LECTURE 12

RNN

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http://hunkim.github.io/ml

NAVER | Clova

LECTURE 12-1

RNN INTRODUCTION

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Sequence Data

01. We don't understand one word only

02. We understand based on the previous words
+ this word. (time series)

03. NN/CNN cannot do this

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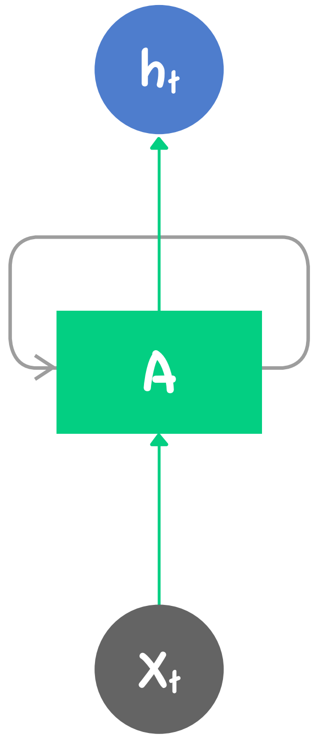
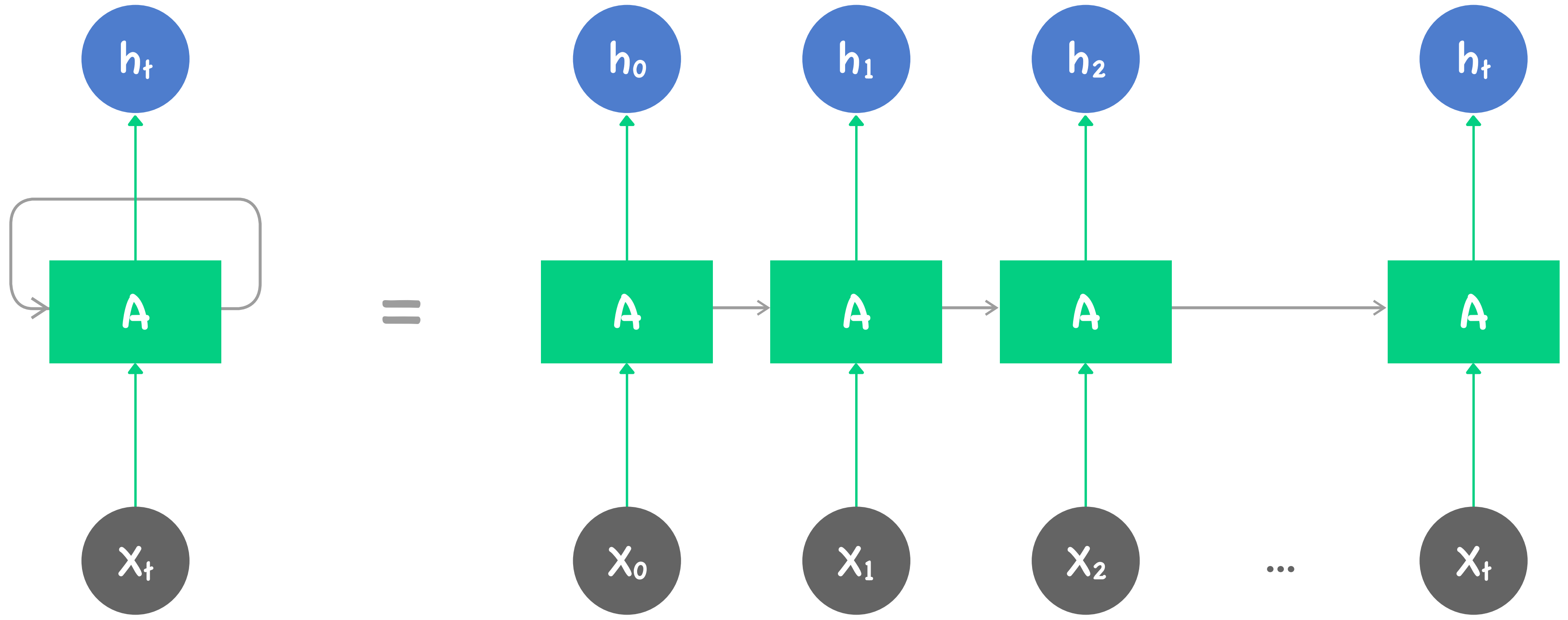


http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Sequence Data



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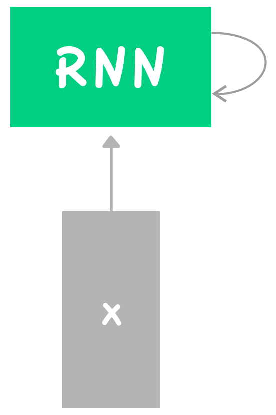
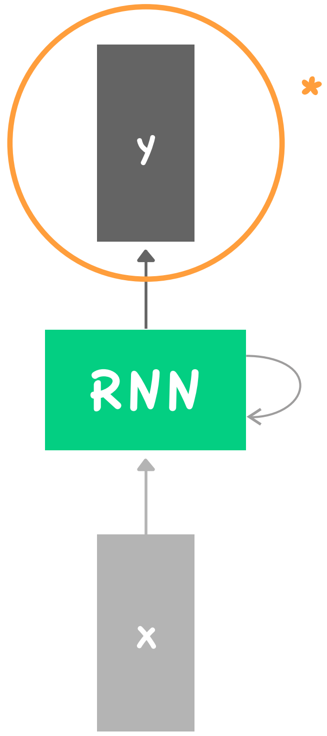
Recurrent Neural Network



Recurrent Neural Network

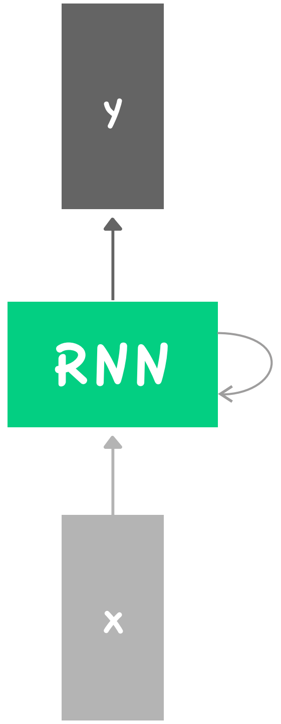


* usually want to predict a vector at some time steps

Recurrent Neural Network

We can process a sequence of vectors x by applying a recurrence formula at every time step:

$$\underbrace{h_t}_{\text{New state}} = \underbrace{f_W}_{\text{Some function with parameters W}}(\underbrace{h_{t-1}}_{\text{Old state}}, \underbrace{x_t}_{\text{Input vector at some time step}})$$

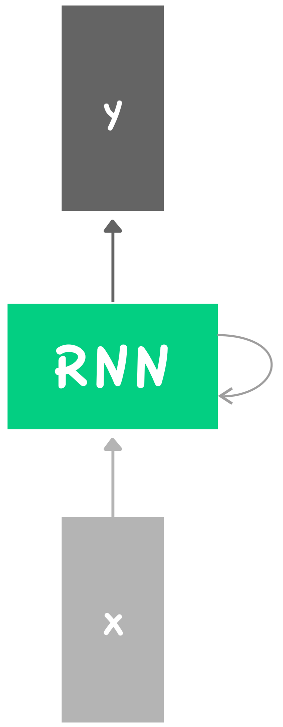


Recurrent Neural Network

We can process a sequence of vectors x by
applying a recurrence formula at every time step:

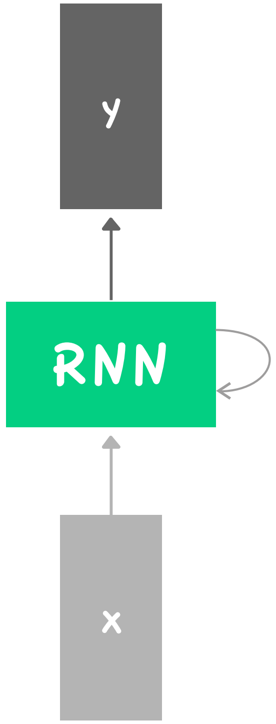
$$h_t = fw(h_{t-1}, x_t)$$

Notice: the same function and the same set of
parameters are used at every time step.



Recurrent Neural Network (Vanilla)

The state consists of a single "hidden" vector h :

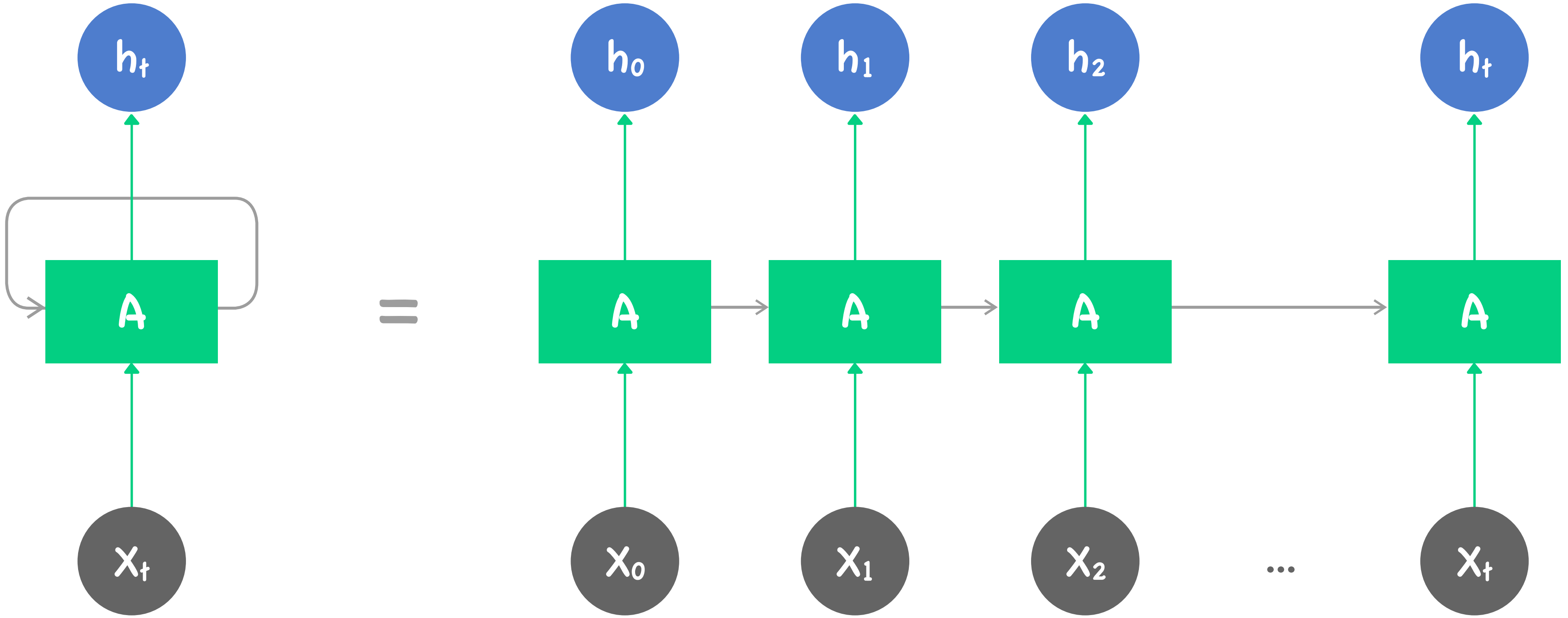


$$h_t = fw(h_{t-1}, x_t)$$

$$\downarrow$$

$$h_t = \tanh(W_{hh}h_{t-1}, W_{xh}x_t)$$

$$y_t = W_{hy}h_t$$



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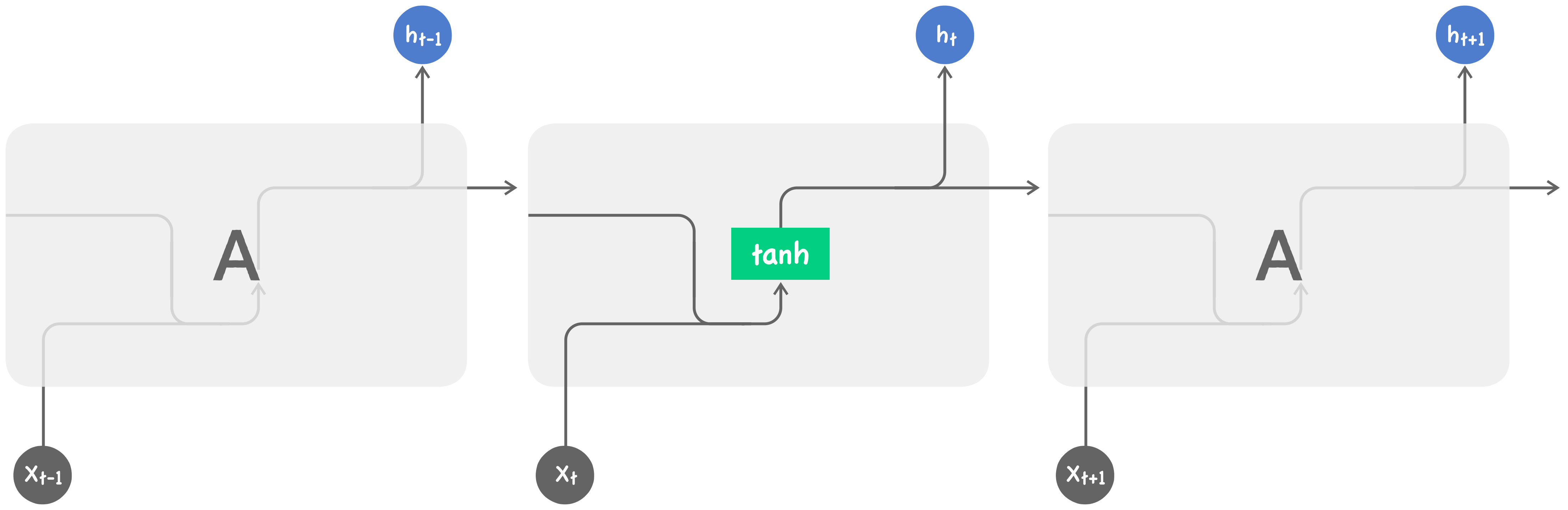


Given list of word vectors : $x_1, \dots, x_{t-1}, x_t, x_{t+1}, \dots, x_T$

At a single time step : $h_t = \sigma(W^{(hh)}h_{t-1} + W^{(hx)}x_{[t]})$

$\hat{y}_t = \text{softmax}(W^{(S)}h_t)$

$\hat{P}(x_{t+1} = v_j \mid x_t, \dots, x_1) = \hat{y}_{t,j}$

Character-level Language Model

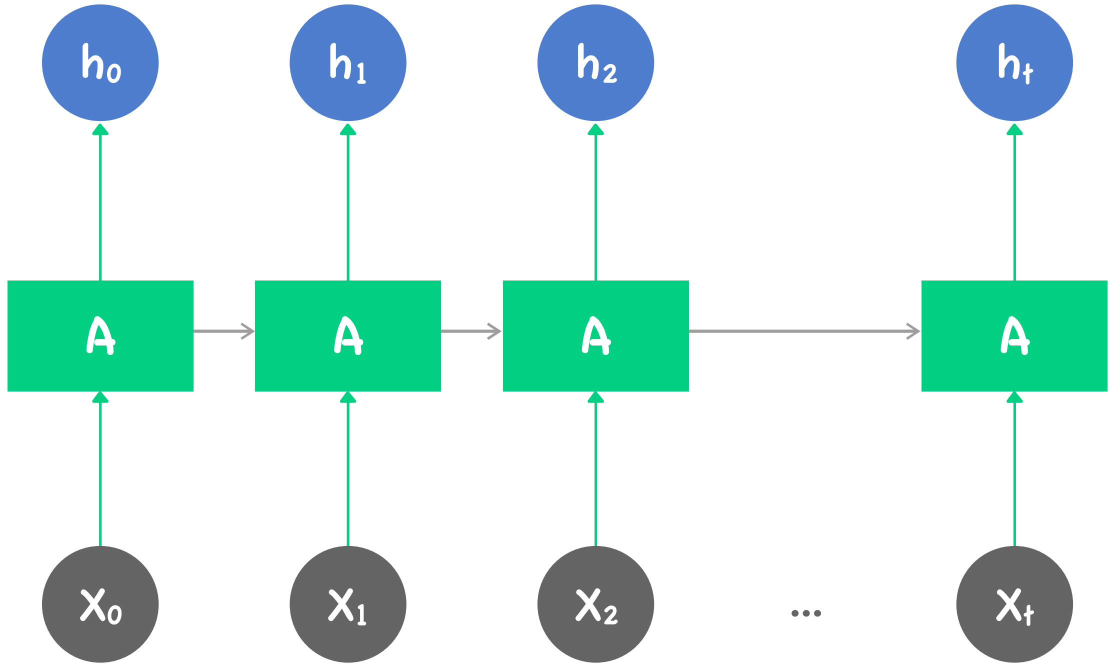
Example

Vocabulary

[h,e,l,o]

Example Training Sequence :

"hello"



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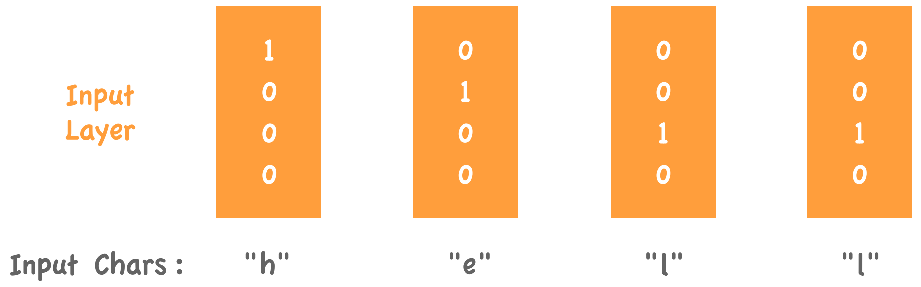

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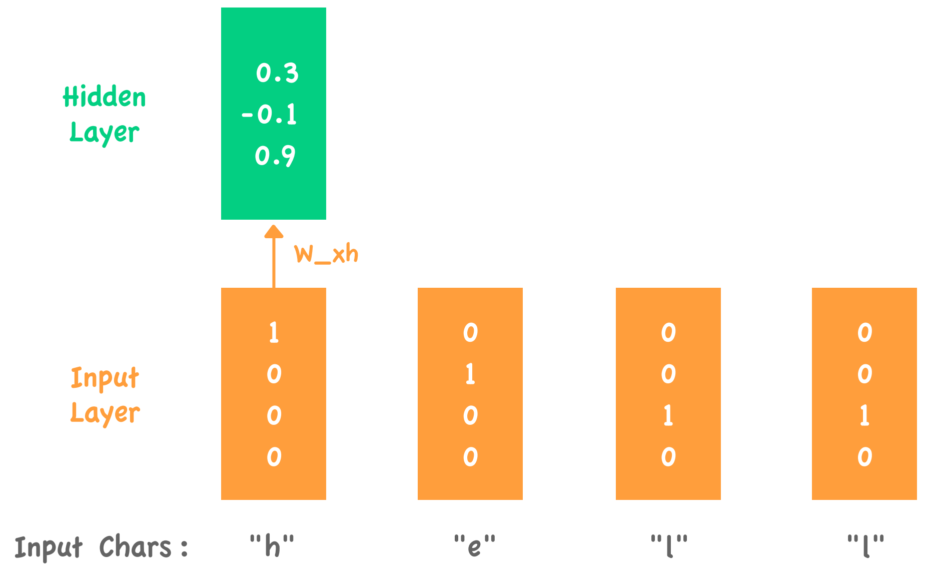

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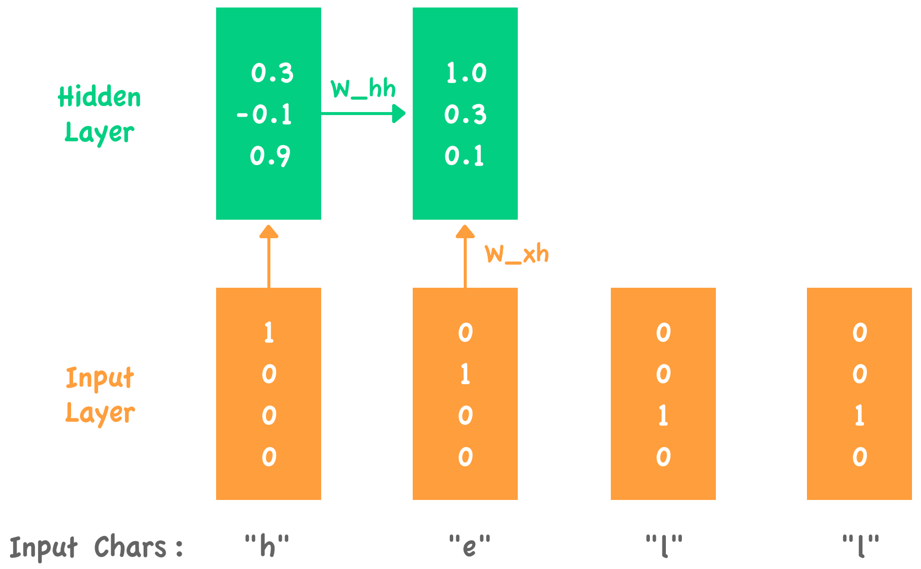

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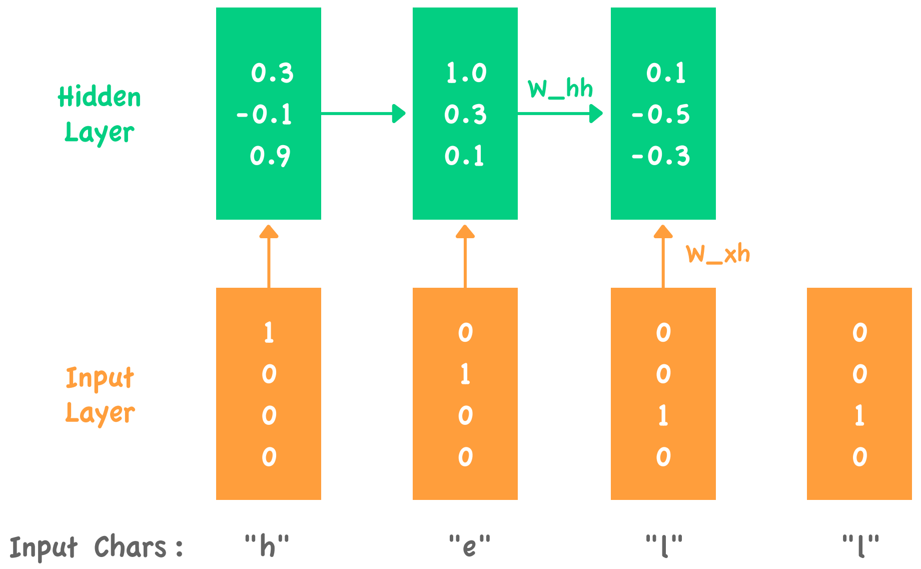

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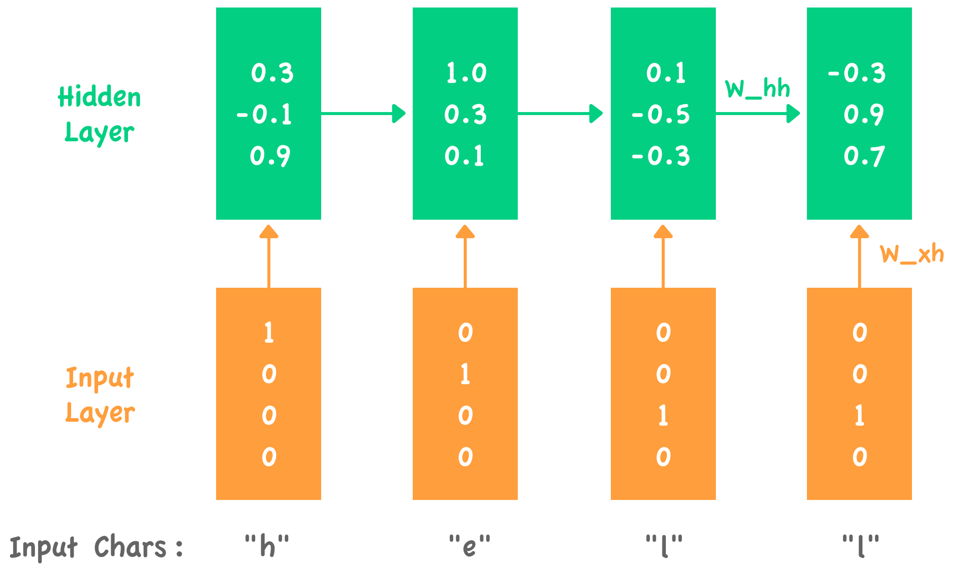
$$\boxed{h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)}$$



Character-level Language Model

Example

Vocabulary

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Example Training Sequence :

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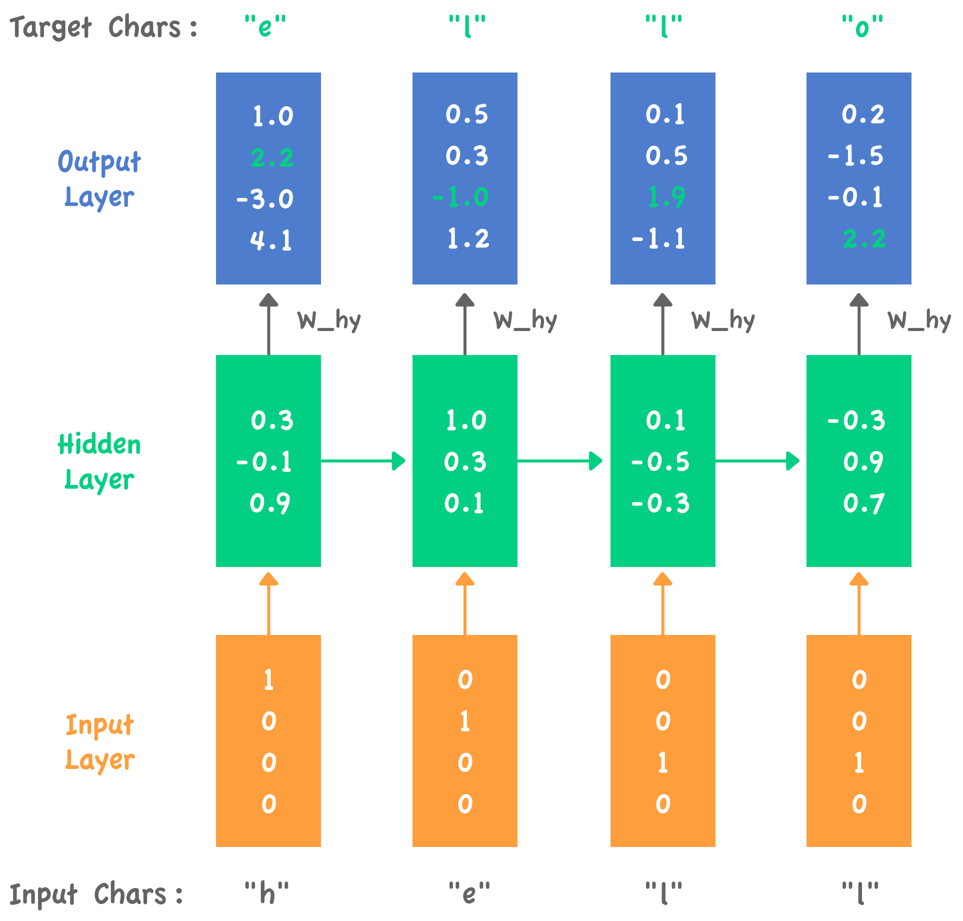
$$y_t = W_{hy} h_t$$



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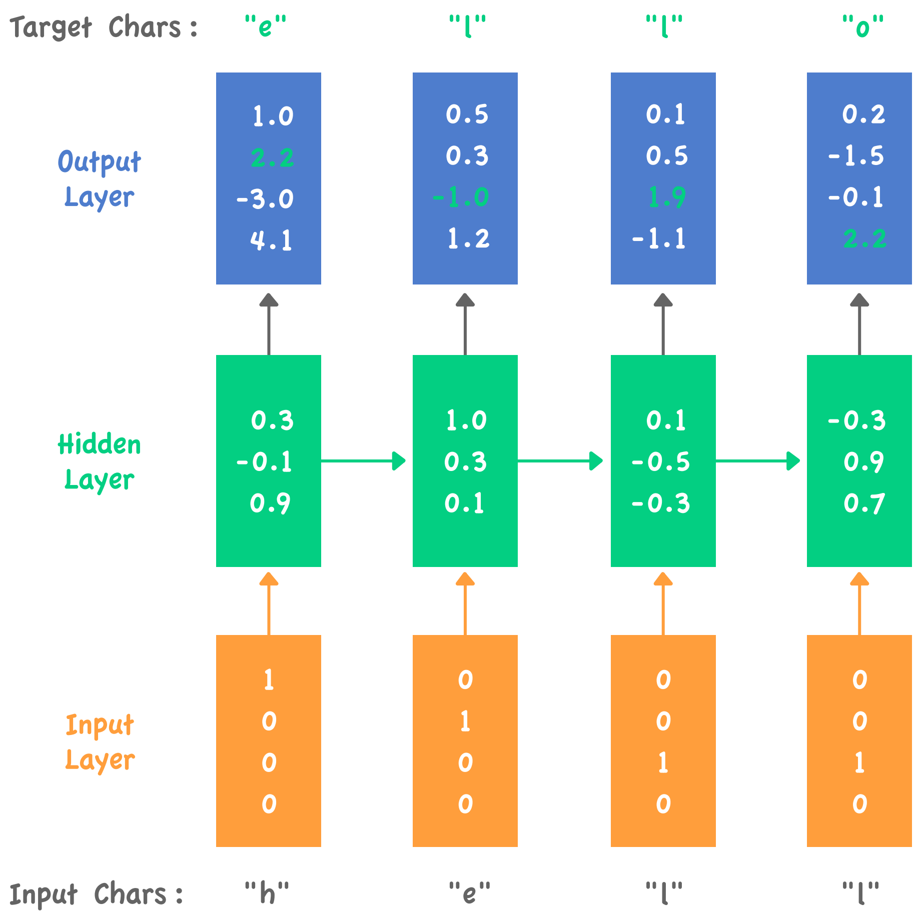
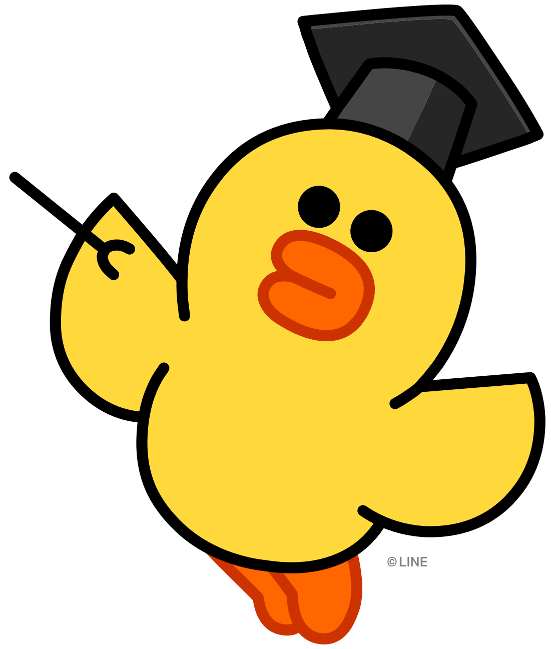


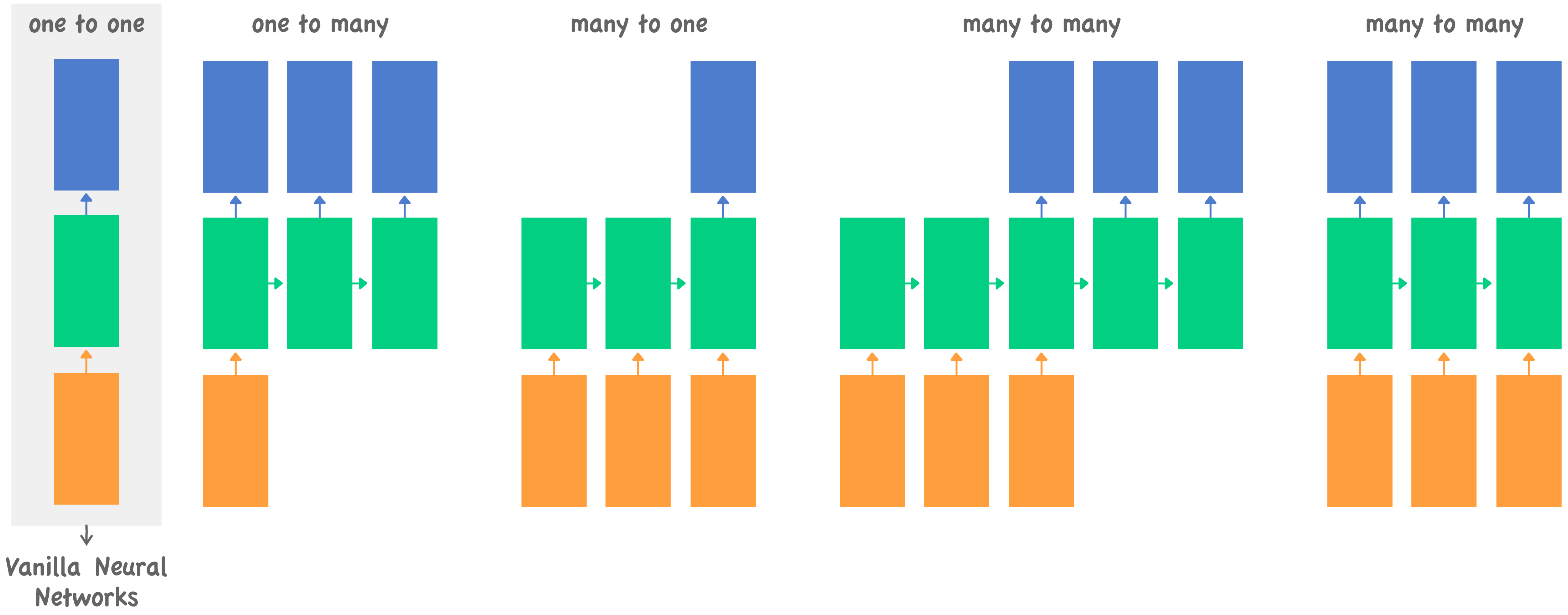
RNN Applications

- Language Modeling
- Speech Recognition
- Machine Translation
- Conversation Modeling / Question Answering
- Image / Video Captioning
- Image / Music / Dance Generation



http://jiwonkim.org/awesome-rnn/
https://github.com/TensorFlowKR/awesome_tensorflow_implementations

Recurrent Networks Offer a Lot of Flexibility



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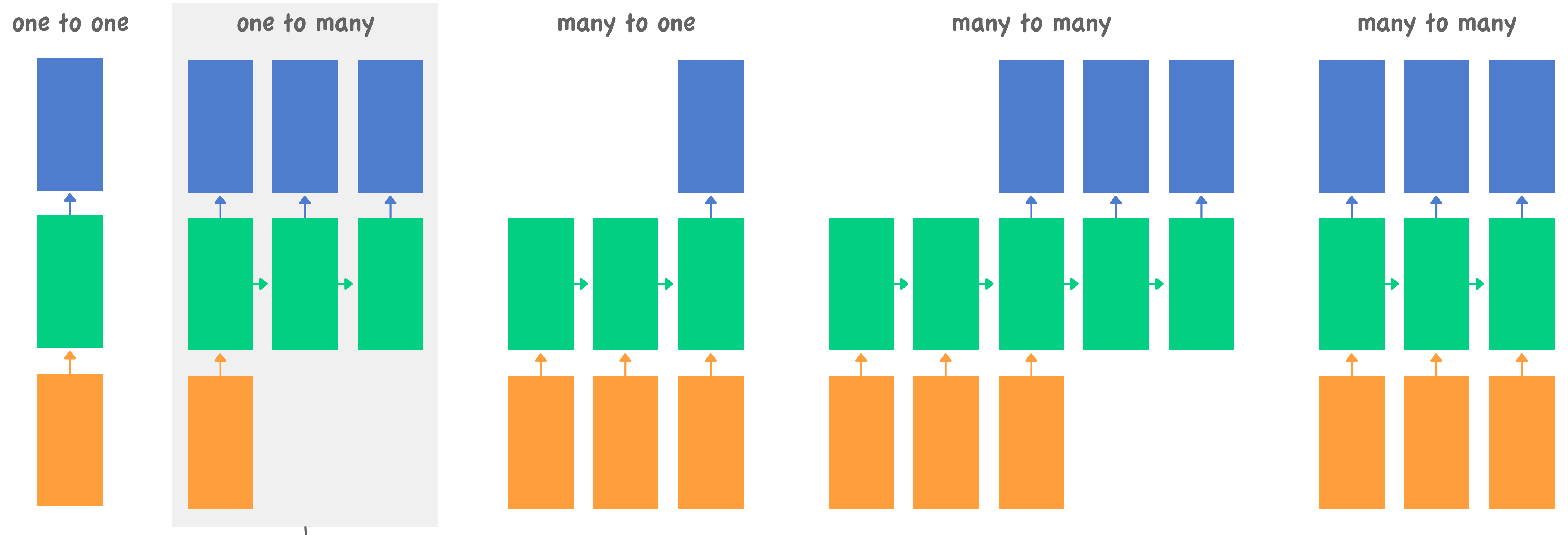
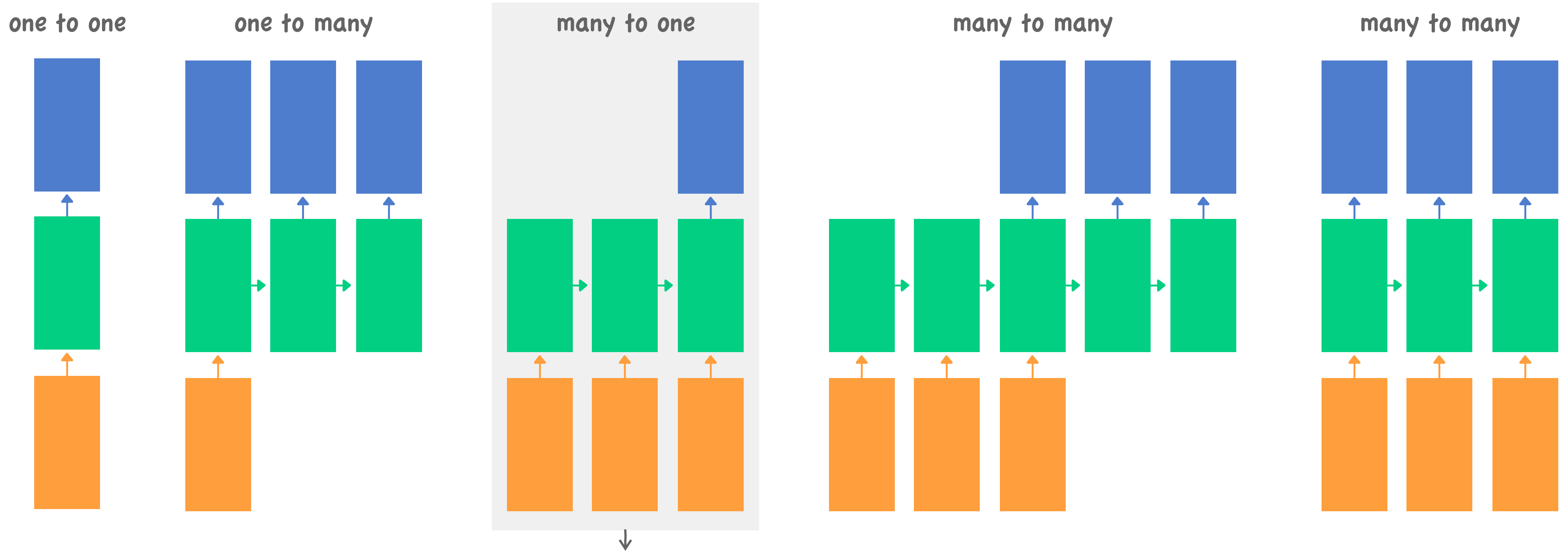


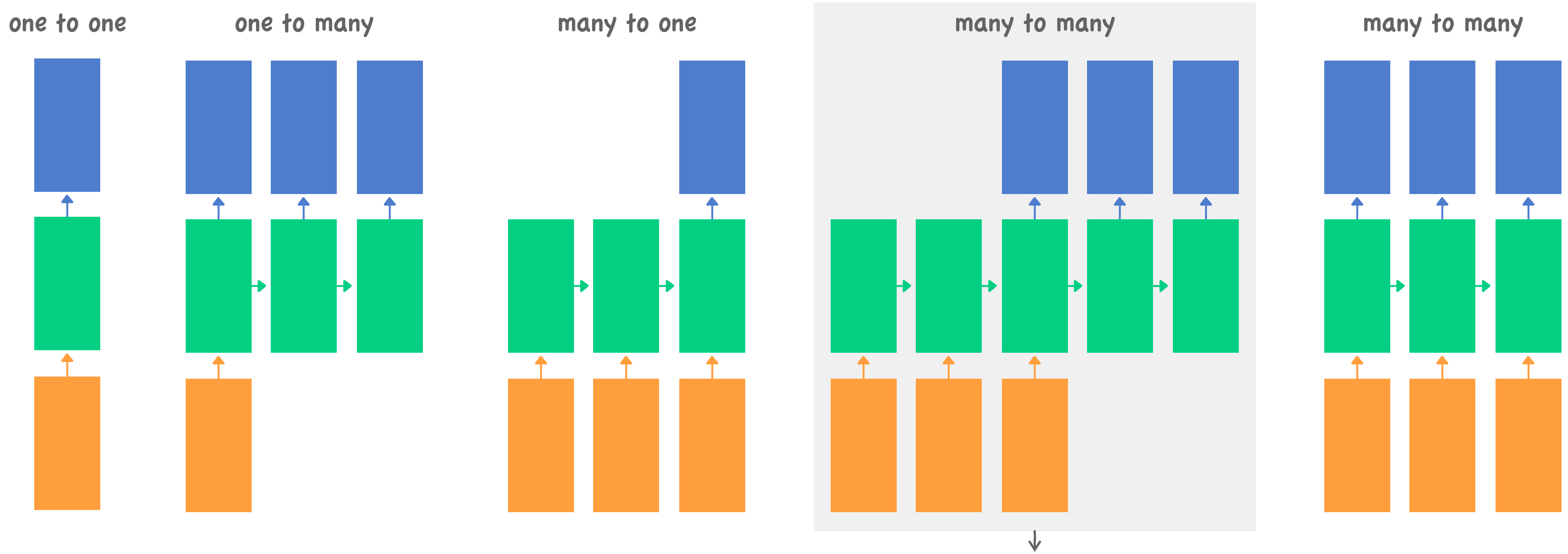
e.g. Image Captioning
Image -> sequence of words

Recurrent Networks Offer a Lot of Flexibility



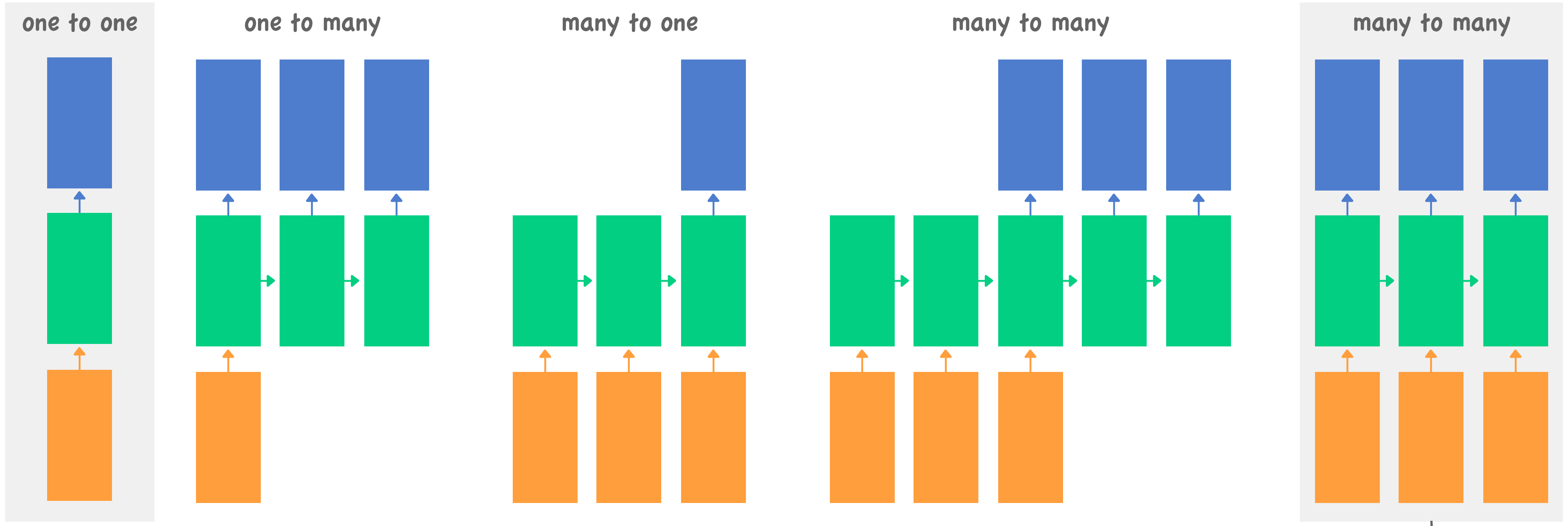
e.g. Sentiment Classification
Sequence of words -> sentiment

Recurrent Networks Offer a Lot of Flexibility



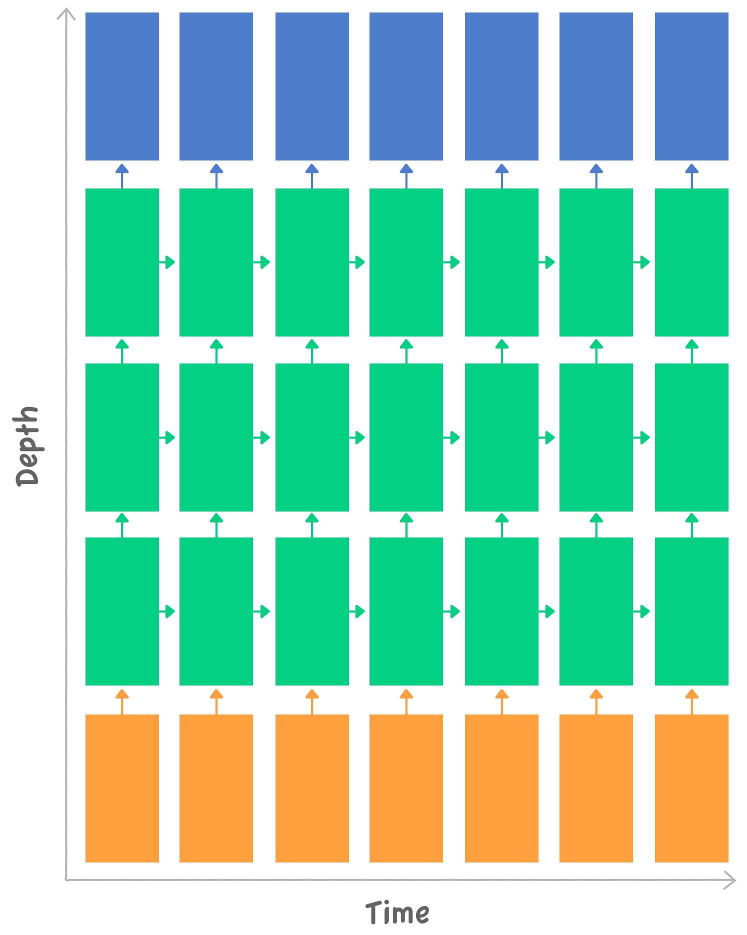
e.g. Machine Translation
Seq of words -> Seq of words

Recurrent Networks Offer a Lot of Flexibility



e.g. Video classification on frame level

Multi-Layer RNN



Training RNNs Is Challenging

- Several advanced models
  - Long Short Term Memory (LSTM)
  - GRU by Cho et al. 2014

NEXT LECTURE

LSTM INTRODUCTION