

SMILES and RNN

Seongok Ryu
Department of Chemistry, KAIST

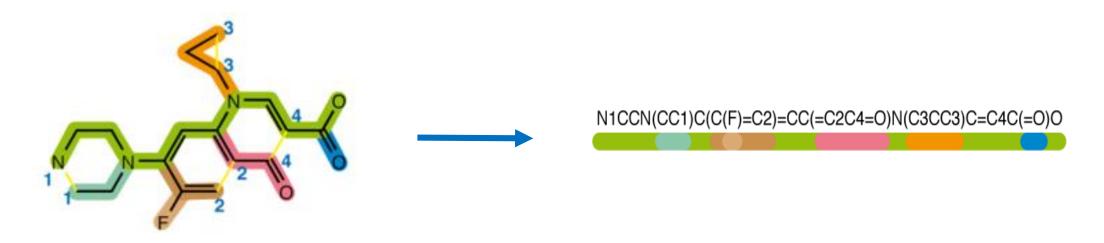


Contents

- SMILES
- Applications of RNN
- Modern advanced RNN
- RNN to predict logP
- Assignment #6



SMILES

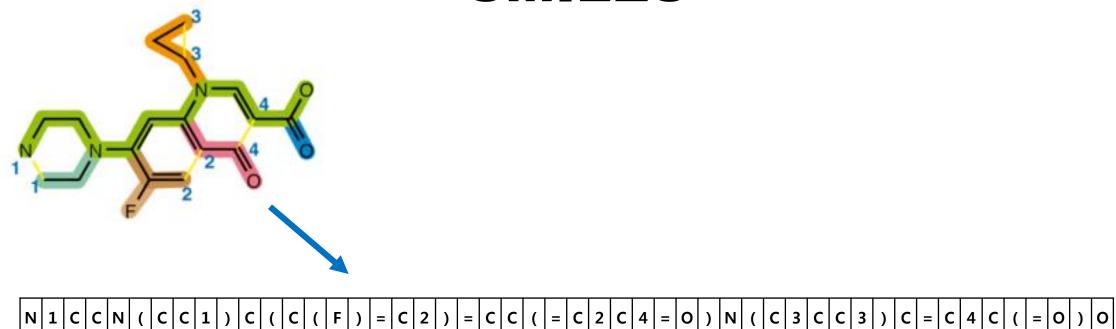


"The **simplified molecular-input line-entry system** (**SMILES**) is a specification in form of a <u>line notation</u> for describing the structure of <u>chemical species</u> using short <u>ASCII strings</u>. SMILES strings can be imported by most <u>molecule editors</u> for conversion back into <u>two-dimensional</u> drawings or <u>three-dimensional</u> models of the molecules."

https://en.wikipedia.org/wiki/Simplified_molecular-input_line-entry_system



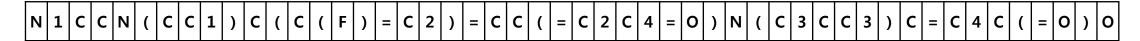
SMILES



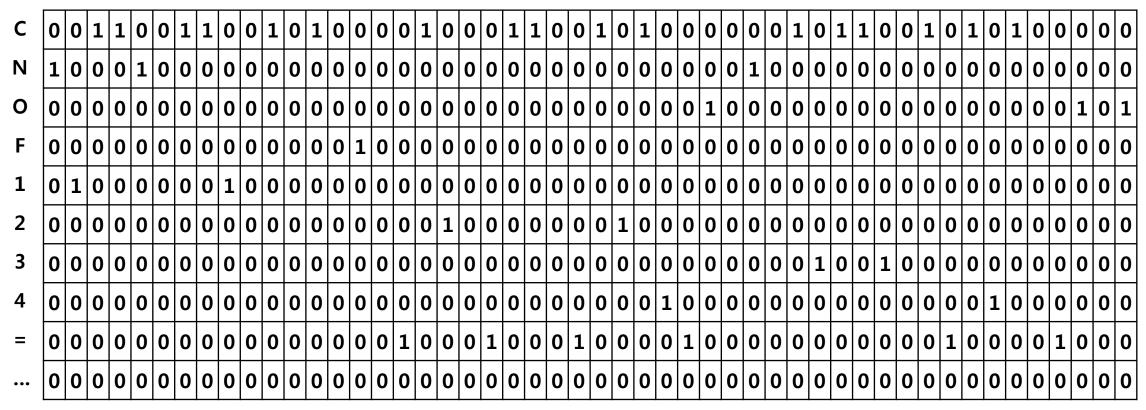
shape = [#batch, #characters]



SMILES



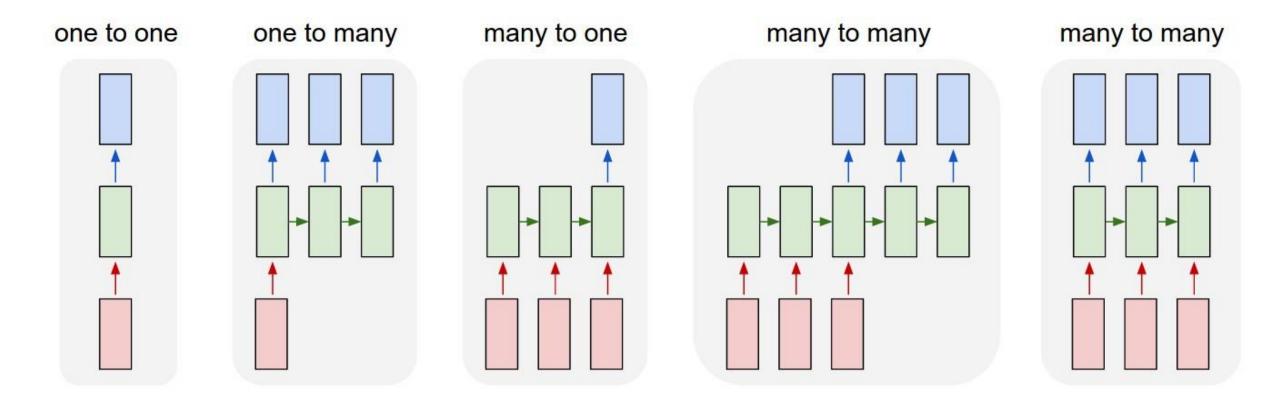
One-hot encoding



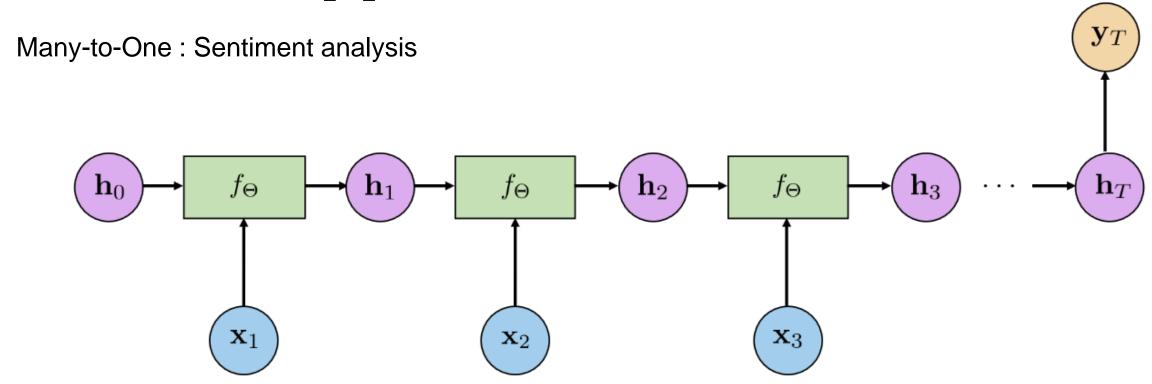




Depending on the architecture, many different tasks can be done using RNN







e.g., **Sentiment Classification** (Sequence of words \rightarrow sentiment)

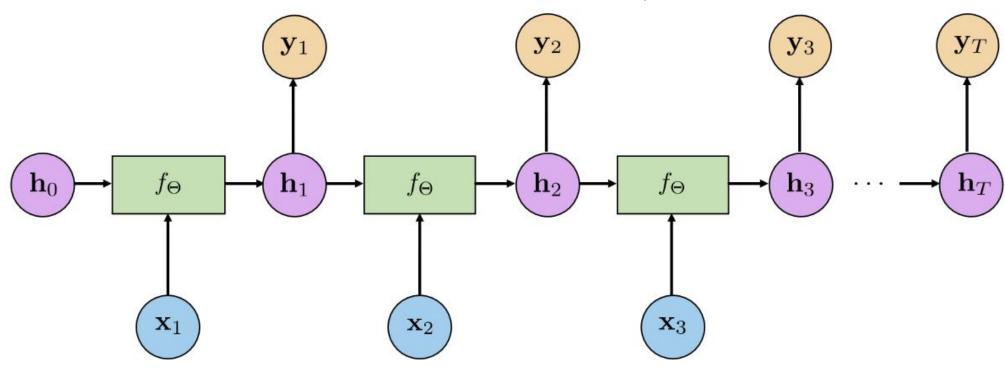


→ Good paper or not?



Many-to-Many: Neural machine translation

http://alinlab.kaist.ac.kr/resource/Lec1_Introduction_to_NN.pdf



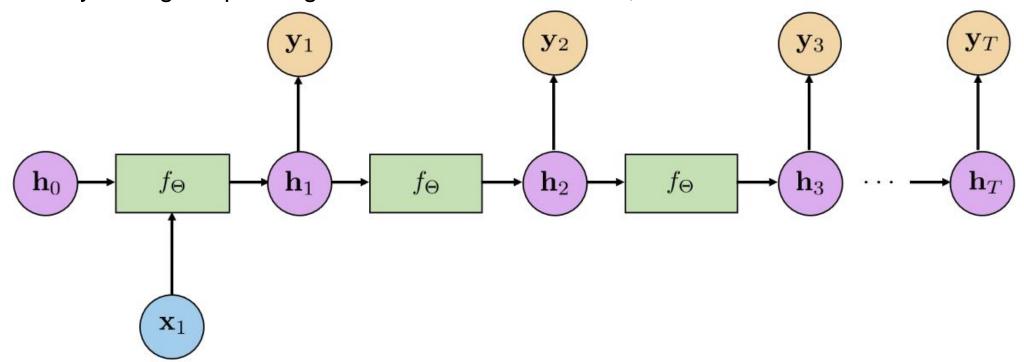
e.g., **Machine Translation**(Sequence of words \rightarrow Sequence of words)

Input sentence:	Translation (PBMT):	Translation (GNMT):	Translation (human):
李克強此行將啟動中加 總理年度對話機制,與 加拿大總理社會多舉行 滿纖維理舊次年度對 話。	Li Keqiang premier added this line to start the annual dialogue mechanism with the Canadian Prime Minister Trudeau two prime ministers held its first annual session.	Li Keqiang will start the annual dialogue mechanism with Prime Minister Trudeau of Canada and hold the first annual dialogue between the two premiers.	Li Keqiang will initiate the annual dialogue mechanism between premiers of China and Canada during this visit, and hold the first annual dialogue with Premier Trudeau of Canada.



One-to-Many: Image captioning

http://alinlab.kaist.ac.kr/resource/Lec1_Introduction_to_NN.pdf



e.g., Image Captioning (Image \rightarrow sequence of words)

No errors



A white teddy bear sitting in the grass

Minor errors



A man in a baseball uniform throwing a ball

Somewhat related



A woman is holding a cat in her hand





Attention is all you need

Recall Graph attention

Attention Is All You Need

Ashish Vaswani*
Google Brain
avaswani@google.com

Google Brain noam@google.com

Noam Shazeer*

Niki Parmar* Google Research nikip@google.com Jakob Uszkoreit* Google Research usz@google.com

Llion Jones*
Google Research
llion@google.com

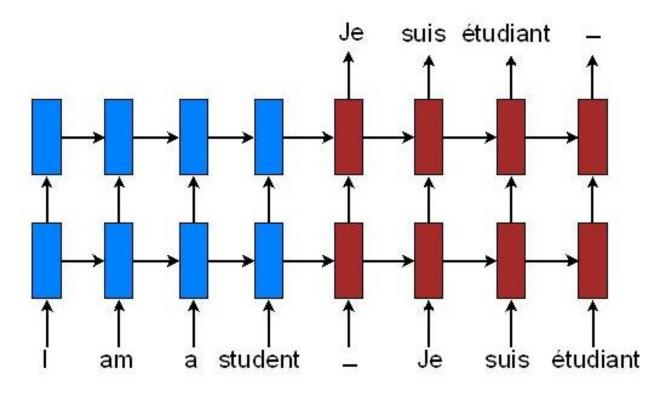
Aidan N. Gomez* †
University of Toronto
aidan@cs.toronto.edu

Łukasz Kaiser*
Google Brain
lukaszkaiser@google.com

Illia Polosukhin* † illia.polosukhin@gmail.com



What is the **attention**?

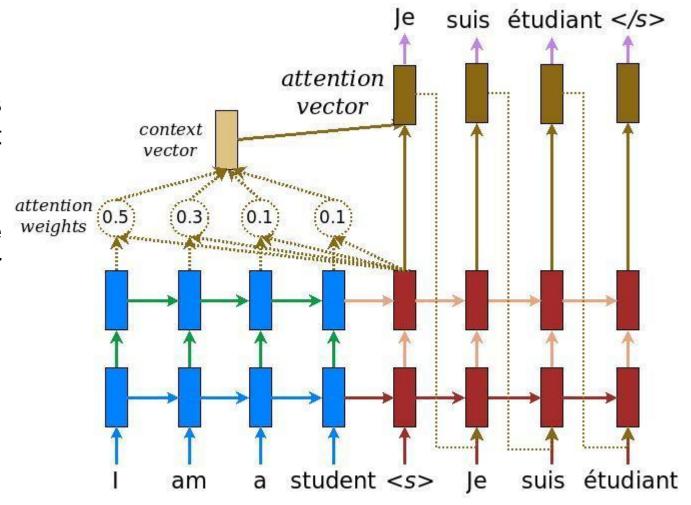


Basic structure of neural translational machine



What is the **attention**?

- However, each output from decoder has different importances in relation with input words.
- Attention mechanism grasps the importance between the words and highlights (larger weight) on more important words.





What is the **attention**?

The attentional vector \tilde{h}_t is provided from the context vector c_t and hidden state h_t .

$$\widetilde{\boldsymbol{h}}_t = \tanh(\boldsymbol{W}_c[\boldsymbol{c}_t, \boldsymbol{h}_t])$$

Then, the predictive output word is given by

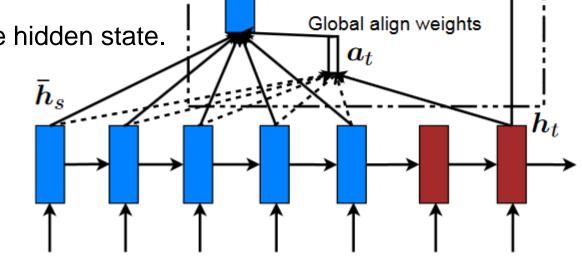
$$p(y_t|y_{< t},x) = \operatorname{softmax}(\boldsymbol{W}_s \widetilde{\boldsymbol{h}}_s)$$

The context vector is weighted average of the source hidden state.

$$c_t = a_t(s) \cdot \overline{h}(s)$$

$$a_t(s) = \frac{\exp(\operatorname{score}(\boldsymbol{h}_t, \overline{\boldsymbol{h}}_s))}{\sum_{s'} \exp(\operatorname{score}(\boldsymbol{h}_t, \overline{\boldsymbol{h}}_{s'}))}$$

$$\operatorname{score}(\boldsymbol{h}_t, \overline{\boldsymbol{h}}_{s'}) = \boldsymbol{v}_a^T \tanh(\boldsymbol{W}_a[\boldsymbol{h}_t; \overline{\boldsymbol{h}}_s])$$

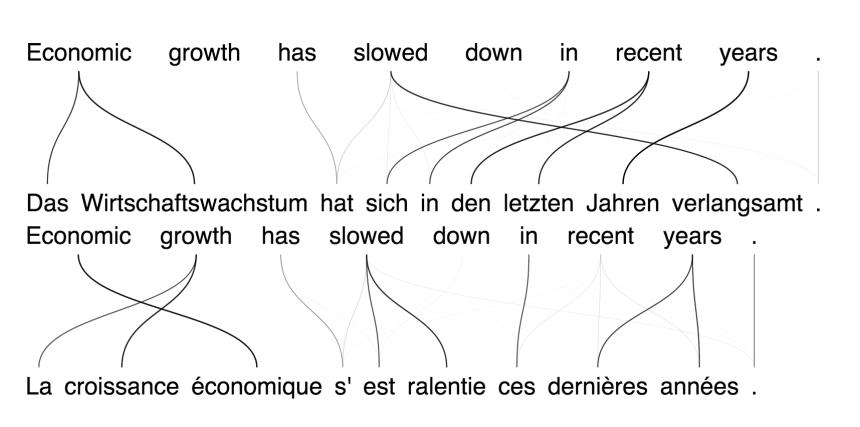


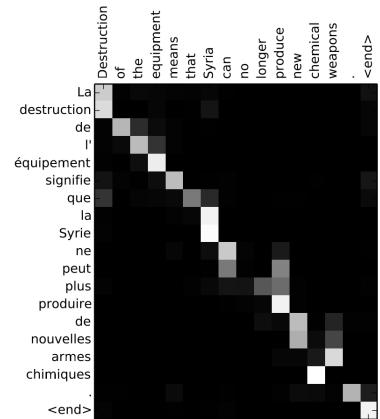
Attention Layer

Context vector



Results of the attention mechanism







What is the **attention**?

While attention is typically thought of as an orienting mechanism for perception, its "spotlight" can also be focused internally, toward the contents of memory. This idea, a recent focus in neuroscience studies, has also inspired work in Al. In some architectures, attentional mechanisms have been used to select information to be read out from the internal memory of the network. This has helped provide recent successes in machine translation and led to important advances on memory and reasoning tasks. These architectures offer a novel implementation of content-addressable retrieval, which was itself a concept originally introduced to Al from neuroscience.

Neuroscience-Inspired Artificial Intelligence

Demis Hassabis,^{1,2,*} Dharshan Kumaran,^{1,3} Christopher Summerfield,^{1,4} and Matthew Botvinick^{1,2}
¹DeepMind, 5 New Street Square, London, UK

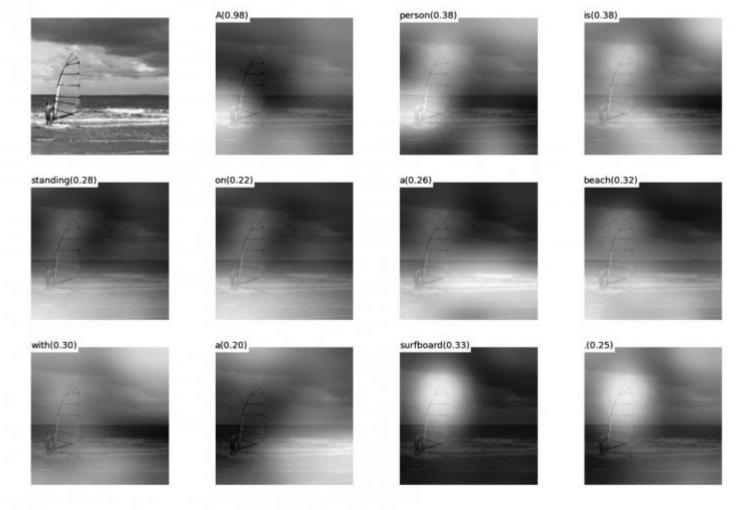
⁴Department of Experimental Psychology, University of Oxford, Oxford, UK



²Gatsby Computational Neuroscience Unit, 25 Howland Street, London, UK

³Institute of Cognitive Neuroscience, University College London, 17 Queen Square, London, UK

Results of the attention mechanism





(b) A person is standing on a beach with a surfboard.

Results of the attention mechanism



A woman is throwing a frisbee in a park.



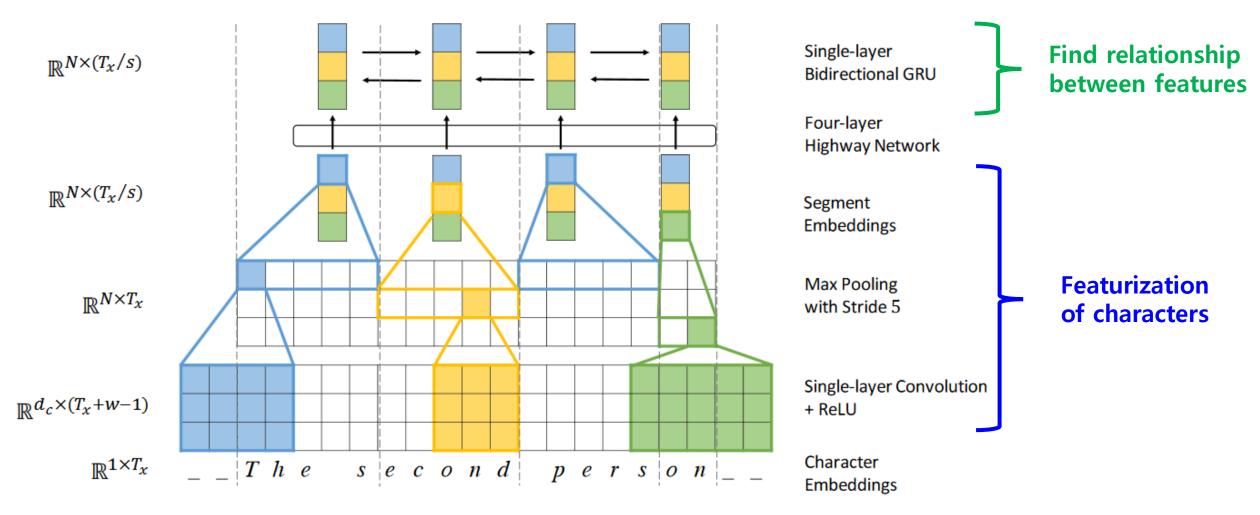
A dog is standing on a hardwood floor.



A <u>stop</u> sign is on a road with a mountain in the background.



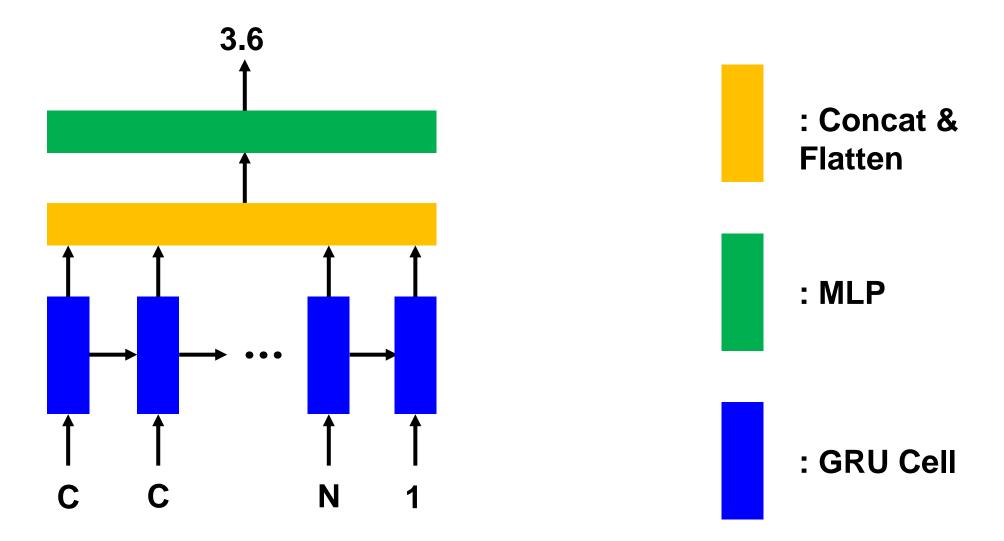
Character level NMT





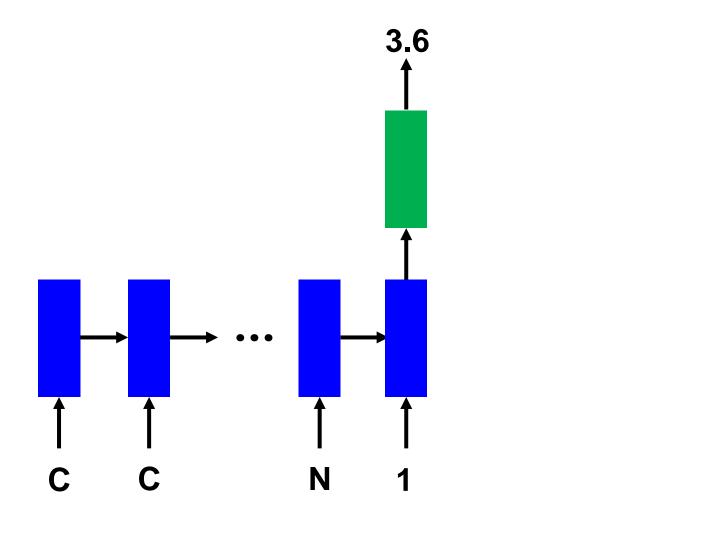


Model 1)





Model 2)



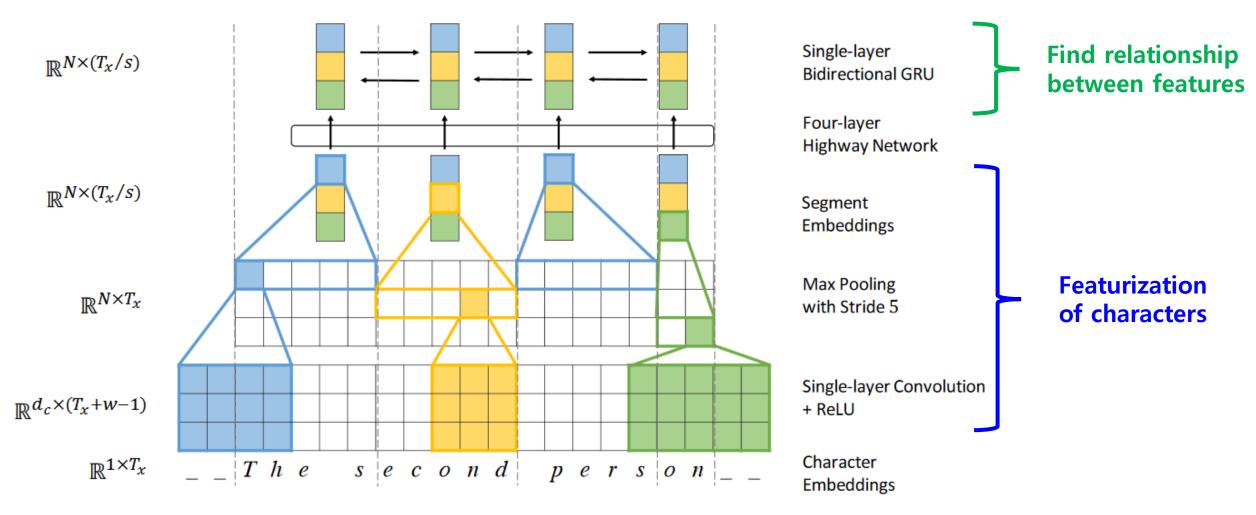
: MLP

: GRU Cell

In this case, you don't need a zero-padding to inputs.

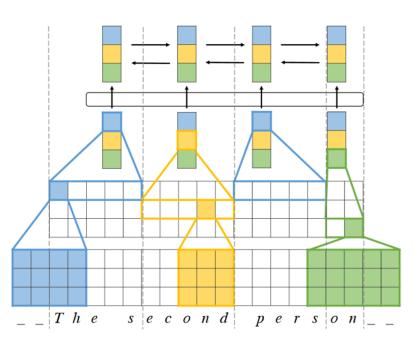


Character level NMT









Single-layer Bidirectional GRU

Four-layer Highway Network

Segment Embeddings

Max Pooling with Stride 5

Single-layer Convolution + ReLU

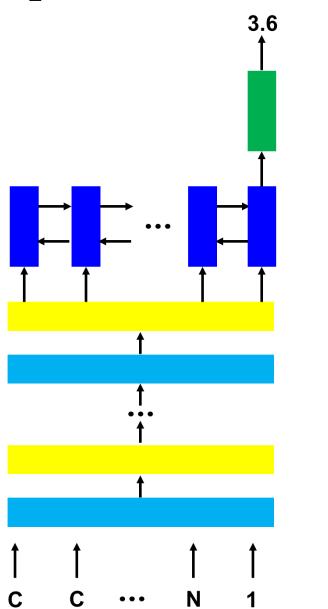
Character Embeddings

Highway network

$$y = \mathbf{g} \odot \text{ReLU}(\mathbf{W}_1 \mathbf{x} + \mathbf{b}_1) + (1 - \mathbf{g}) \odot \mathbf{x}$$

$$\mathbf{g} = \sigma(\mathbf{W}_2 \mathbf{x} + \mathbf{b}_2)$$





: Conv

: Highway

: MLP

: Bi-GRU Cell

Comparison: (input data representation, model architecture)

	FP - MLP	SMILES - CNN	Graph – GCN	SMILES - RNN1	SMILES – RNN2	SMILES – RNN3		My best (???)
MAE	0.31	0.15	0.088	0.13	0.05	0.072	•••	0.01
Std.dev	0.42	0.20	0.137	0.18	0.08	0.11	•••	-



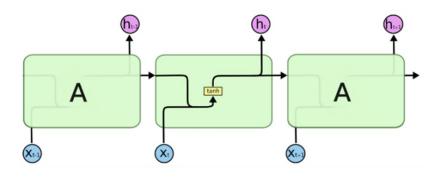
Assignment #6

Build your own RNN for logP prediction

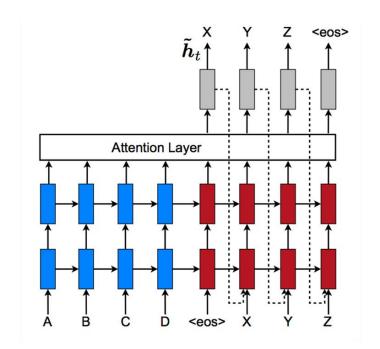
- In this class, TA showed the several RNN models for logP prediction
- In this week, we learned i) RNN, and ii) modern advanced RNNs.
- Therefore, building your own RNN is an objective of this assignment.
- Report your results MAE, std. dev, and truth-prediction plot.
- Your models do not need to be better than the TA's RNN model, improving the TA's model is not the goal of this assignment. However, please discuss why and how your neural network gives such results.



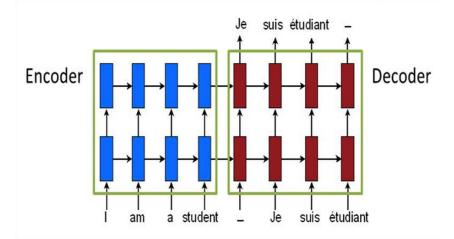
교수님이 수업에서 다루신 것



과제



조교가 연습반에서 다룬 것



Final term project

