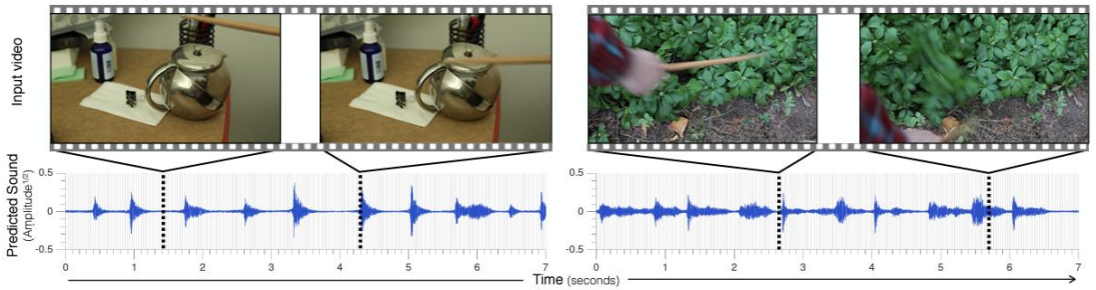

Figure 1: We train a model to synthesize plausible impact sounds from silent videos, a task that requires implicit knowledge of material properties and physical interactions. In each video, someone probes the scene with a drumstick, hitting and scratching different objects. We show frames from two videos and below them the predicted audio tracks. The locations of these sampled frames are indicated by the dotted lines on the audio track. The predicted audio tracks show seven seconds of sound, corresponding to multiple hits in the videos.

Abstract

Objects make distinctive sounds when they are hit or scratched. These sounds reveal aspects of an object's material properties, as well as the actions that produced them. In this paper, we propose the task of predicting what sound

by the physical interaction being depicted: you *see* what is making the sound.

We call these events *visually indicated sounds*, and we propose the task of predicting sound from videos as a way to study physical interactions within a visual scene (Figure 1). To accurately predict a video's held-out soundtrack,

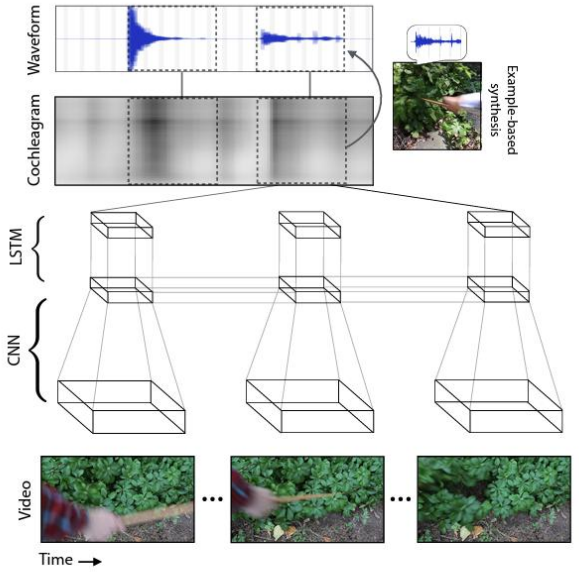

Figure 4: We train a neural network to map video sequences to sound features. These sound features are subsequently converted into a waveform using either parametric or example-based synthesis. We represent the images using a convolutional network, and the time series using a recurrent neural network. We show a subsequence of images corresponding to one impact.

https://www.youtube.com/watch?v=0FW99AQmMc8

https://arxiv.org/abs/1512.08512

Applications

- Generating handwriting

Generating Sequences With Recurrent Neural Networks

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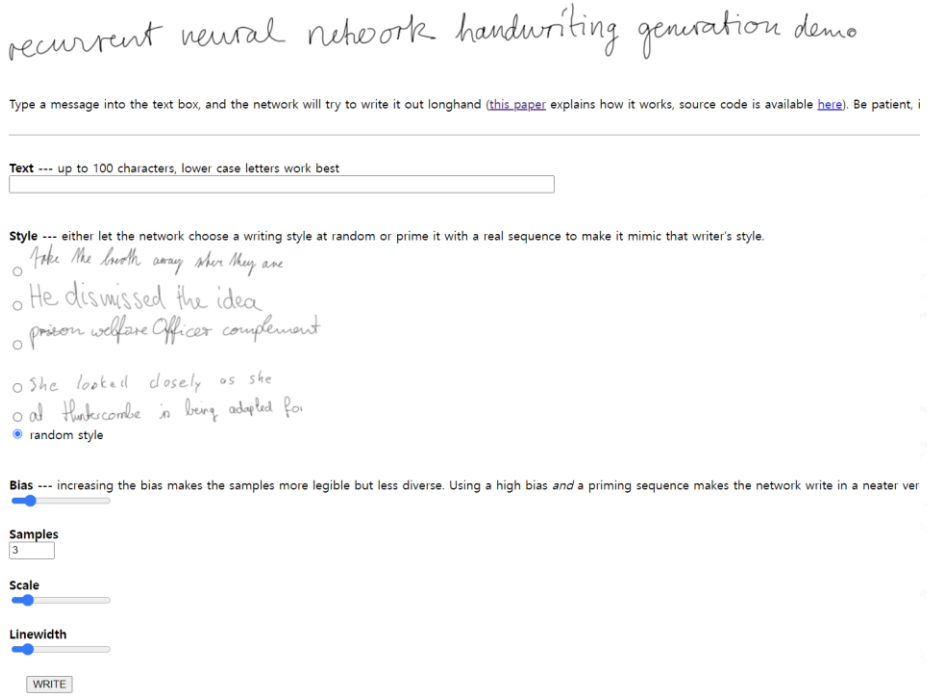
Abstract

This paper shows how Long Short-term Memory recurrent neural networks can be used to generate complex sequences with long-range structure, simply by predicting one data point at a time. The approach is demonstrated for text (where the data are discrete) and online handwriting (where the data are real-valued). It is then extended to handwriting synthesis by allowing the network to condition its predictions on a text sequence. The resulting system is able to generate highly realistic cursive handwriting in a wide variety of styles.

1 Introduction

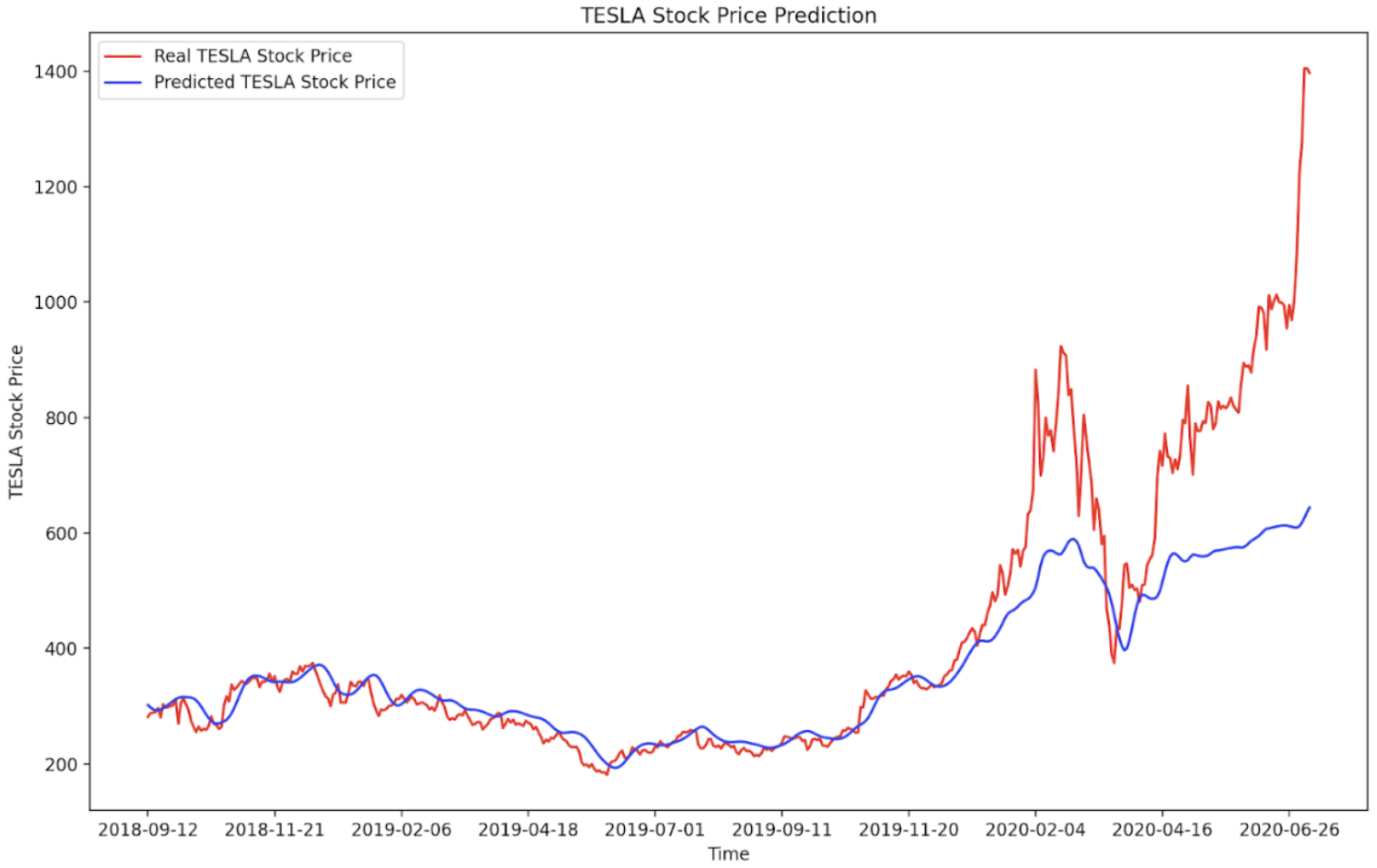
Recurrent neural networks (RNNs) are a rich class of dynamic models that have been used to generate sequences in domains as diverse as music [6, 4], text [30] and motion capture data [29]. RNNs can be trained for sequence generation by



https://arxiv.org/abs/1308.0850

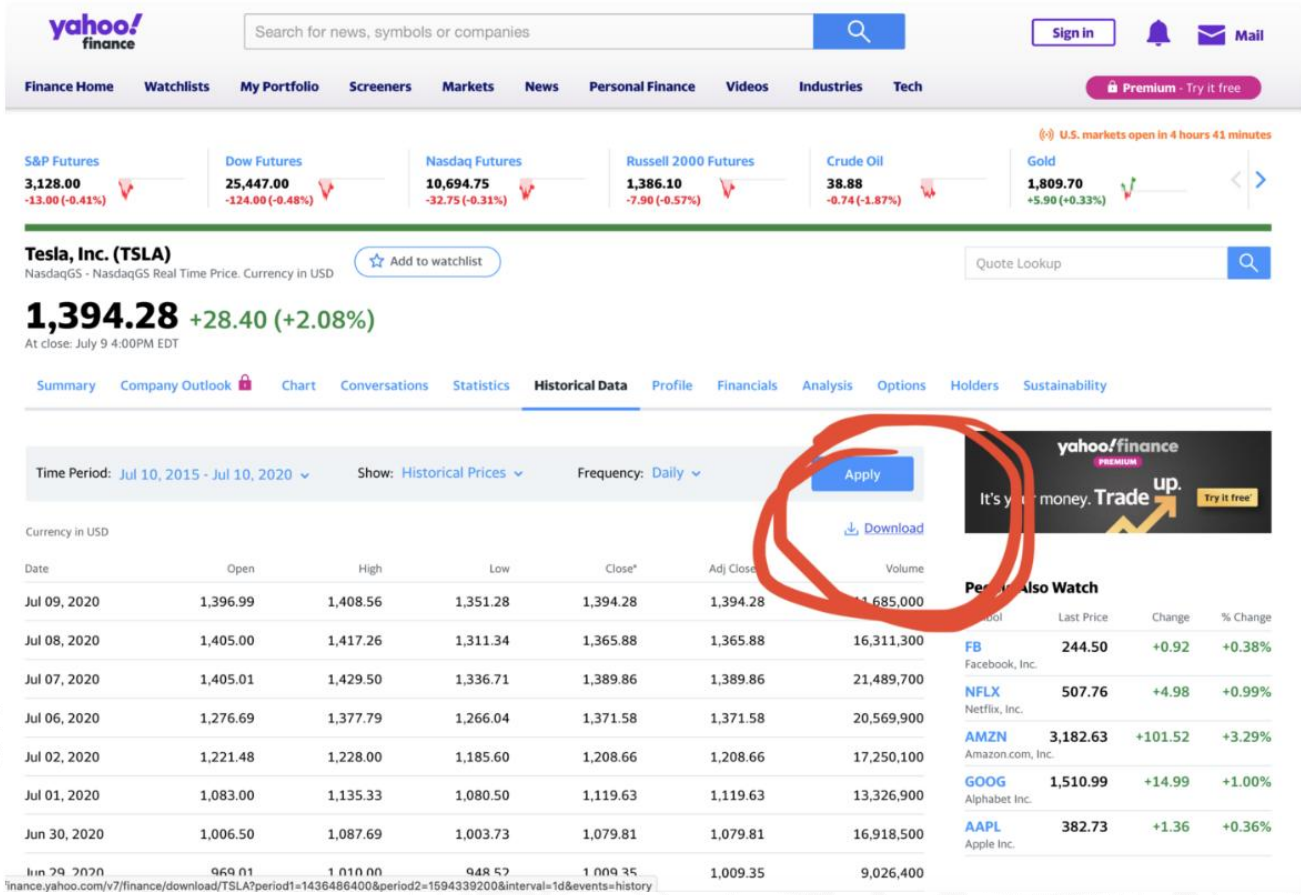
Applications

- Stock prediction



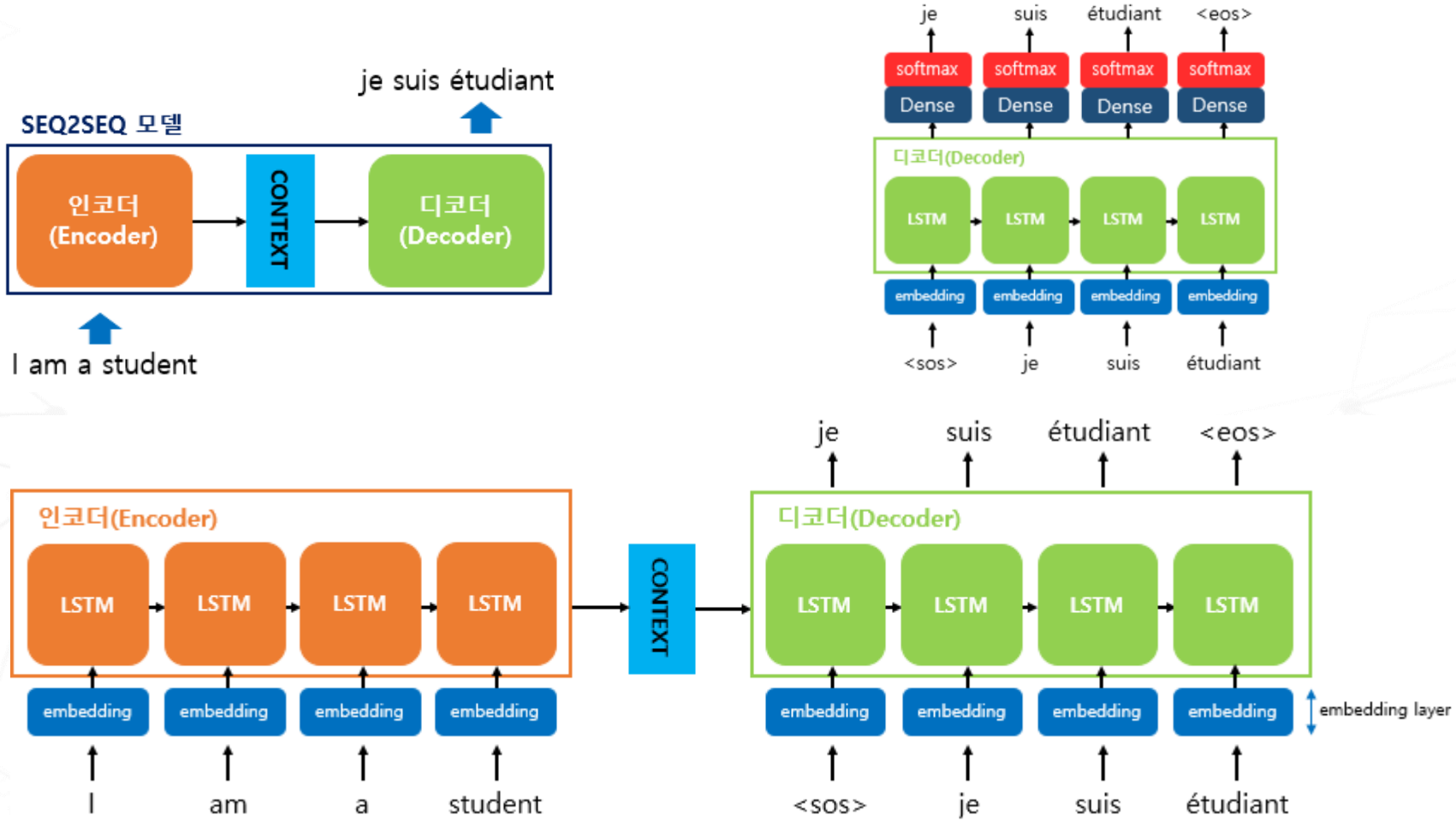
Applications

- Stock prediction



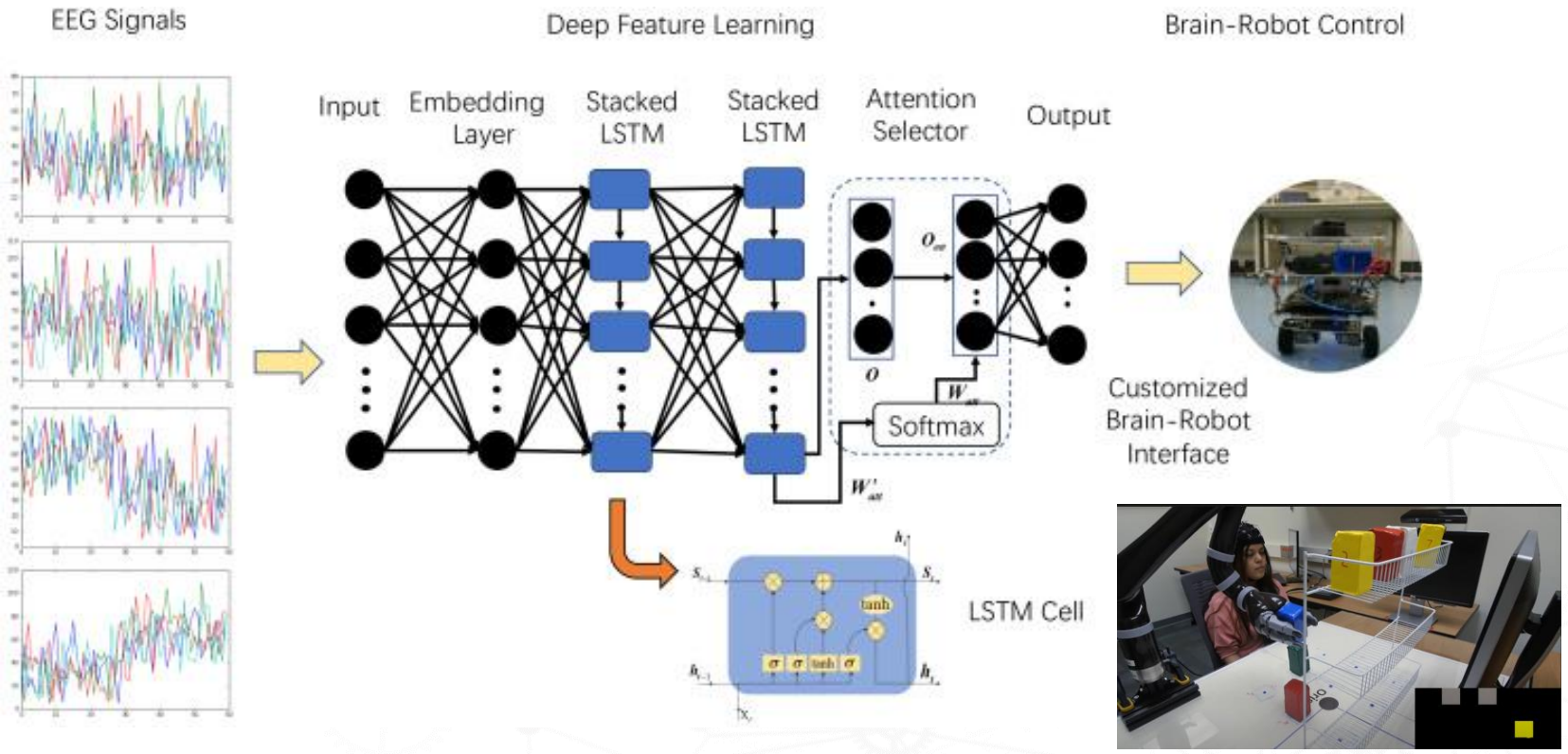
Applications

❖ Text generation (seq2seq model)



Applications

- Neurophysiological signal decoding



https://www.youtube.com/watch?v=w6QEGeIKHw0

Applications

❖ Mental state detection

brain sciences

MDPI

Article

Classification of Drowsiness Levels Based on a Deep Spatio-Temporal Convolutional Bidirectional LSTM Network Using Electroencephalography Signals

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Abstract: Non-invasive brain-computer interfaces (BCI) have been developed for recognizing human mental states with high accuracy and for decoding various types of mental conditions. In particular, accurately decoding a pilot's mental state is a critical issue as more than 70% of aviation accidents are caused by human factors, such as fatigue or drowsiness. In this study, we report the classification of not only two mental states (i.e., alert and drowsy states) but also five drowsiness levels from electroencephalogram (EEG) signals. To the best of our knowledge, this approach is the first to classify drowsiness levels in detail using only EEG signals. We acquired EEG data from ten pilots in a simulated night flight environment. For accurate detection, we proposed a deep spatio-temporal convolutional bidirectional long short-term memory network (DSTCLN) model. We evaluated the classification performance using Karolinska sleepiness scale (KSS) values for two mental states and five drowsiness levels. The grand-averaged classification accuracies were 0.87 (±0.01) and 0.69 (±0.02), respectively. Hence, we demonstrated the feasibility of classifying five drowsiness levels with high accuracy using deep learning.

Keywords: Brain-Computer Interface; electroencephalogram; mental states; drowsiness levels classification; deep learning

1. Introduction

A brain-computer interface (BCI) is used between human and devices for recognizing user intention. Non-invasive BCI technology allows users to communicate with external devices without