ISO 29990:2010

NATIONAL INFOCOMM COMPETENCY FRAMEWORK

NUS National University of Singapore

ISS INSTITUTE OF SYSTEMS SCIENCE

Text Processing using Machine Learning

Memory Network and Conditioned Generation

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04 Dec 2019

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OFFERING OVER 120 ENTERPRISE IT, INNOVATION & LEADERSHIP PROGRAMMES

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Overview

Lecture

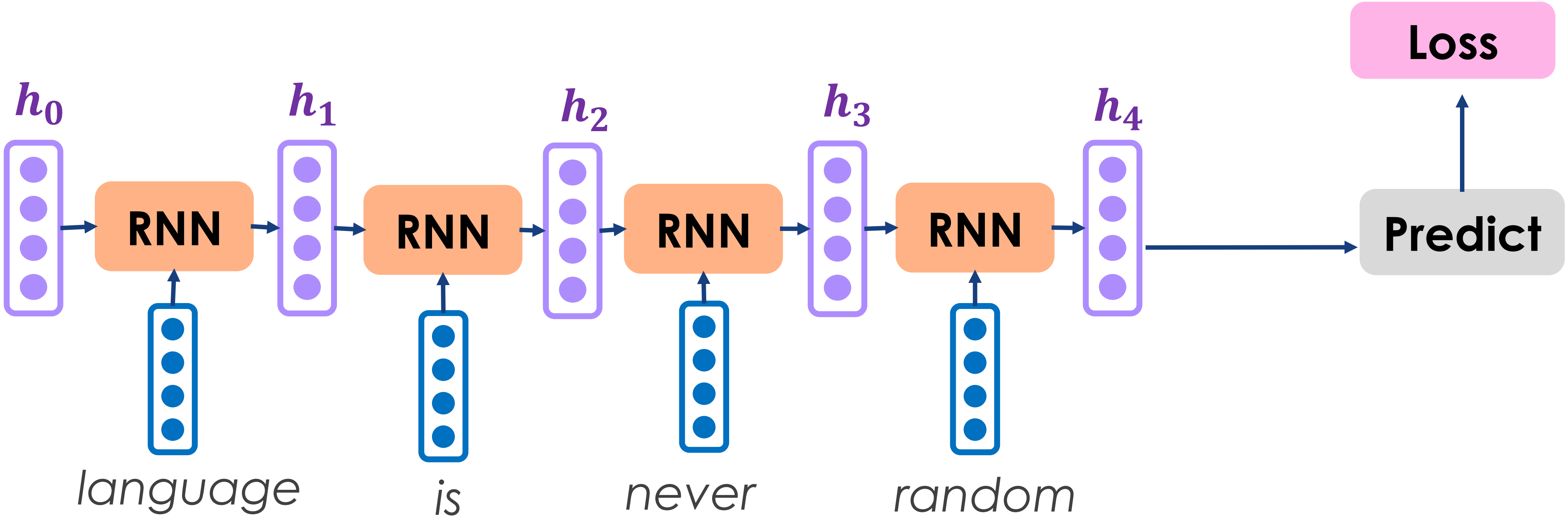
- Gated Memory RNNs
- Conditioned Generation

Hands-on

- Sequence Generation

Gated Memory RNNs

Recurrent Neural Nets



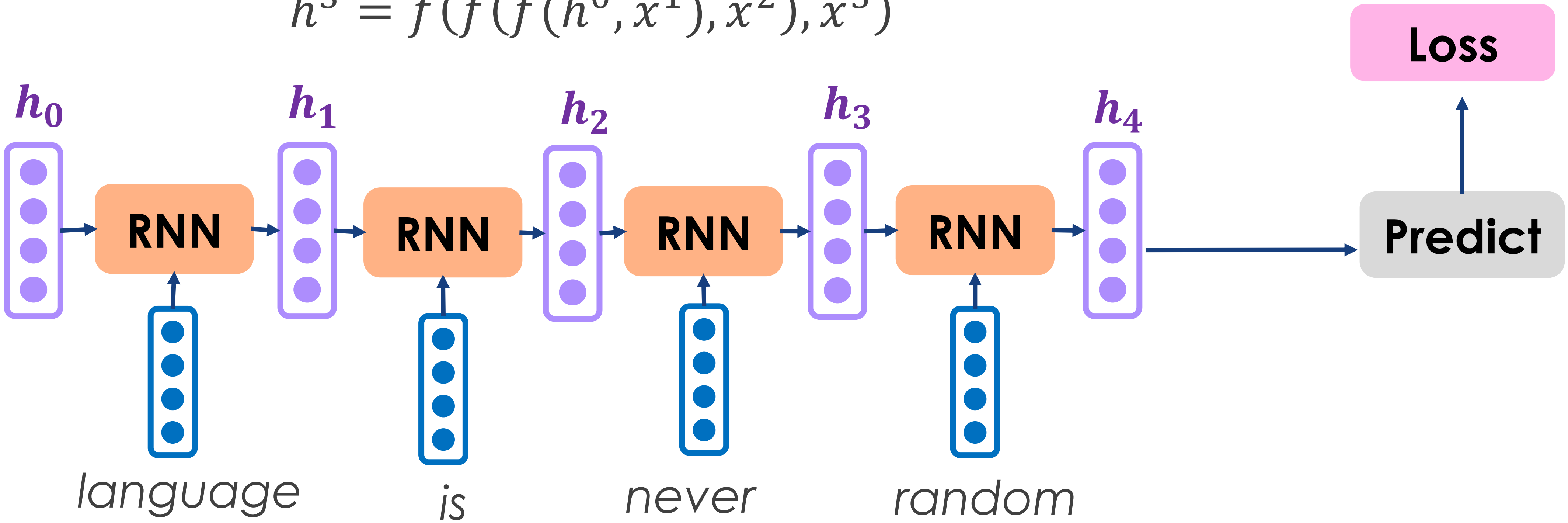
RNN Exploding gradient

Lets look at the **"curled up" RNN:**

$$h^t = f(h^{t-1}, x^t)$$

If we **unroll the RNN** that has 3 time-step, we get:

$$h^3 = f(f(f(h^0, x^1), x^2), x^3)$$



Exploding gradient

Lets look at the **“curled up” RNN:**

$$h^t = f(h^{t-1}, x^t)$$

If we **unroll the RNN** that has 3 time-step, we get:

$$h^3 = f(f(f(h^0, x^1), x^2), x^3)$$

And if consider $f(x)$ as a “harmless-looking”

$$f(x) = 3.5x(1-x)$$

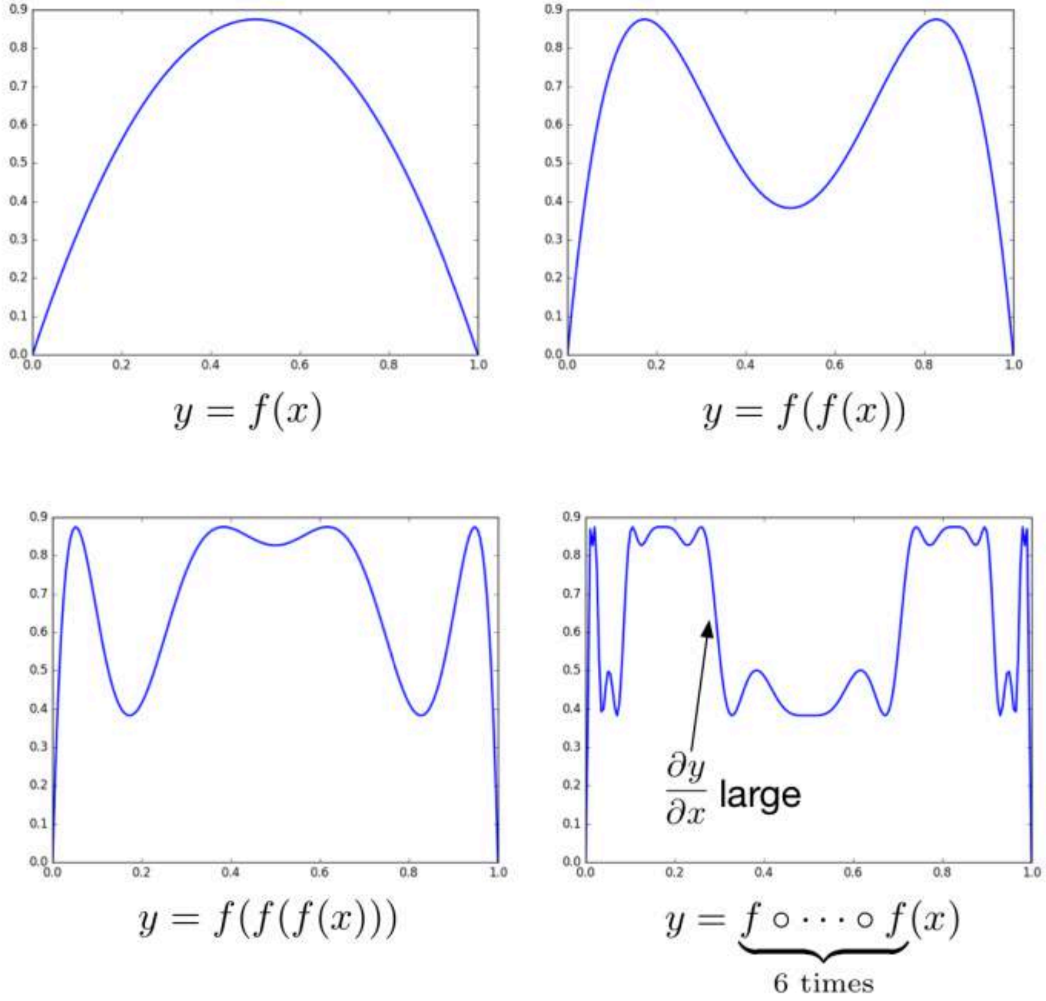


Figure and example from (Grosse 2017)

Solution: Gradient Clipping

- **General idea:** if we don't like the big numbers, just put a max to the gradient values

Algorithm 1 Pseudo-code for norm clipping

$\hat{\mathbf{g}} \leftarrow \frac{\partial \mathcal{E}}{\partial \theta}$

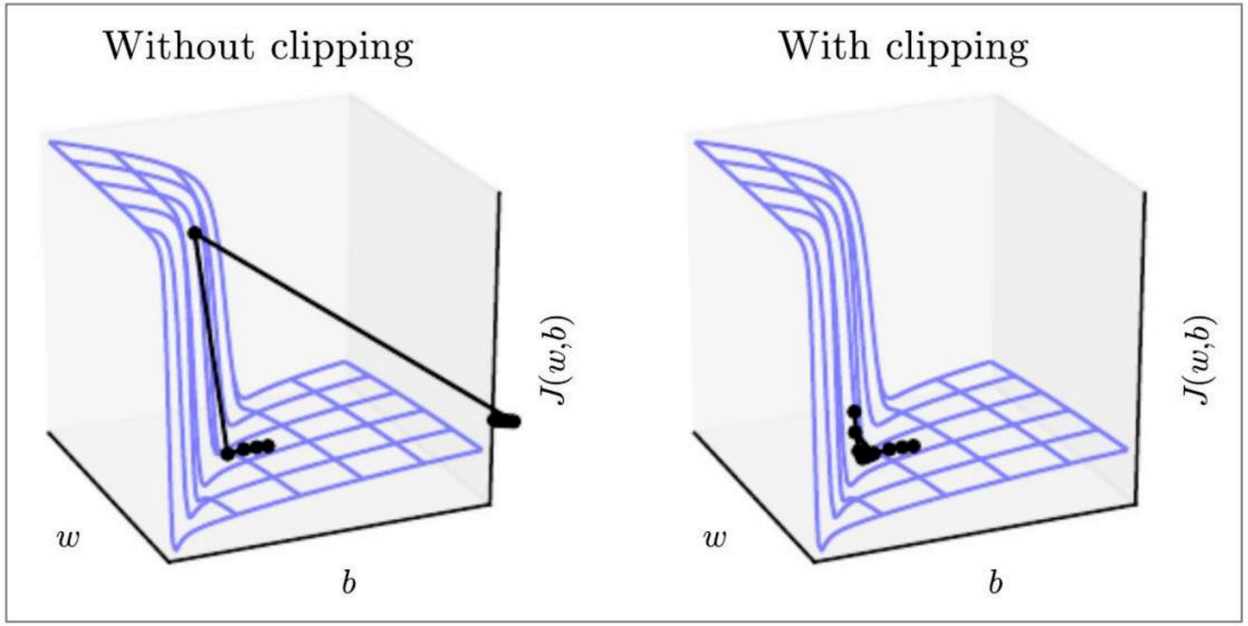
if $\|\hat{\mathbf{g}}\| \geq threshold$ **then**

  $\hat{\mathbf{g}} \leftarrow \frac{threshold}{\|\hat{\mathbf{g}}\|} \hat{\mathbf{g}}$

end if

Source: (Pascanu et al, 2013)

Solution: Gradient Clipping



- Figure above shows a loss surface of an RNN

- **(Left) without clipping**, weights values increases and so does gradient causing loss to "jump off the clip"

- **(Right) with clipping**, weights are kept to a max and loss doesn't inflate

Source: (Goodfellow et al. 2016)

Partial Gradients

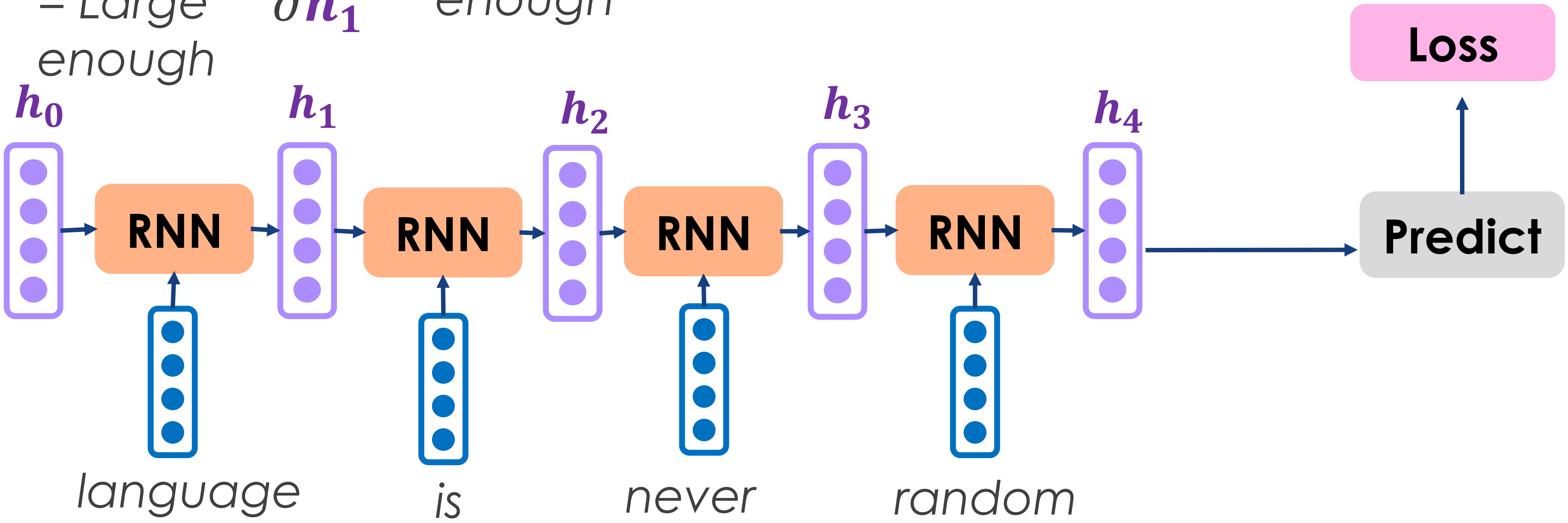
$$\frac{\partial(loss)}{\partial h_4}$$ = Large enough

$$\frac{\partial(h_4)}{\partial h_3}$$ = Large enough

$$\frac{\partial(h_3)}{\partial h_2}$$ = Large enough

$$\frac{\partial(h_2)}{\partial h_1}$$ = Large enough

$$\frac{\partial(h_1)}{\partial h_0}$$ = Large enough



RNN Vanishing Gradients

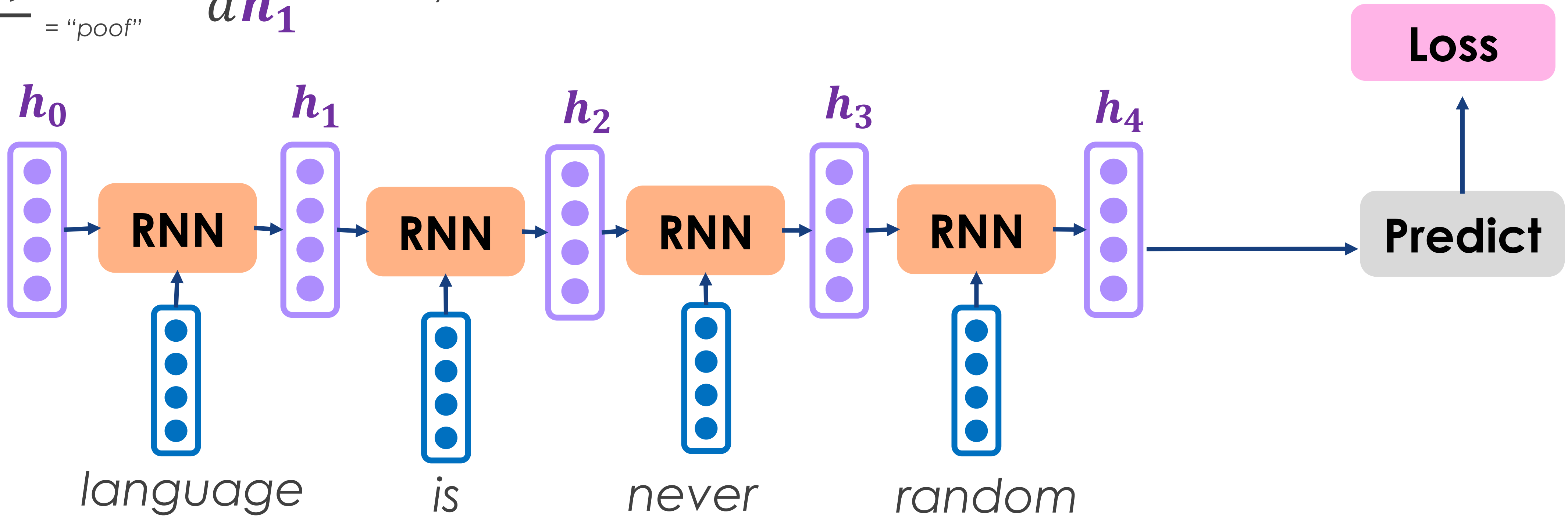
$$\frac{d(loss)}{d\boldsymbol{h}_4} = \text{Large enough}$$

$$\frac{d(loss)}{d\boldsymbol{h}_3} = \text{Okay}$$

$$\frac{d(loss)}{d\boldsymbol{h}_2} = \text{small}$$

$$\frac{d(loss)}{d\boldsymbol{h}_1} = \text{tiny}$$

$$\frac{d(loss)}{d\boldsymbol{h}_0} = \text{“poof”}$$



Why is vanishing gradient a problem?

- When moving along the timestep of RNN, gradient can be thought as "***the effects of the past on the future***" **(See, 2019)**

Why is vanishing gradient a problem?

- When moving along the timestep of RNN, gradient can be thought as "***the effects of the past on the future***" **(See, 2019)**

- Vanishing gradient means info from the ***previous words are less influential to predict words in the future***

"**Trump** haz **cheezburger**"

"**Trump** haz the **kat** tat haz **cheezburger**"

"**Trump** haz the kat buy tat **cheezburger**"

Why is vanishing gradient a problem?

- When moving along the timestep of RNN, gradient can be thought as "***the effects of the past on the future***" ***(See, 2019)***
- Vanishing gradient means info from the ***previous words are less influential to predict words in the future***
- When gradients are small over longer distance, it's hard to know whether
  - **Trump** has no relation to the **cheezburger** or
  - the model learns to **wrong parameter** that doesn't capture relation between **Trump** and **cheezburger**

Solution: Information Controlling RNN

- **General idea:** make additive connections between time steps

- ***Keeping a memory of past time steps and add them to the current one***

- ***Addition don't change gradient***, no vanishing

- ***Gates control different information strengths*** from the past

Long Short Term Memory (LSTM)

- At each time step, perform the following operations

Input: controls how much new cell info is written to cell

$$i_t = \sigma\left(W^{(i)}x_t + U^{(i)}h_{t-1}\right)$$

Forget: controls how much previous cell info should be forgotten

$$f_t = \sigma\left(W^{(f)}x_t + U^{(f)}h_{t-1}\right)$$

Output: controls how much info is written to hidden state

$$o_t = \sigma\left(W^{(o)}x_t + U^{(o)}h_{t-1}\right)$$

New cell info: new content to write to cell

$$\tilde{c}_t = \tanh\left(W^{(c)}x_t + U^{(c)}h_{t-1}\right)$$

Cell state (Memory): forget some of the previous cell info and write some new cell info

$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t$$

Hidden state: output some bits of info from the cell state for next cell to "remember"

$$h_t = o_t \circ \tanh(c_t)$$

Long Short Term Memory (LSTM)

- At each time step, perform the following operations

Sigmoid to make sure all outputs are (0,1)

Elementwise product

$$i_t = \sigma\left(W^{(i)}x_t + U^{(i)}h_{t-1}\right)$$

$$f_t = \sigma\left(W^{(f)}x_t + U^{(f)}h_{t-1}\right)$$

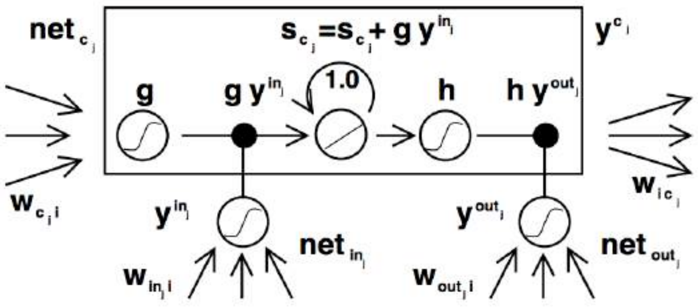
$$o_t = \sigma\left(W^{(o)}x_t + U^{(o)}h_{t-1}\right)$$

$$\tilde{c}_t = \tanh\left(W^{(c)}x_t + U^{(c)}h_{t-1}\right)$$

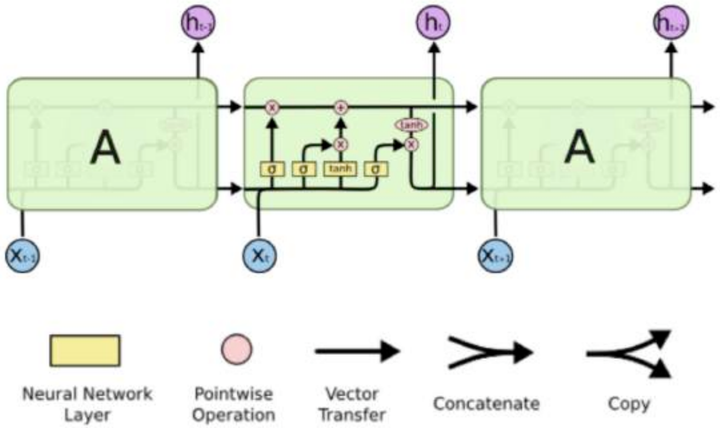
$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t$$

$$h_t = o_t \circ \tanh(c_t)$$

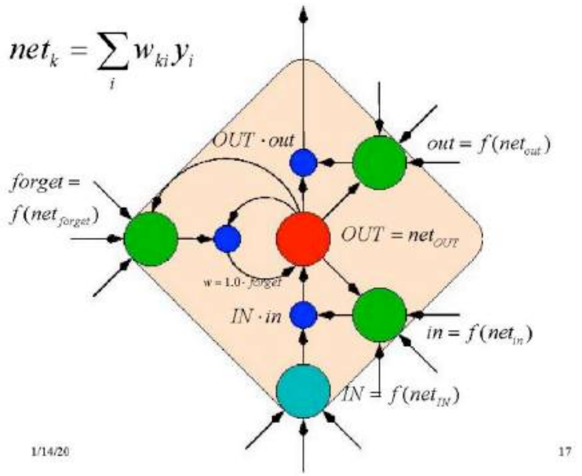
LSTM Galore



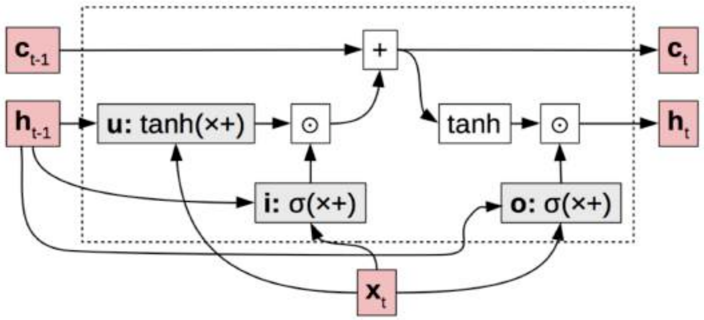
From Hochreiter and Schmidhuber (1997)



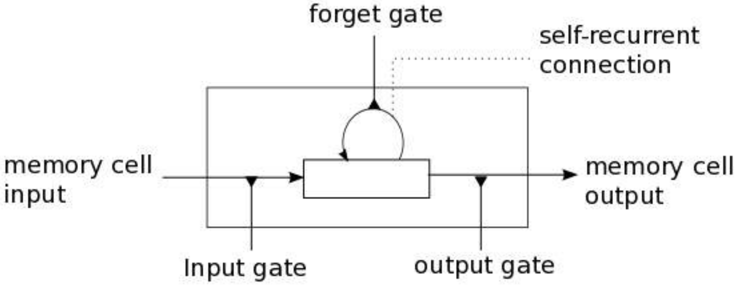
From Olah (2015) blogpost



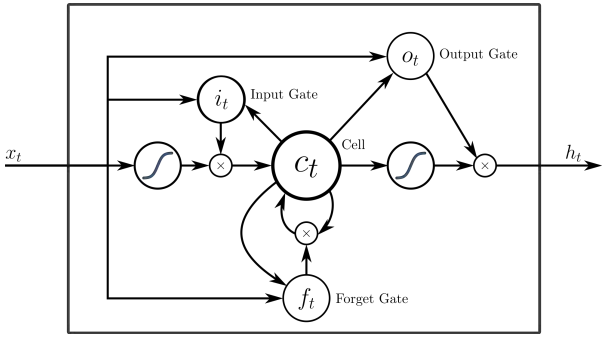
From Schmidhuber (2017) page



From Neubig (2019) CMU NN4NLP Course

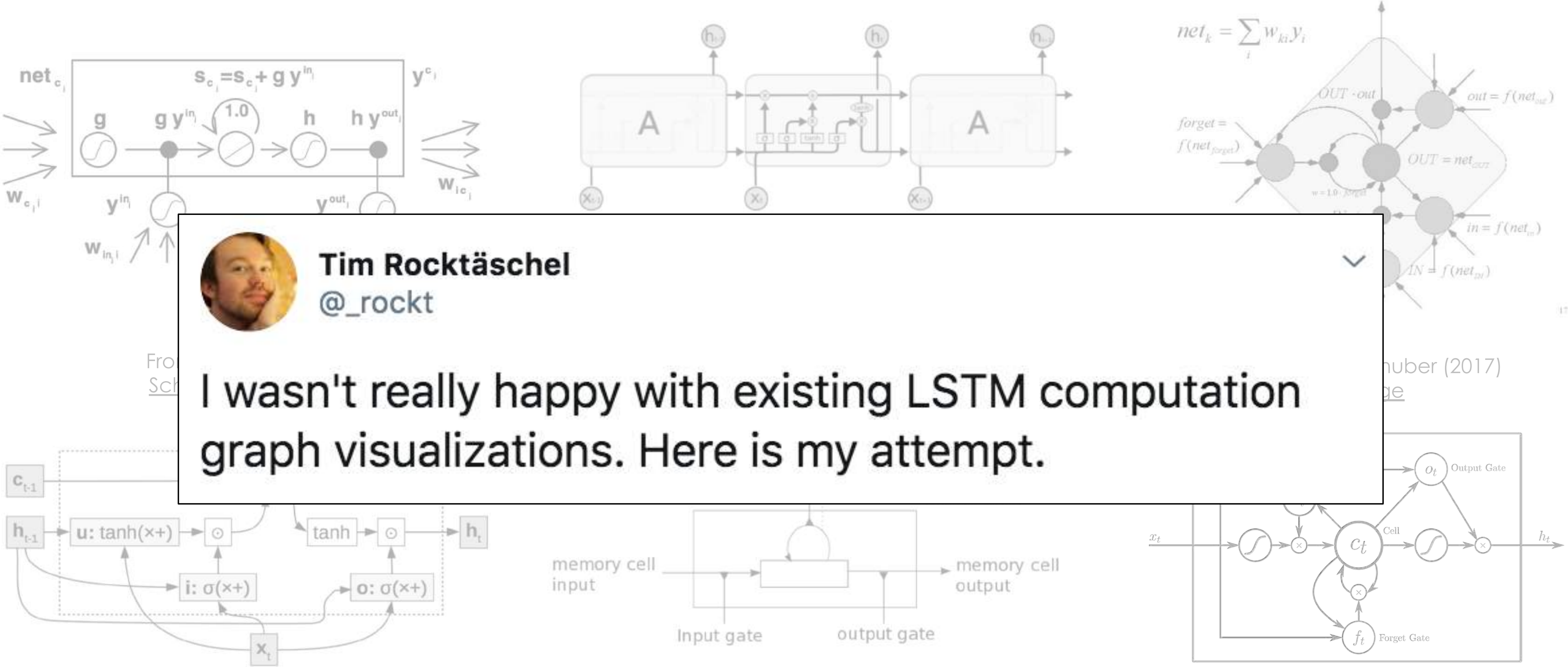


From http://deeplearning.net



From Wikipedia

LSTM Galore



From Neubig (2019) CMU NN4NLP Course

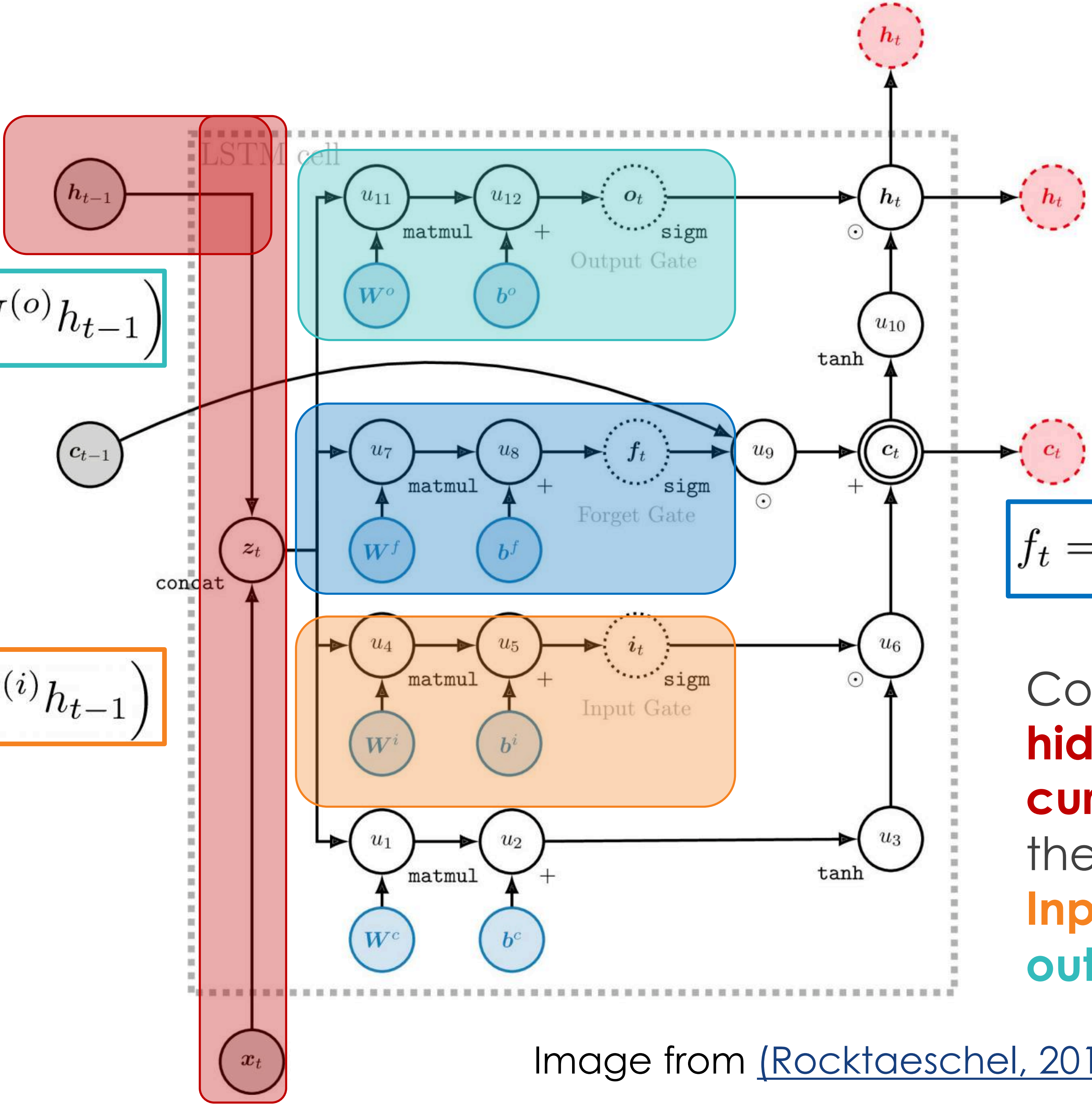
From http://deeplearning.net

From Wikipedia

LSTM

$$o_t = \sigma\left(W^{(o)}x_t + U^{(o)}h_{t-1}\right)$$

$$i_t = \sigma\left(W^{(i)}x_t + U^{(i)}h_{t-1}\right)$$



$$f_t = \sigma\left(W^{(f)}x_t + U^{(f)}h_{t-1}\right)$$

Concat the previous **hidden state** and **current input** and put them through the **Input**, **forget** and **output** gates

Image from [(Rocktaeschel, 2017)]

LSTM

Compute the **non-linearity** like a vanilla RNN **for this time step**

$$\tilde{c}_t = \tanh\left(W^{(c)}x_t + U^{(c)}h_{t-1}\right)$$

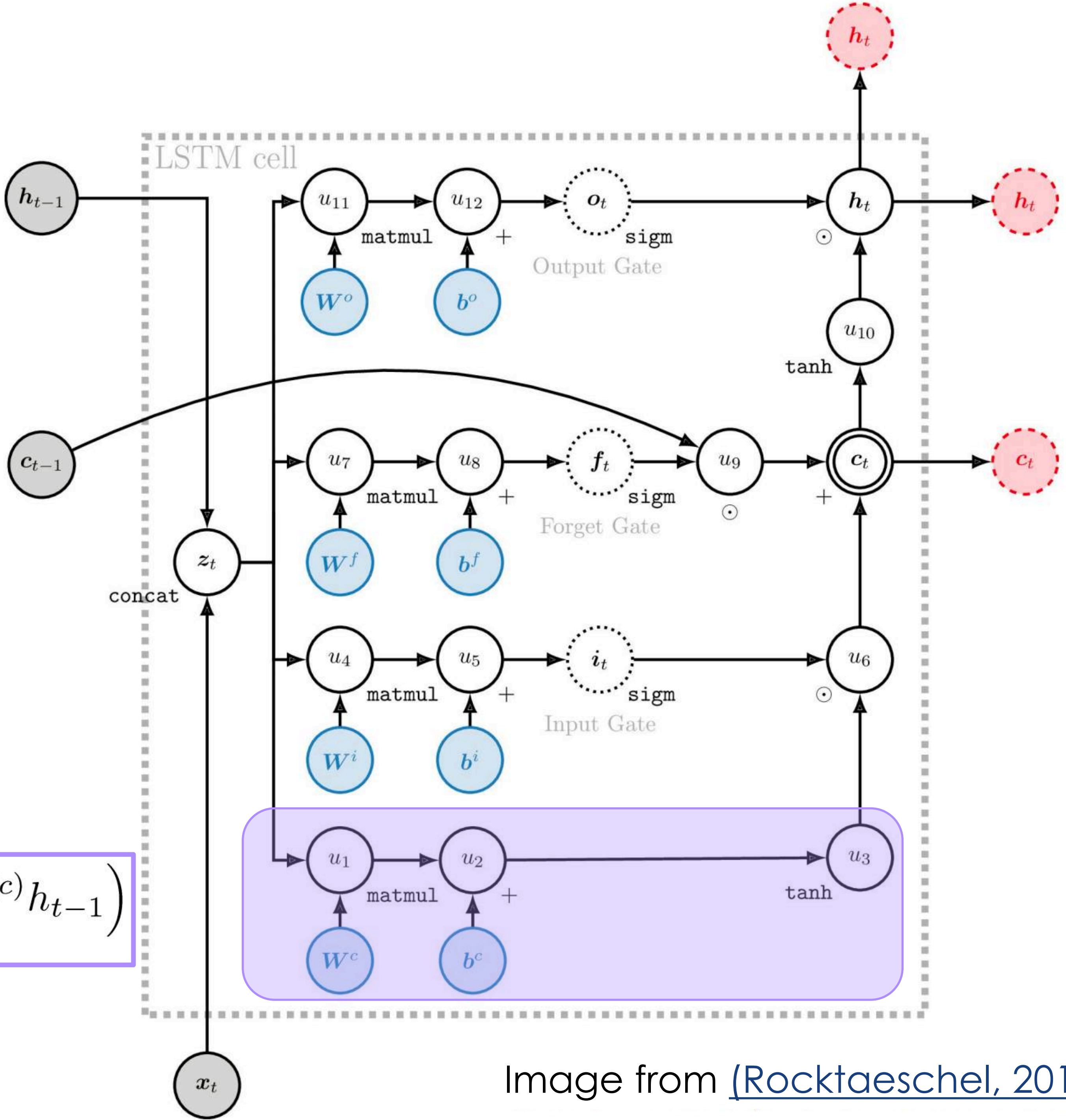
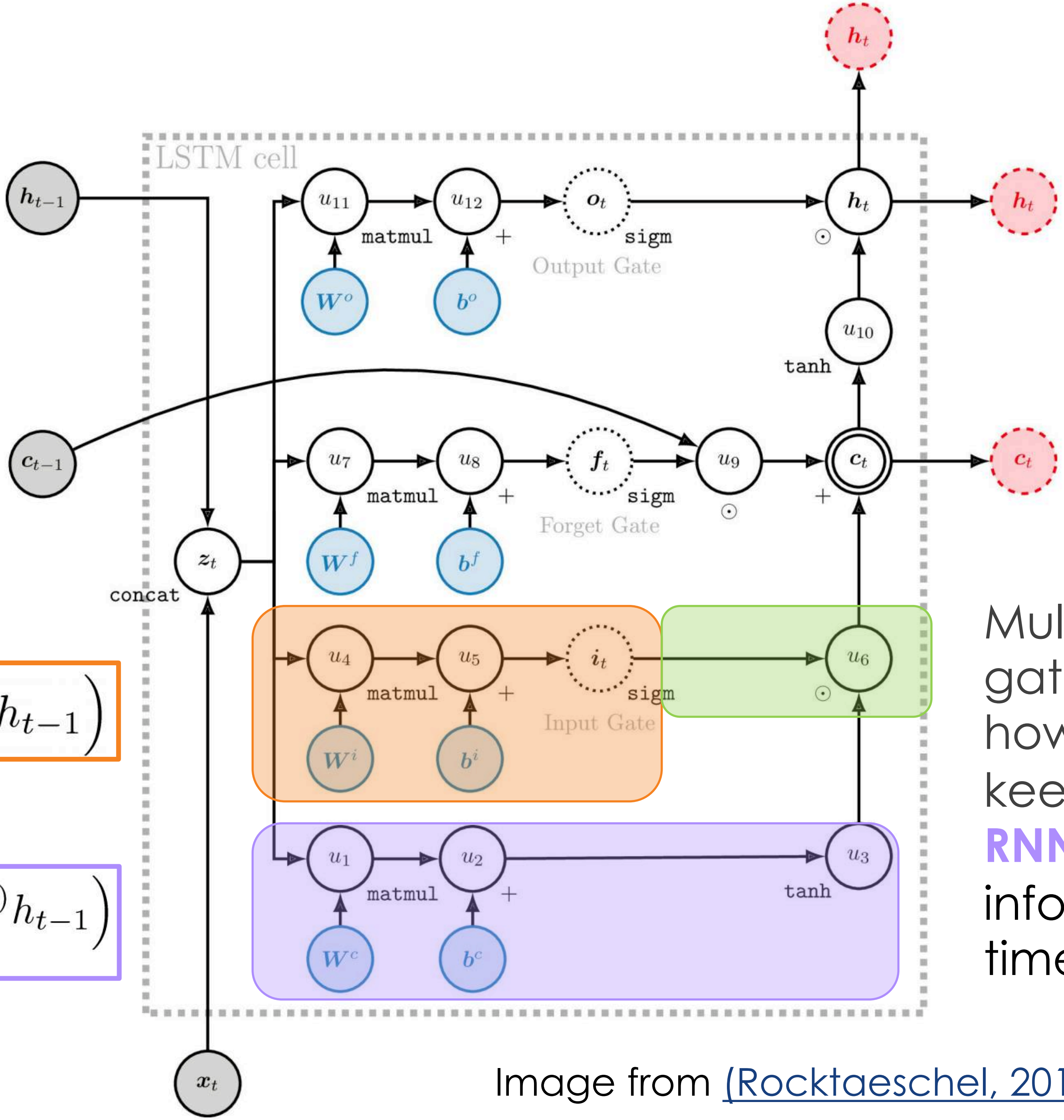


Image from (Rocktaeschel, 2017)

LSTM



$$i_t = \sigma\left(W^{(i)}x_t + U^{(i)}h_{t-1}\right)$$

$$\tilde{c}_t = \tanh\left(W^{(c)}x_t + U^{(c)}h_{t-1}\right)$$

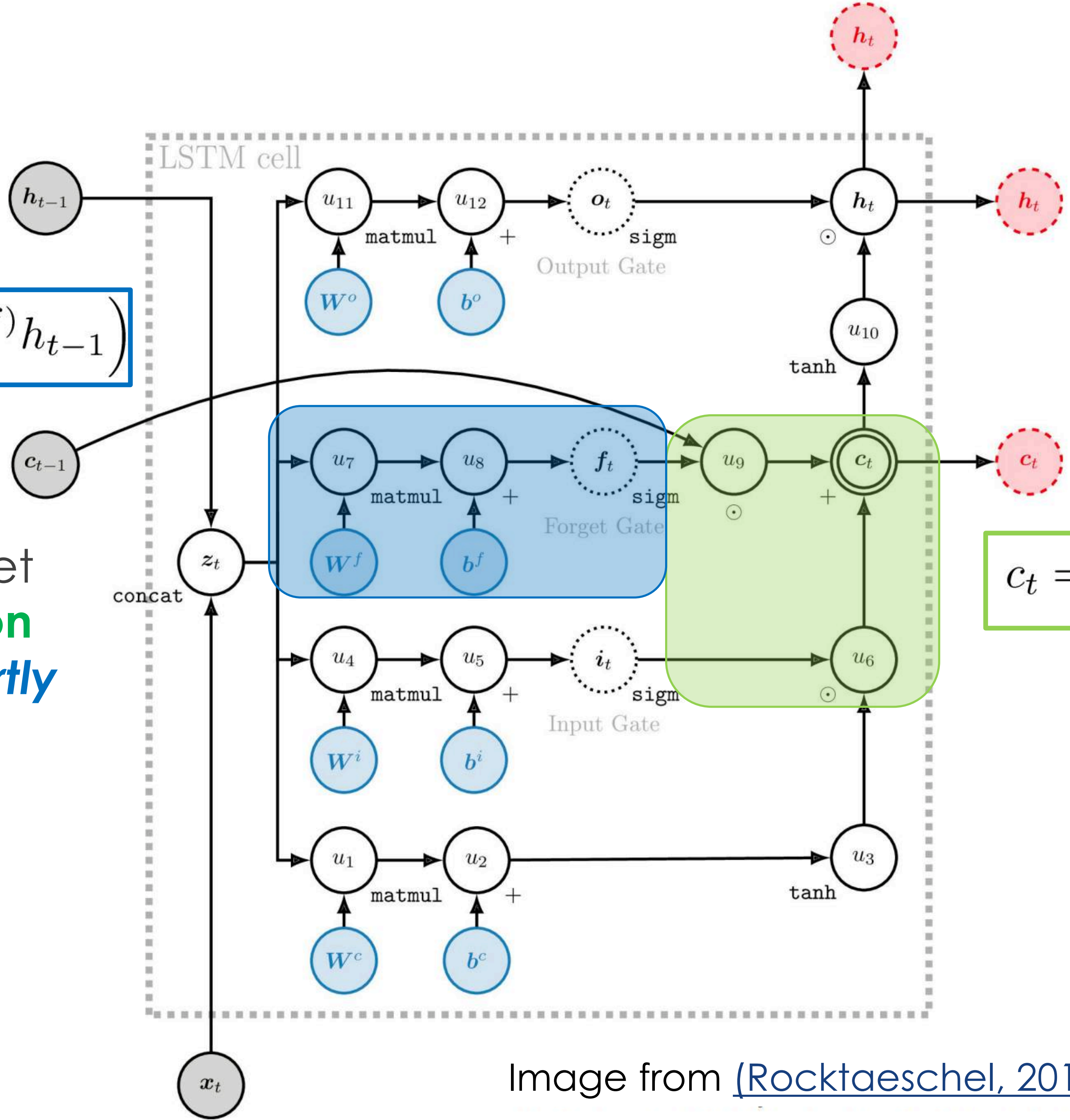
Multiply the **Input** gate output to control how much info to keep from the **vanilla RNN** using the kept info for the current timestep **prediction**

Image from (Rocktaeschel, 2017)

LSTM

$$f_t = \sigma\left(W^{(f)}x_t + U^{(f)}h_{t-1}\right)$$

Rather than multiplying, we get the **final prediction** c_t by adding "***partly forgotten***" c_{t-1}



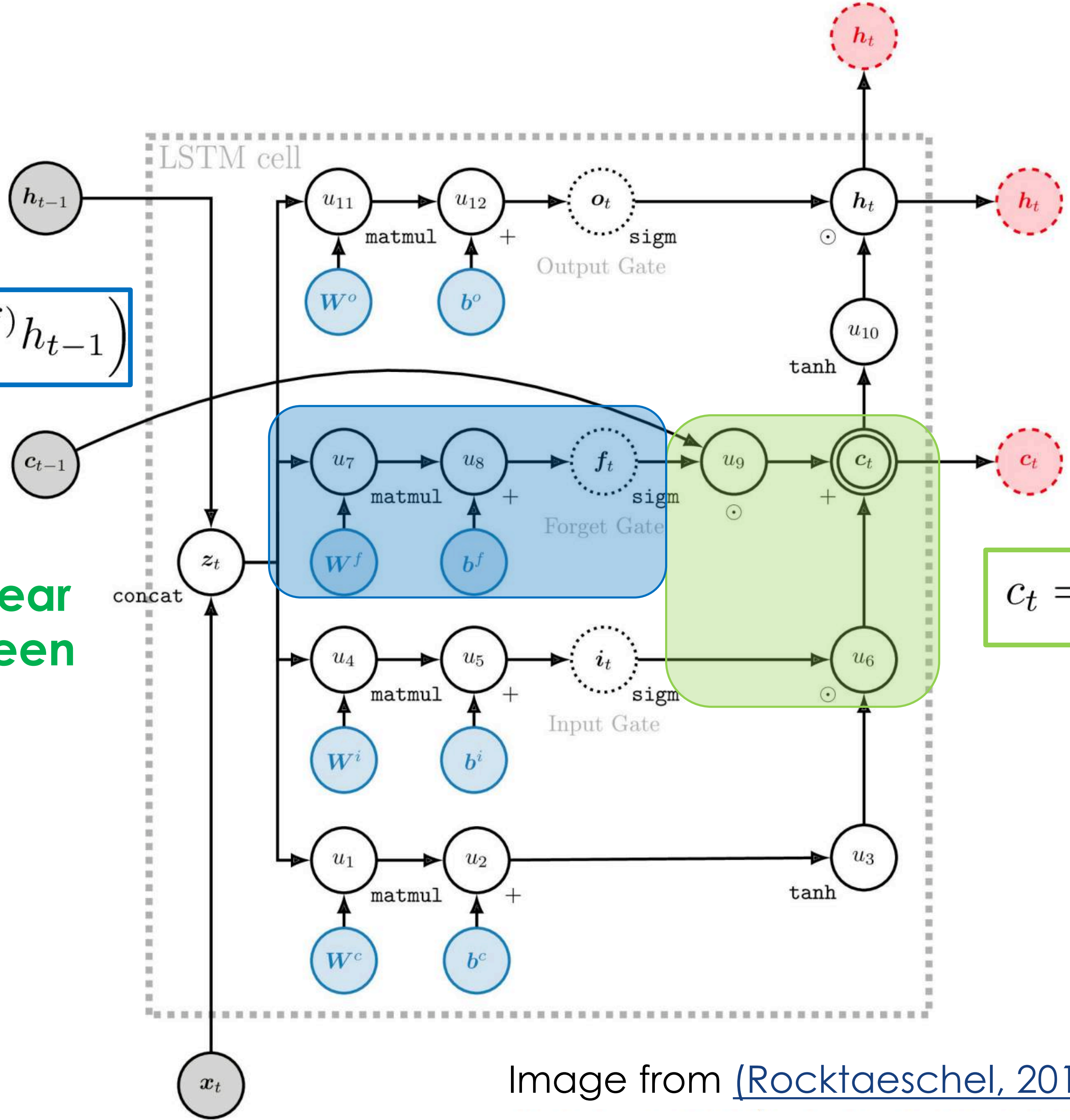
$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t$$

Image from [(Rocktaeschel, 2017)]

LSTM

$$f_t = \sigma\left(W^{(f)} x_t + U^{(f)} h_{t-1}\right)$$

This creates an **additive direct linear connection between c_t and c_{t-1}**

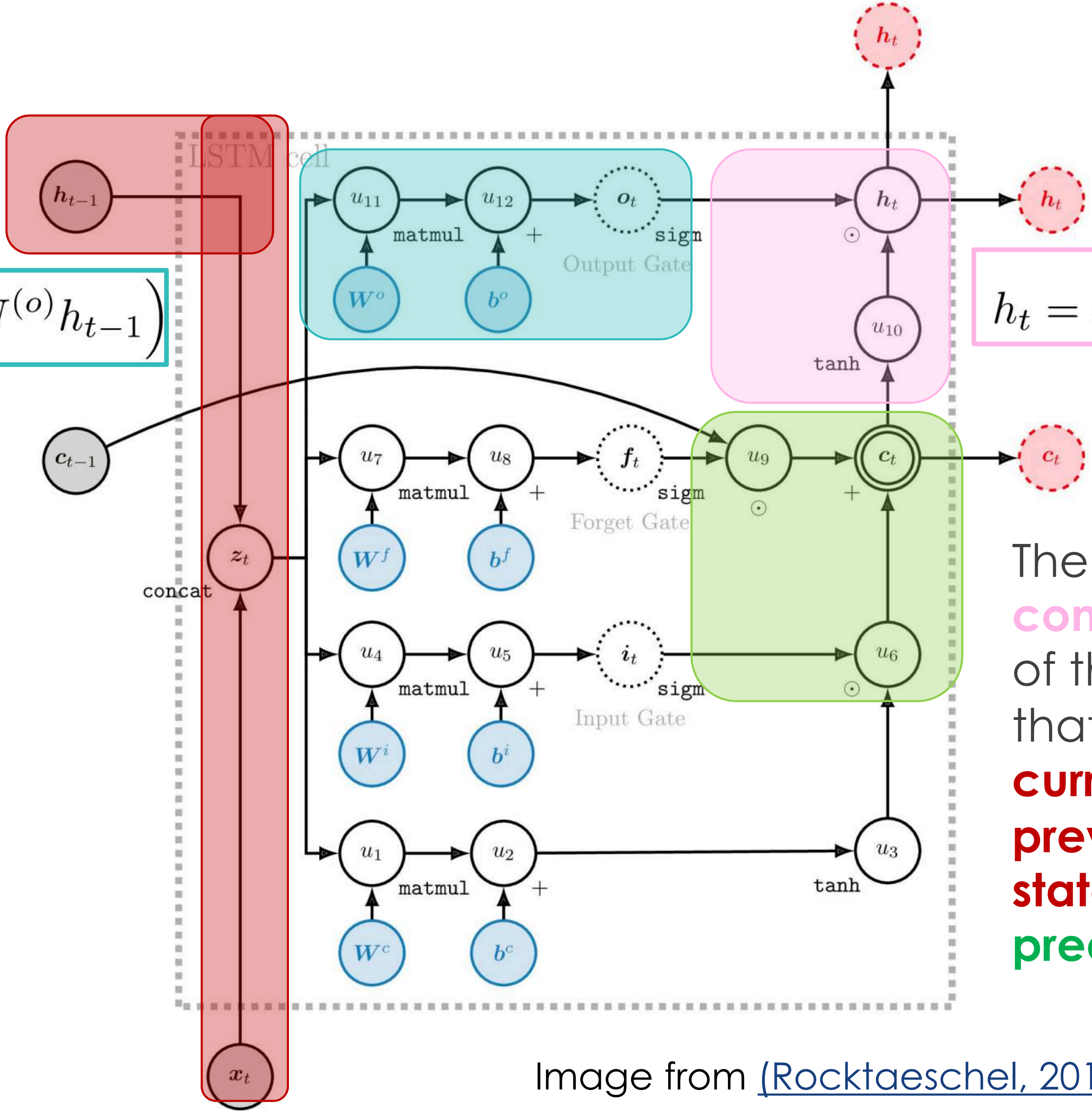


$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t$$

Image from [(Rocktaeschel, 2017)]

LSTM

$$o_t = \sigma\left(W^{(o)}x_t + U^{(o)}h_{t-1}\right)$$



$$h_t = o_t \circ \tanh(c_t)$$

The final cell combines the output of the output gates (that controls info from **current input** and **previous hidden state**) and the current **prediction**

Image from (Rocktaeschel, 2017)

Bruce Lee on LSTM

"*Absorb* ***what is useful***,
discard what is not,
add what is uniquely
your own."
– Bruce Lee

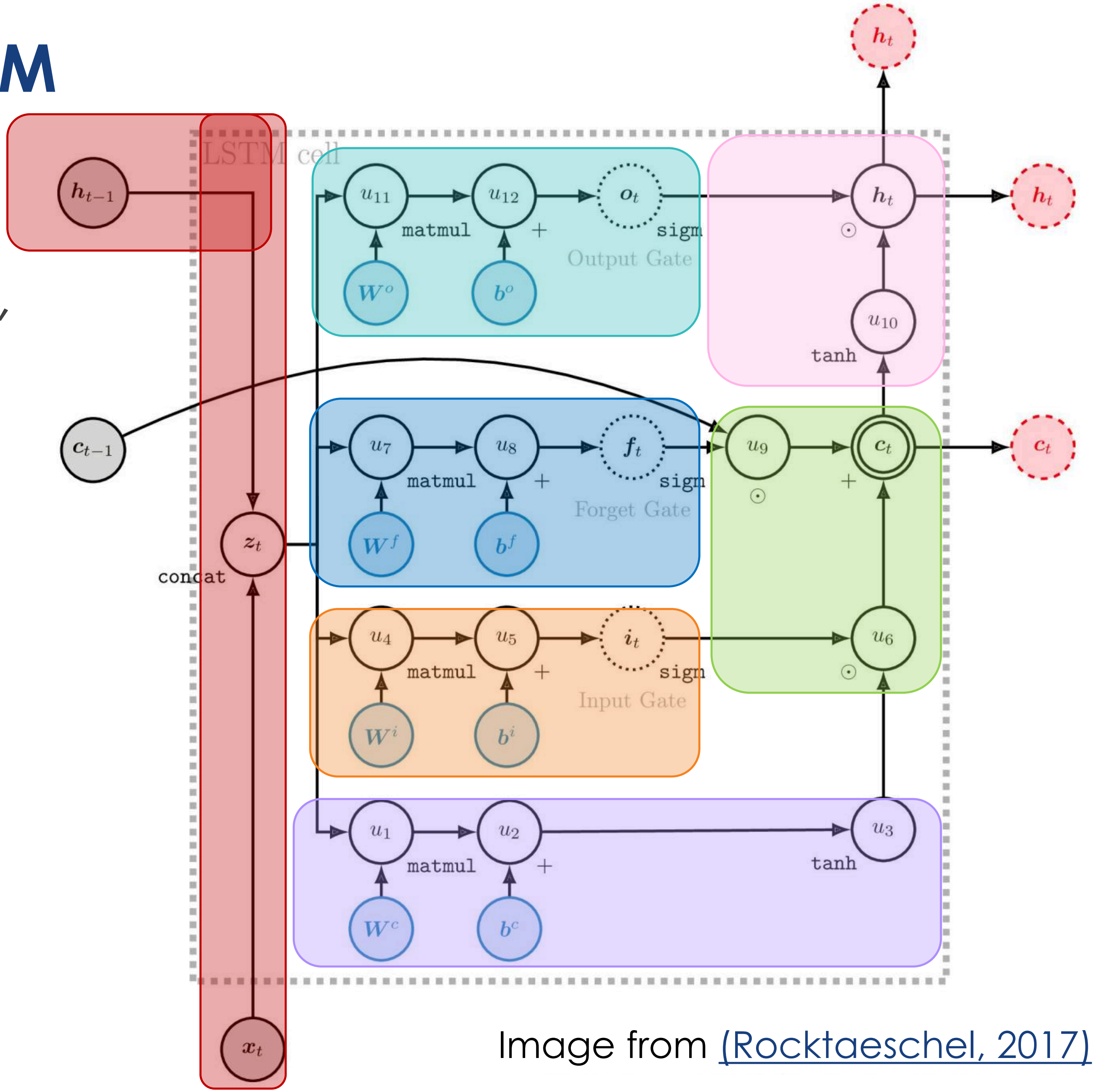


Image from [(Rocktaeschel, 2017)]

Gated Recurrent Neural Nets

- At each time step, perform the following operations

Update: controls how much info in the new hidden states are kept or updated

$$\boldsymbol{u}^{(t)} = \sigma\left(\boldsymbol{W}_u \boldsymbol{h}^{(t-1)} + \boldsymbol{U}_u \boldsymbol{x}^{(t)} + \boldsymbol{b}_u\right)$$

Reset: controls how much info in the previous hidden states are kept

$$\boldsymbol{r}^{(t)} = \sigma\left(\boldsymbol{W}_r \boldsymbol{h}^{(t-1)} + \boldsymbol{U}_r \boldsymbol{x}^{(t)} + \boldsymbol{b}_r\right)$$

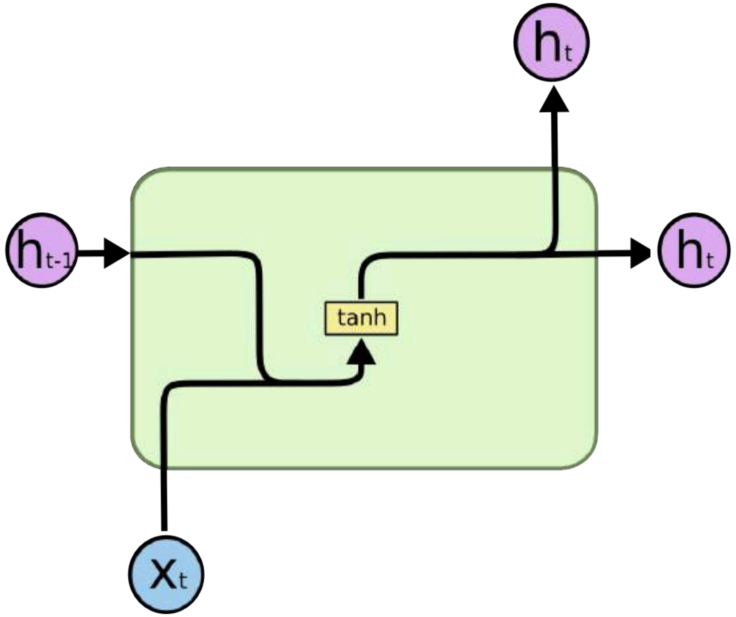
New Hidden state: Reset selects info from previous hidden state and combines it with the current input

$$\tilde{\boldsymbol{h}}^{(t)} = \tanh\left(\boldsymbol{W}_h(\boldsymbol{r}^{(t)} \circ \boldsymbol{h}^{(t-1)}) + \boldsymbol{U}_h \boldsymbol{x}^{(t)} + \boldsymbol{b}_h\right)$$

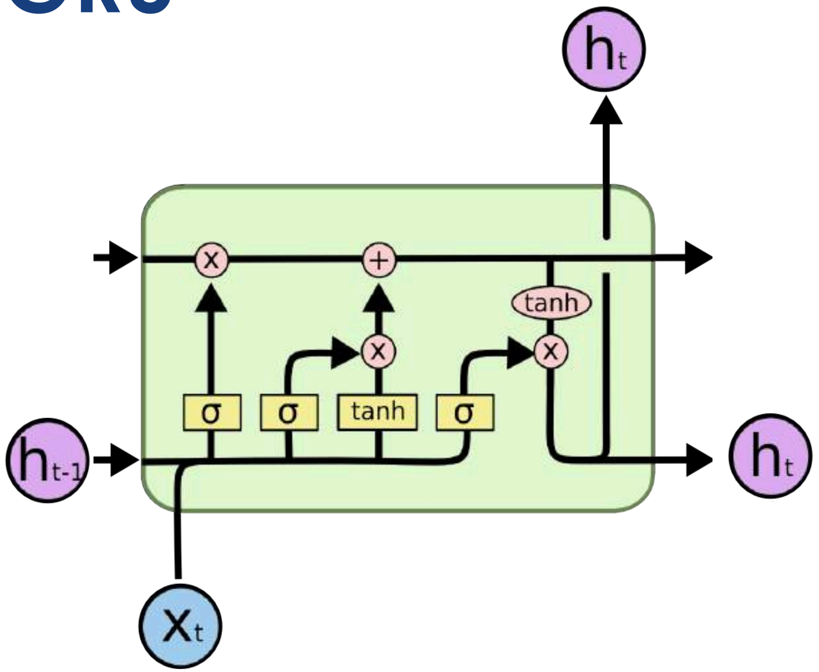
Hidden state: Update selects info from previous hidden state and combines it with the current input

$$\boldsymbol{h}^{(t)} = (1 - \boldsymbol{u}^{(t)}) \circ \boldsymbol{h}^{(t-1)} + \boldsymbol{u}^{(t)} \circ \tilde{\boldsymbol{h}}^{(t)}$$

RNN vs LSTM vs GRU



$$h_t = \tanh(W x_t + U h_{t-1})$$



$$i_t = \sigma\left(W^{(i)} x_t + U^{(i)} h_{t-1}\right)$$

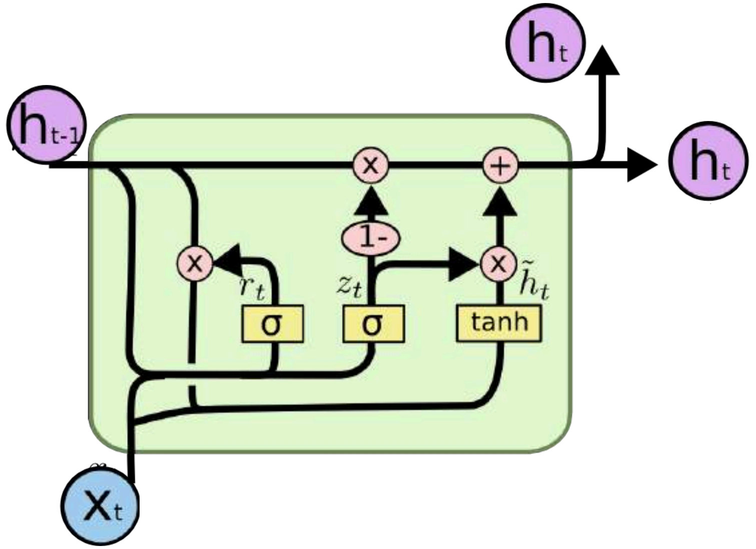
$$f_t = \sigma\left(W^{(f)} x_t + U^{(f)} h_{t-1}\right)$$

$$o_t = \sigma\left(W^{(o)} x_t + U^{(o)} h_{t-1}\right)$$

$$\tilde{c}_t = \tanh\left(W^{(c)} x_t + U^{(c)} h_{t-1}\right)$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t$$

$$h_t = o_t \circ \tanh(c_t)$$



$$\boldsymbol{u}^{(t)} = \sigma\left(\boldsymbol{W}_u \boldsymbol{h}^{(t-1)} + \boldsymbol{U}_u \boldsymbol{x}^{(t)} + \boldsymbol{b}_u\right)$$

$$\boldsymbol{r}^{(t)} = \sigma\left(\boldsymbol{W}_r \boldsymbol{h}^{(t-1)} + \boldsymbol{U}_r \boldsymbol{x}^{(t)} + \boldsymbol{b}_r\right)$$

$$\tilde{\boldsymbol{h}}^{(t)} = \tanh\left(\boldsymbol{W}_h(\boldsymbol{r}^{(t)} \circ \boldsymbol{h}^{(t-1)}) + \boldsymbol{U}_h \boldsymbol{x}^{(t)} + \boldsymbol{b}_h\right)$$

$$\boldsymbol{h}^{(t)} = (1 - \boldsymbol{u}^{(t)}) \circ \boldsymbol{h}^{(t-1)} + \boldsymbol{u}^{(t)} \circ \tilde{\boldsymbol{h}}^{(t)}$$

Images from (Colah 2015)

LSTM vs GRU

- **No conclusive evidence on which performs better**

- ***"I am impatient"*** -> Use **GRU** (fewer parameters)

- ***"I want good results easily"*** -> Use **LSTM** (more papers used it)

- In both cases, enjoy the grind of tuning hyperparameters…

Throw away your RNN

- *"We fell for RNN, LSTM, and all their variants.* ***Now it is time to drop them!***" – Eugenio Culurciello
- RNNs are **not hardware friendly**
- **Attention-base models** (e.g. Transformer) outperforms RNN (Vaswani et al. 2017)
- **Hierarchical Attention** (Yang et al. 2016) or **Casual Convolution Networks** (Elbayad et al. 2018) outperforms LSTMs and Transformers

LSTM: A Search Space Odyssey

- Greff et al. (2017) explored 8 variants of LSTMs

- No Peepholes == GRU

- Original LSTM works well

- CIFG and GRU simplifies LSTM but no drop in performance

NIG: No Input Gate: $\mathbf{i}^t = \mathbf{1}$
NFG: No Forget Gate: $\mathbf{f}^t = \mathbf{1}$
NOG: No Output Gate: $\mathbf{o}^t = \mathbf{1}$
NIAF: No Input Activation Function: $g(\mathbf{x}) = \mathbf{x}$
NOAF: No Output Activation Function: $h(\mathbf{x}) = \mathbf{x}$
CIFG: Coupled Input and Forget Gate: $\mathbf{f}^t = \mathbf{1} - \mathbf{i}^t$
NP: No Peepholes:

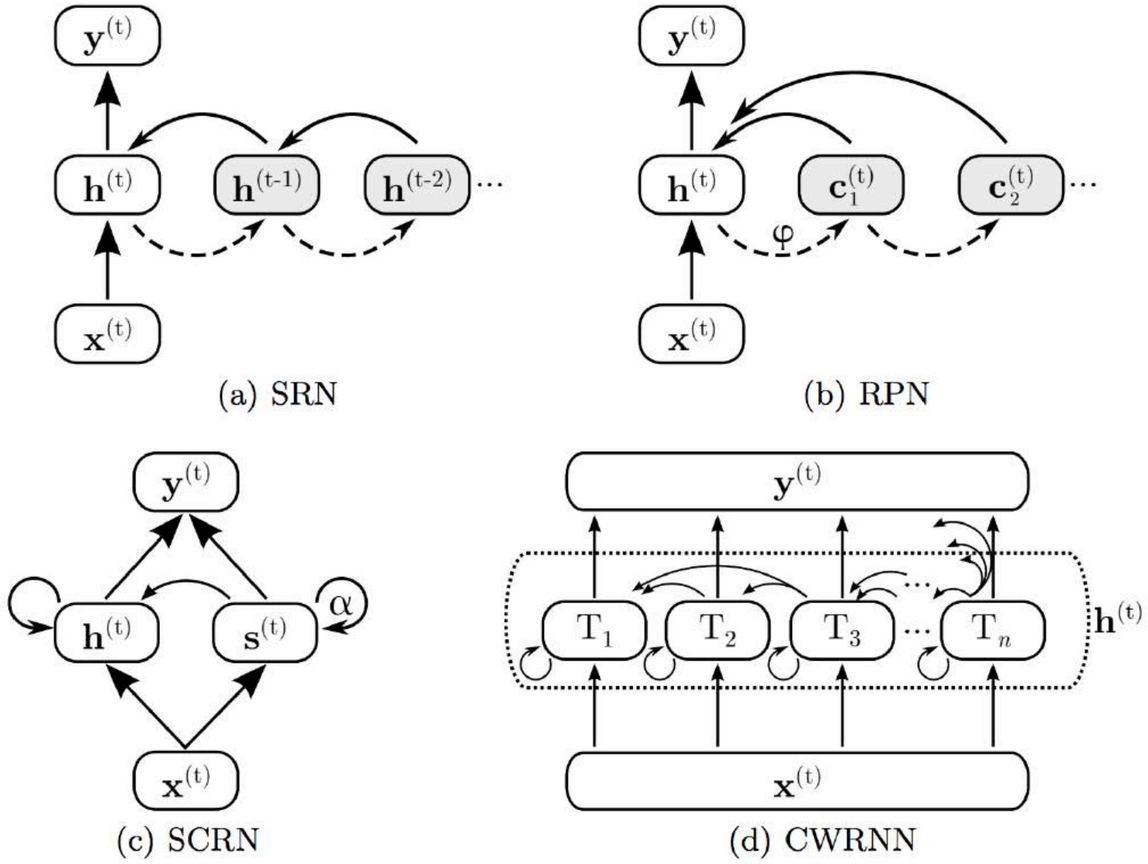
$$\bar{\mathbf{i}}^t = \mathbf{W}_i\mathbf{x}^t + \mathbf{R}_i\mathbf{y}^{t-1} + \mathbf{b}_i$$
$$\bar{\mathbf{f}}^t = \mathbf{W}_f\mathbf{x}^t + \mathbf{R}_f\mathbf{y}^{t-1} + \mathbf{b}_f$$
$$\bar{\mathbf{o}}^t = \mathbf{W}_o\mathbf{x}^t + \mathbf{R}_o\mathbf{y}^{t-1} + \mathbf{b}_o$$

FGR: Full Gate Recurrence:

$$\begin{aligned}
\bar{\mathbf{i}}^t &= \mathbf{W}_i\mathbf{x}^t + \mathbf{R}_i\mathbf{y}^{t-1} + \mathbf{p}_i \odot \mathbf{c}^{t-1} + \mathbf{b}_i \\
&\quad + \mathbf{R}_{ii}\mathbf{i}^{t-1} + \mathbf{R}_{fi}\mathbf{f}^{t-1} + \mathbf{R}_{oi}\mathbf{o}^{t-1} \\
\bar{\mathbf{f}}^t &= \mathbf{W}_f\mathbf{x}^t + \mathbf{R}_f\mathbf{y}^{t-1} + \mathbf{p}_f \odot \mathbf{c}^{t-1} + \mathbf{b}_f \\
&\quad + \mathbf{R}_{if}\mathbf{i}^{t-1} + \mathbf{R}_{ff}\mathbf{f}^{t-1} + \mathbf{R}_{of}\mathbf{o}^{t-1} \\
\bar{\mathbf{o}}^t &= \mathbf{W}_o\mathbf{x}^t + \mathbf{R}_o\mathbf{y}^{t-1} + \mathbf{p}_o \odot \mathbf{c}^{t-1} + \mathbf{b}_o \\
&\quad + \mathbf{R}_{io}\mathbf{i}^{t-1} + \mathbf{R}_{fo}\mathbf{f}^{t-1} + \mathbf{R}_{oo}\mathbf{o}^{t-1}
\end{aligned}$$

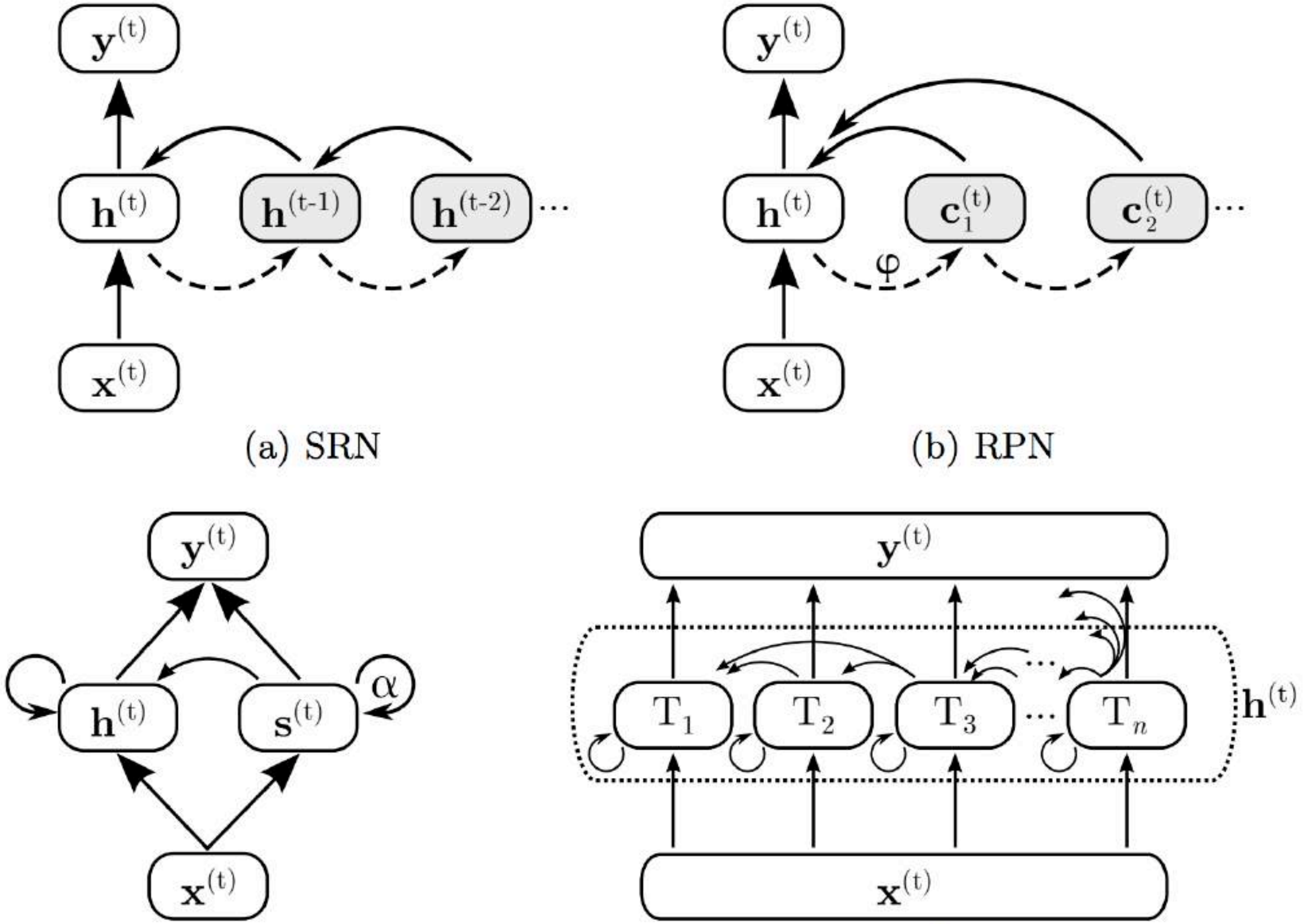
Learning Multiple Timescales in RNNs

- Alpay (2016) investigated different ways to manipulate the time-steps in RNNs



Learning Multiple Timescales in RNNs

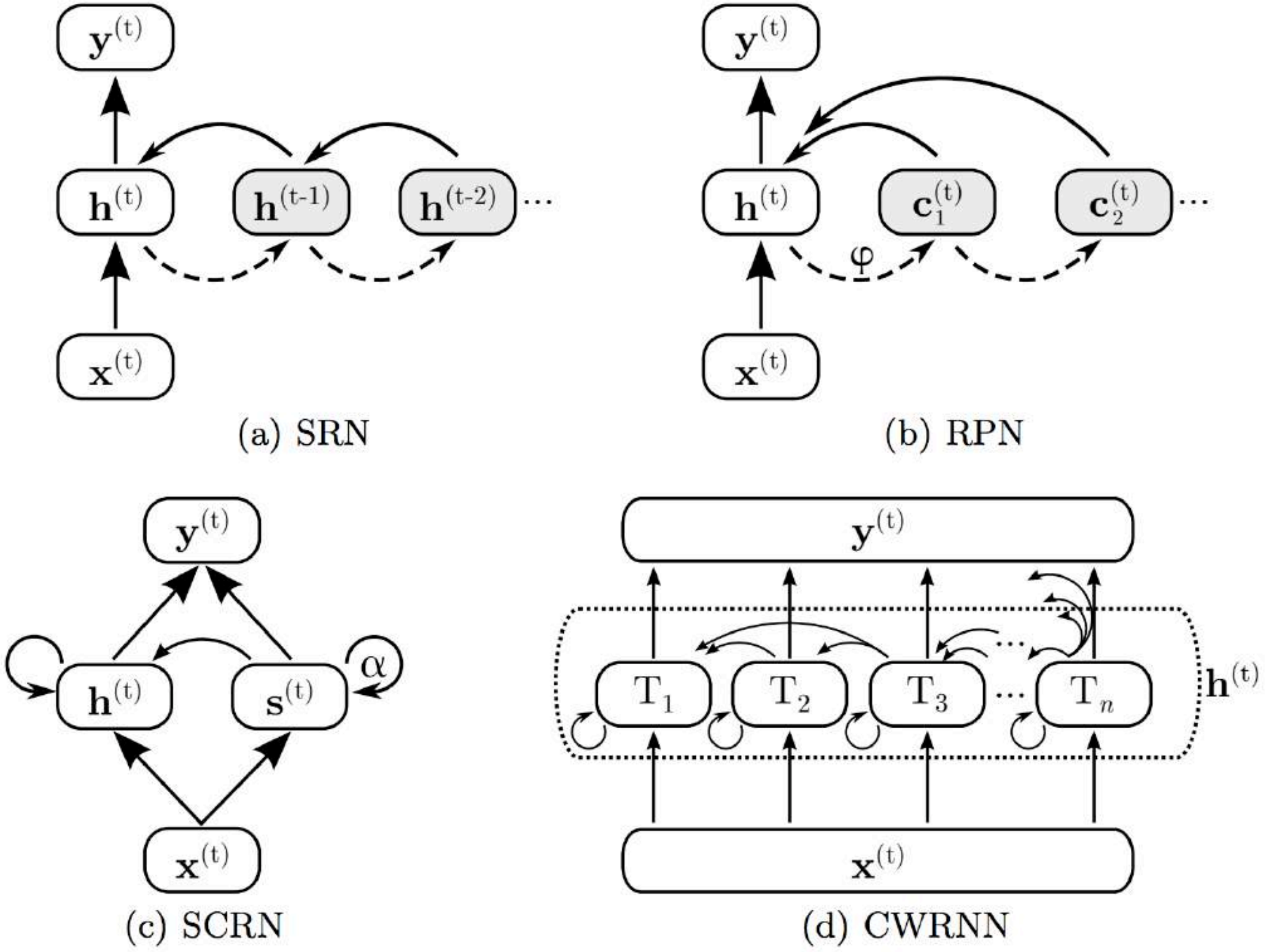
- Simple Recurrent Network (SRN) == Vanilla RNN
- Next prediction conditioned on previous timestep
- Backpropagation through time sequentially



(a) SRN (b) RPN (c) SCRN (d) CWRNN

Learning Multiple Timescales in RNNs

- Recurrent Plausible Network (RPN) (Wermter et al. 1995)
- Short cutting the connections between timesteps
- Needs to account for a timelag factor φ



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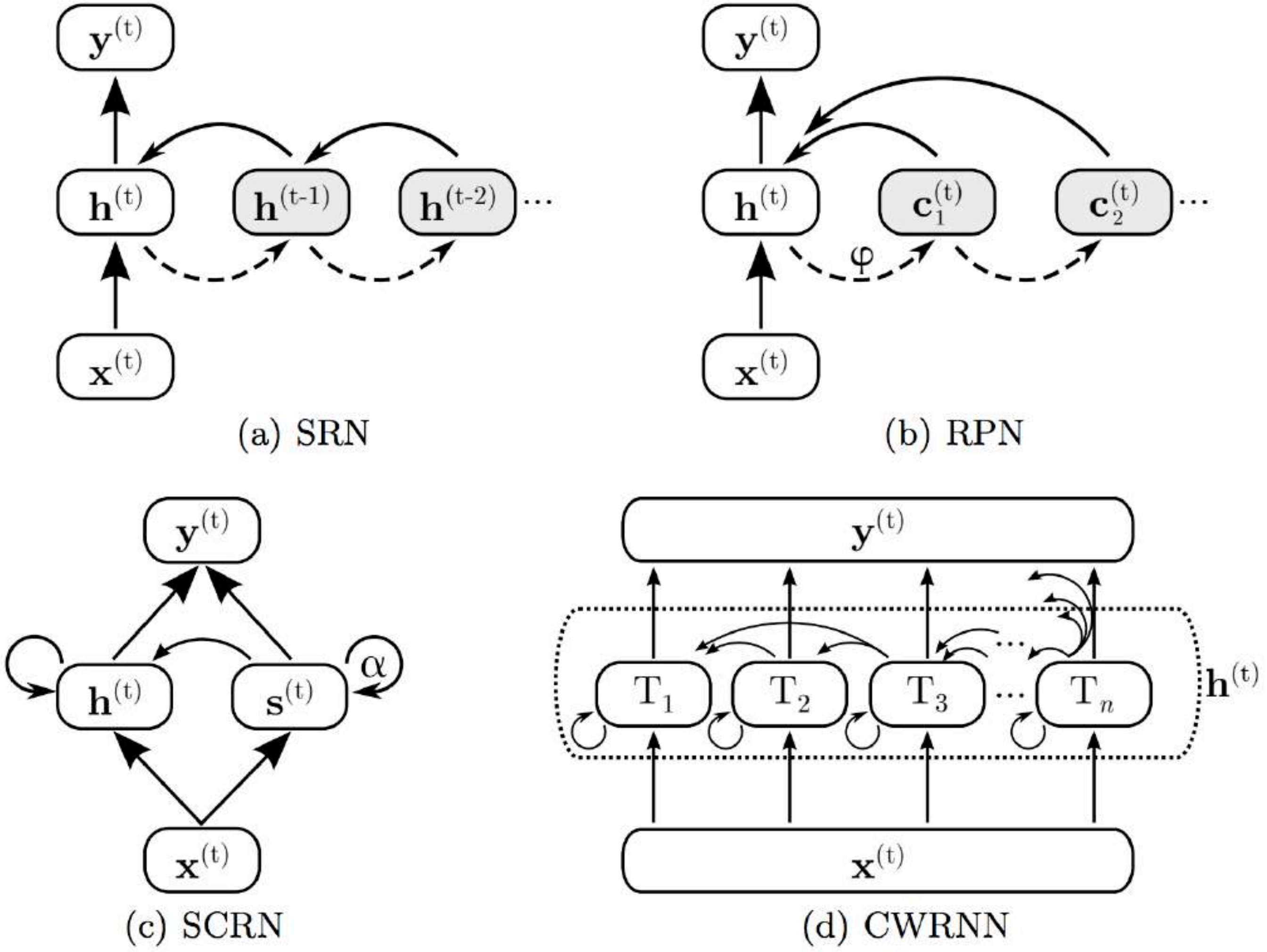
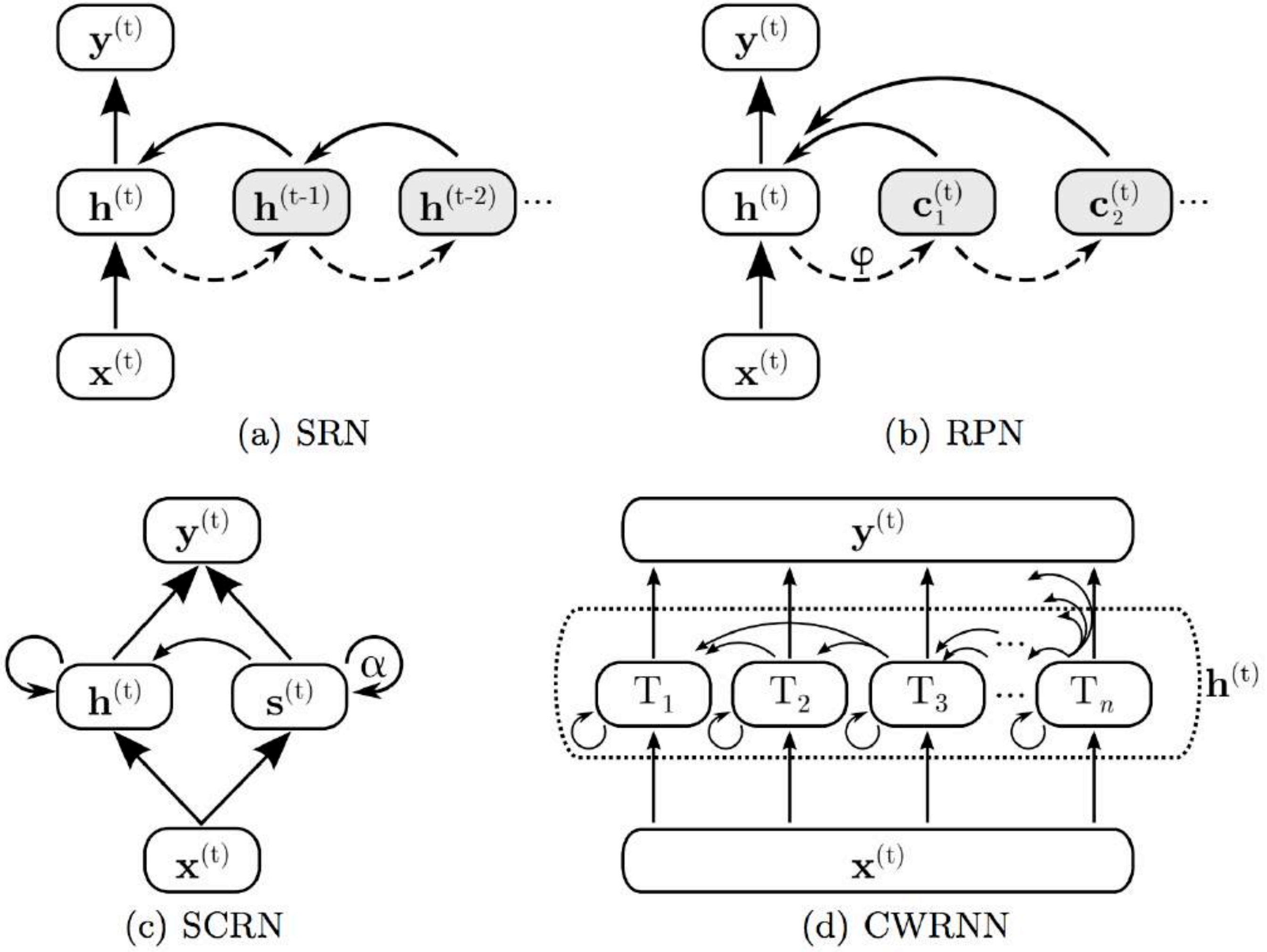


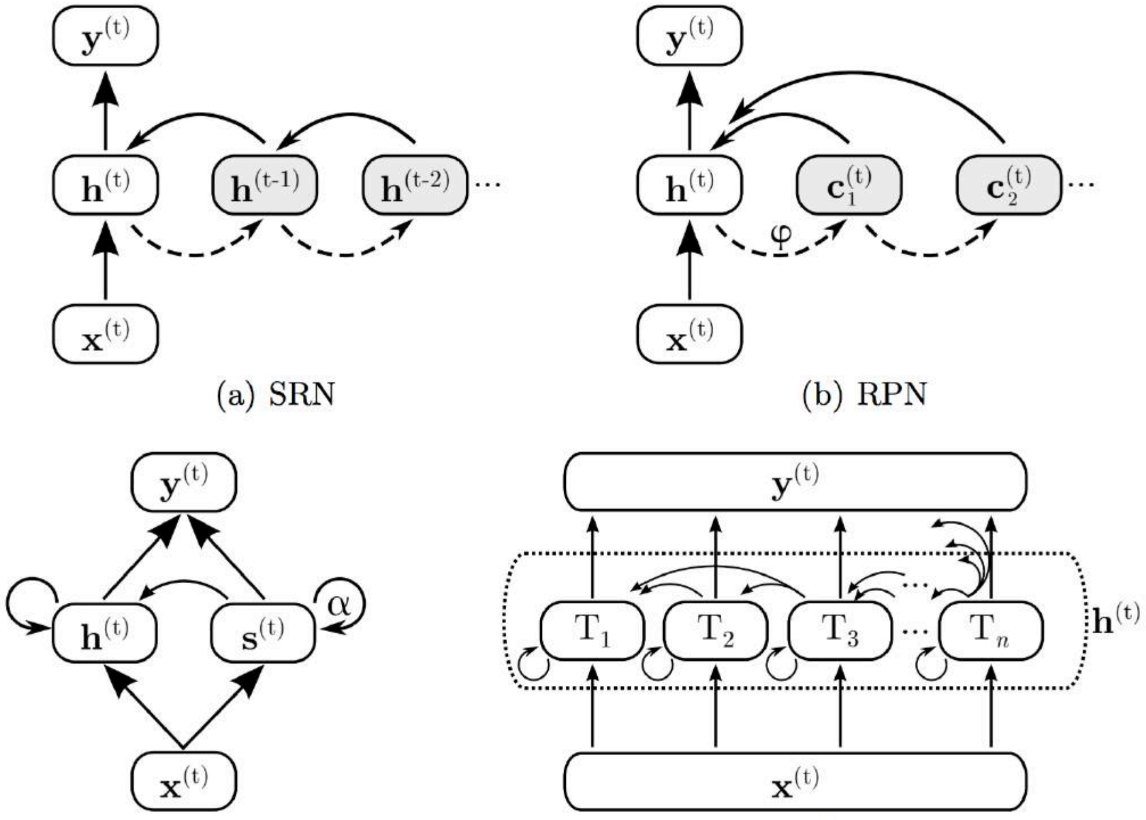
Learning Multiple Timescales in RNNs

- Clockwork RNN (CWRNN) (Koutnik et al. 2014)
- No time lag parameter
- An external module controls how much temporal information to propagate



Learning Multiple Timescales in RNNs

- Alpay (2016) investigated different ways to manipulate the time-steps in RNNs
- Manipulating timesteps connection allows units to self-organize long vs short term contexts
- Not sure which is really the best for NLP =(



(a) SRN (b) RPN (c) SCRN (d) CWRNN

LSTM/GRU solves the vanishing gradients?

- The additive memory of the "**forget gate**" prevents small partial gradients from disappearing

- It remembers information over multiple timesteps so the **hidden states** don't disappear across time

- But **LSTM/GRU doesn't guarantee no gradient vanishing/exploding**, it's just better than the vanilla RNN

Is vanishing/exploding gradient just an RNN problem?

- Nope, as long as ***functions keeps getting nested*** in the network and the ***partial derivations needs to be multiplied*** causing unstable gradients

- As long as there are many layers, the functions and gradients gets multiplied in a nested manner

- Without using gates, we can just "***short-circuit" the network and make previous layers interact directly with the current layers***

Non-Gate Connections

- He et al. (2015) proposed Residual Networks, that skip connections for alternate layers

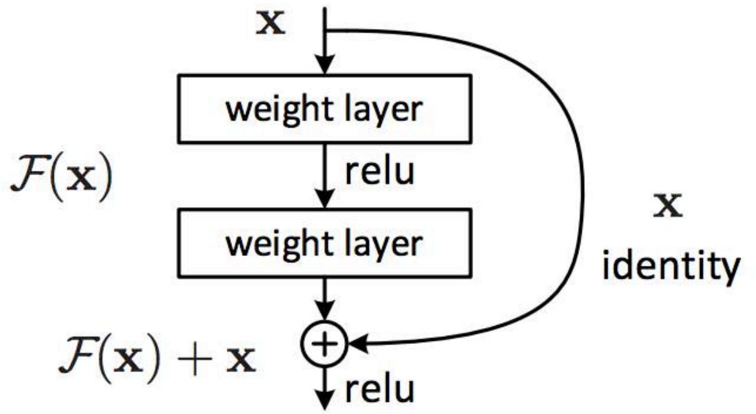


Figure 2. Residual learning: a building block.

Non-Gate Connections

- He et al. (2015) proposed Residual Networks, that skip connections for alternate layers

- Huang et al. (2018) proposed connects every previous layer to every layer down the network

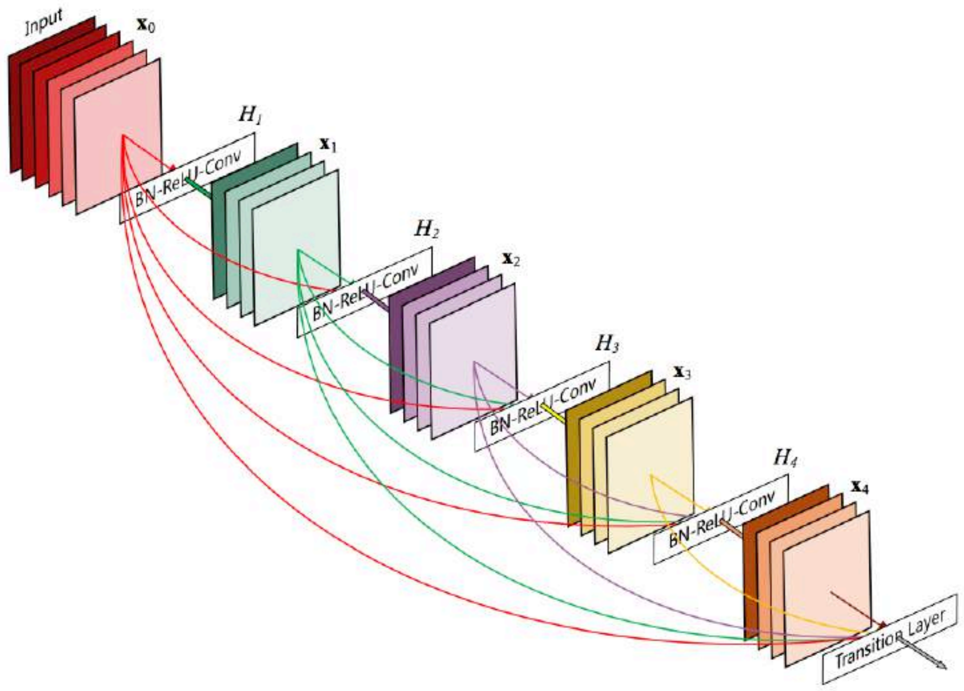


Figure 1: A 5-layer dense block with a growth rate of $k = 4$. Each layer takes all preceding feature-maps as input.

LSTMs: Real-Word Success (Briefly)

- In **2013-2015**, LSTMs started achieving state-of-the-art results
  - Successful tasks include: handwriting recognition, speech recognition, machine translation, parsing, image captioning
  - **LSTM** became the **dominant approach**

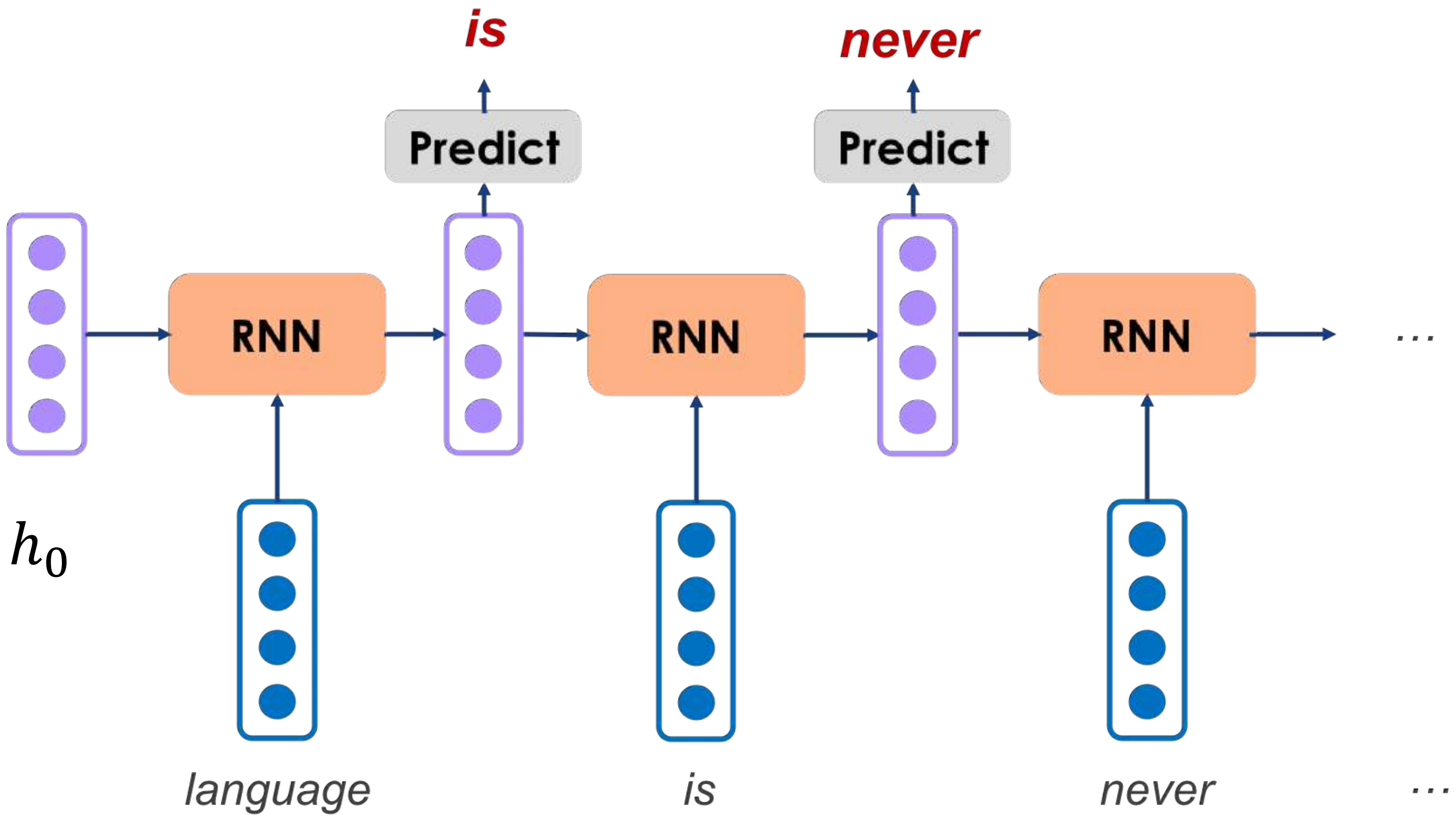
- **Now (2019),** other approaches (e.g. **Transformers**) have become more dominant for certain tasks.
  - For example in WMT (a MT conference + competition):
  - In WMT **2016**, the summary report contains **"RNN" 44 times**
  - In WMT **2018**, the report contains **"RNN" 9 times** and **"Transformer" 63 times**

Almost entirely cite from [(See, 2019), Stanford CS244N course]

Conditioned Generation

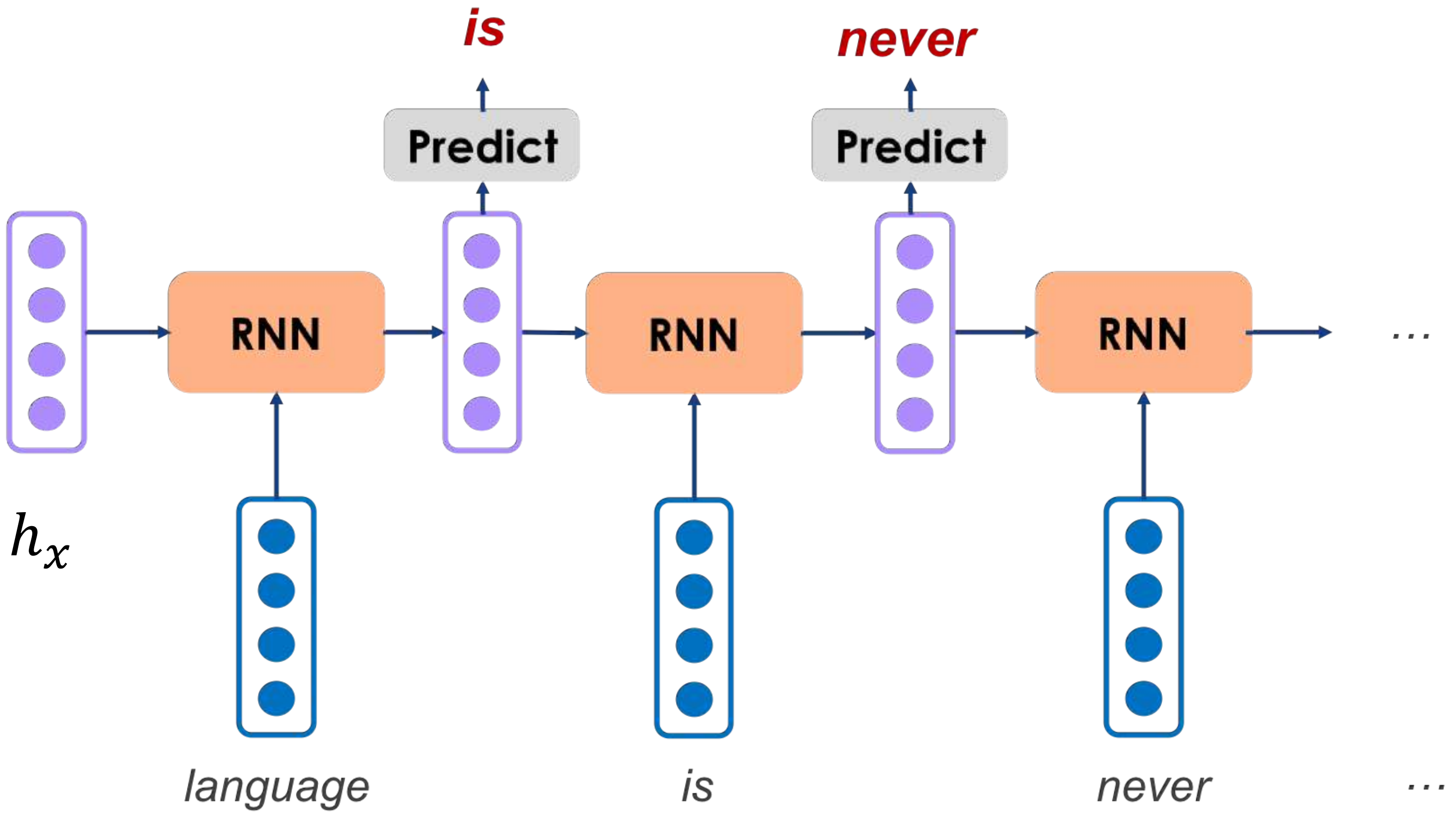
RNN Generation

- RNN generation starts with a random hidden state h_0



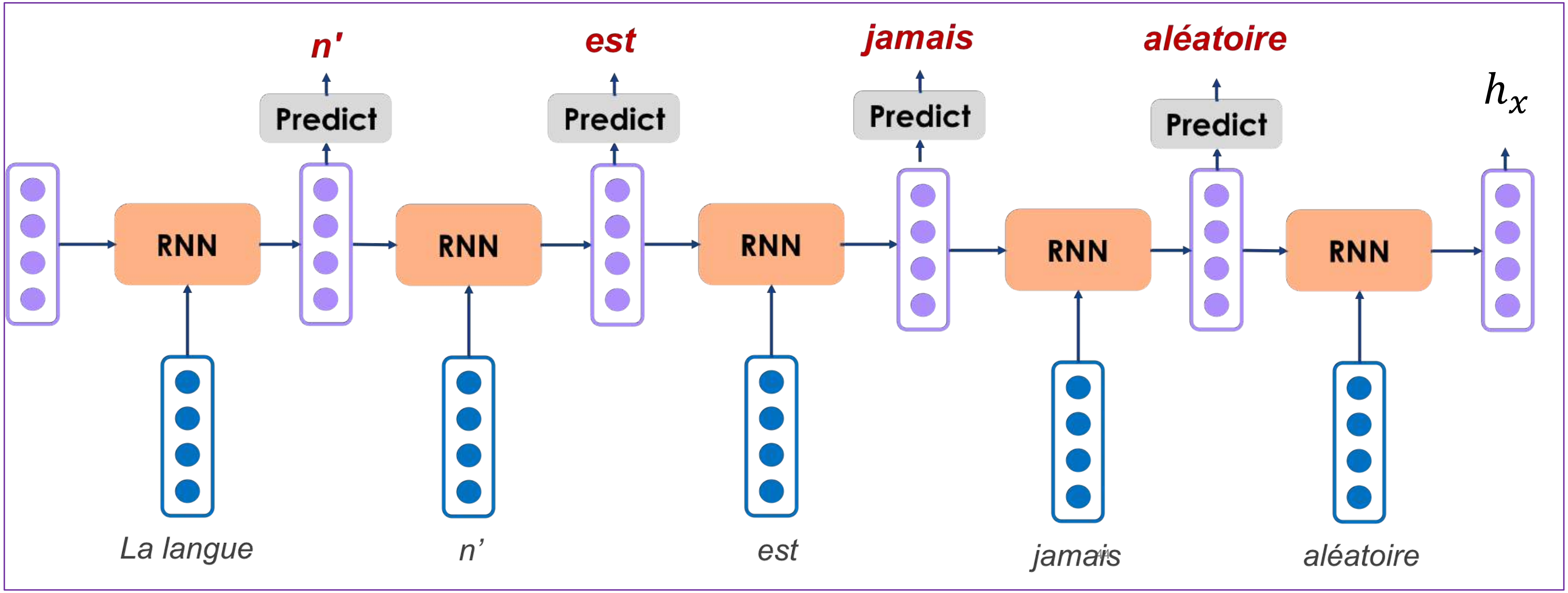
RNN Generation

- What if h_0 is something non-random?



RNN Generation

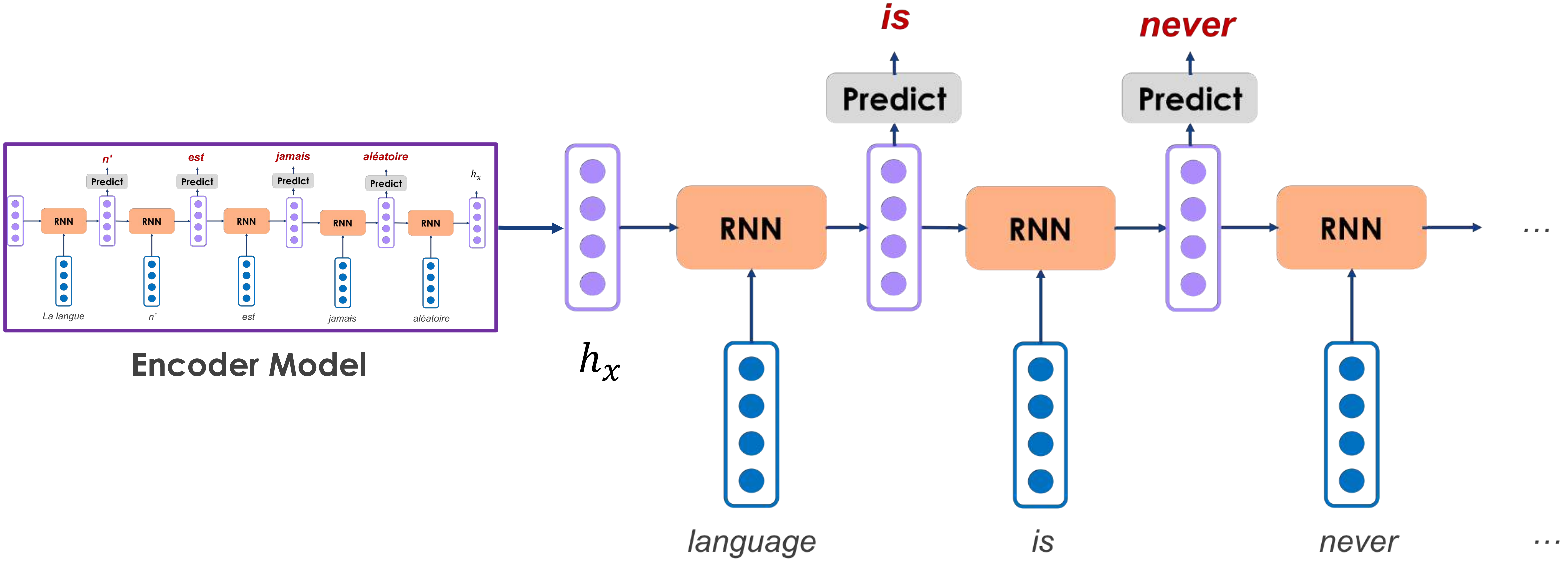
- What if h_0 is something non-random?



Encoder Model

RNN Generation

- What if h_0 is something non-random?



RNN Generation

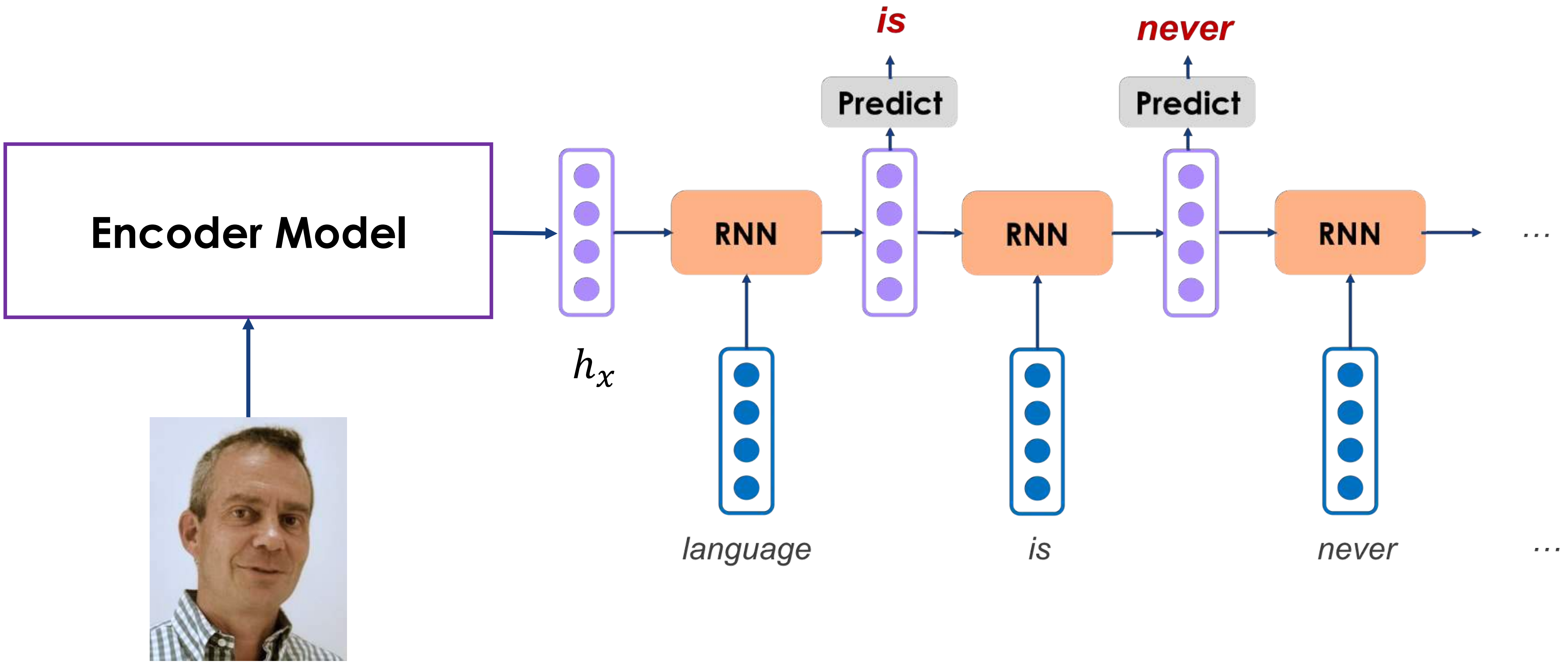
- RNN generation starts with a random hidden state h_0

- What if h_0 is something non-random?

- **FR->EN Translation:** Initialize English model h_0 inputs with h_x outputs from a French model

RNN Generation

- What if input of model that produces h_x isn't text?



RNN Generation

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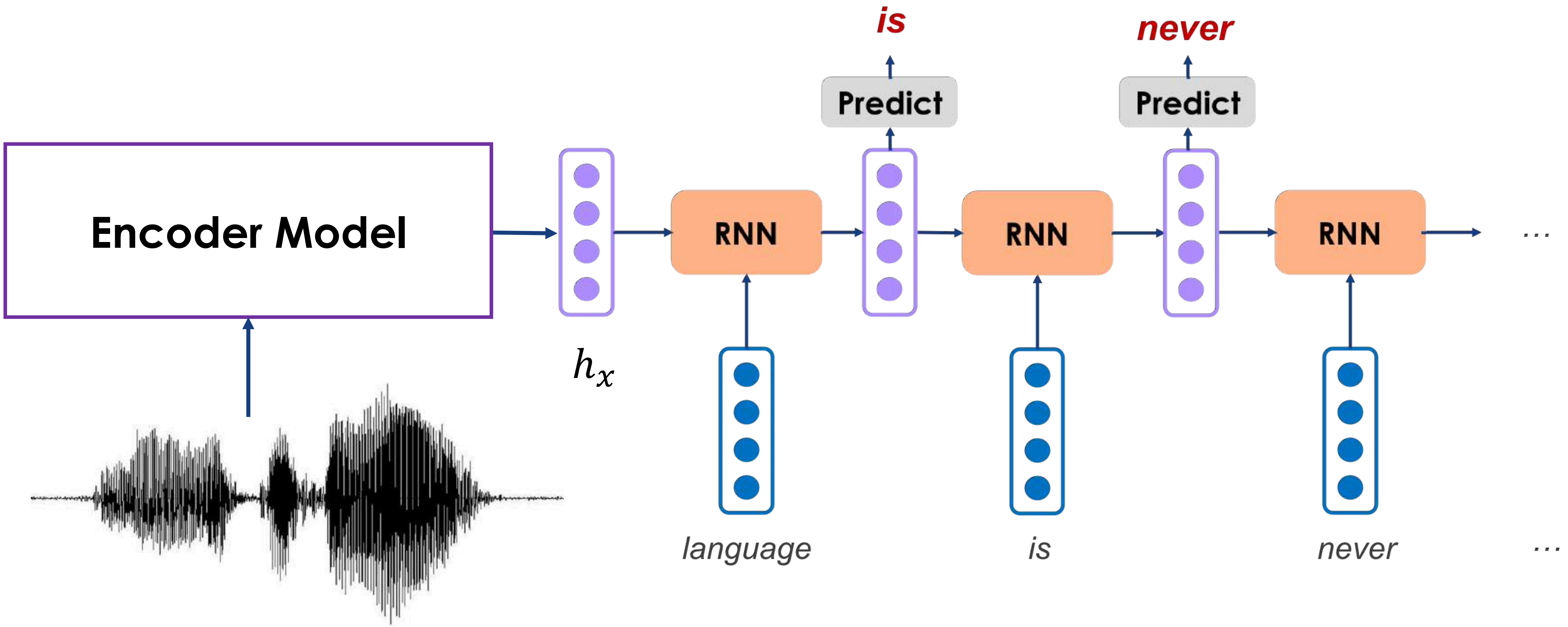


RNN Generation

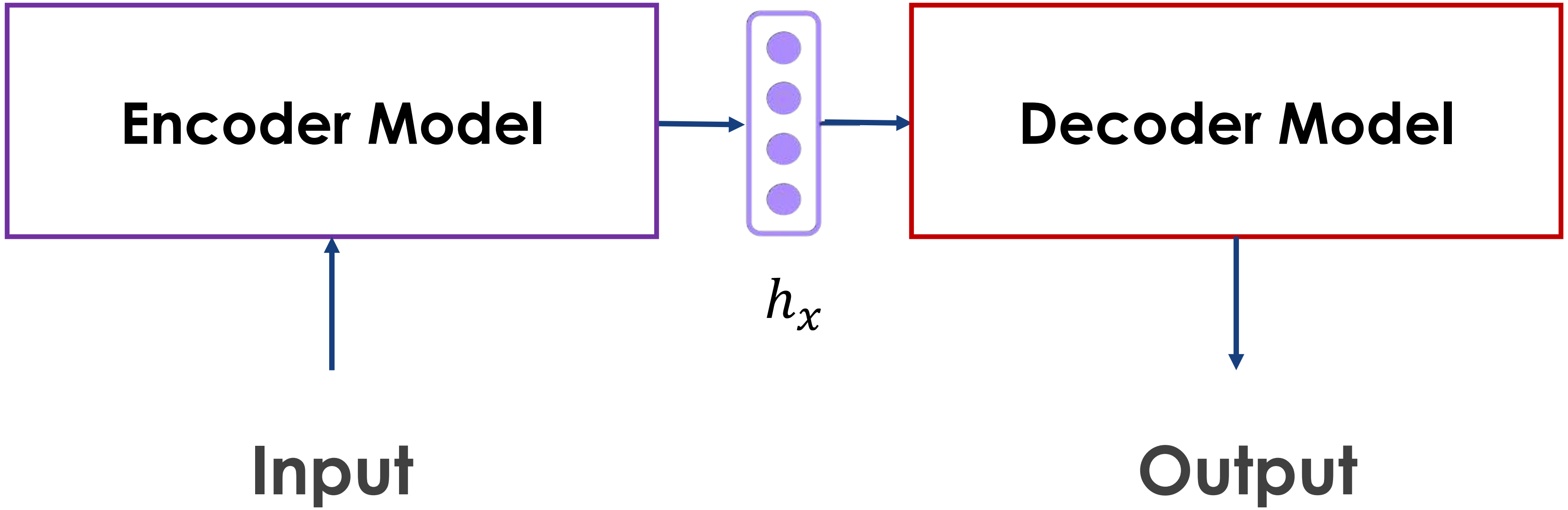
- RNN generation starts with a random hidden state h_0

- What if h_0 is something non-random?

- **Translation:** French -> English
- **Image Captioning:** Image -> Text
- **Speech Recognition:** Audio -> Text

RNN Generation

- Generalized Encode-Decoder Framework



Conditional RNN Generation

- RNN generation starts with a random hidden state h_0

- What if h_0 is something non-random?

- **Translation:** French -> English
- **Image Captioning:** Image -> Text
- **Speech Recognition:** Audio -> Text
- **Summarization:** Document -> Summary
- **Chatbots:** Utterance -> Response

Conditioned RNN Generation

- **Endless possibilities** of what to condition on and what to generate

- But training requires the **paired condition and target generation**

- And relatively **large amount of data is needed** for model to train well

Language Model Probability

$$P(X) = \prod_{i=1}^{I} P(\boldsymbol{x_i} | \boldsymbol{x_1}, \dots, \boldsymbol{x_{i-1}})$$

Next word **Context**

Conditioned Language Model Probability

Encoder hidden context

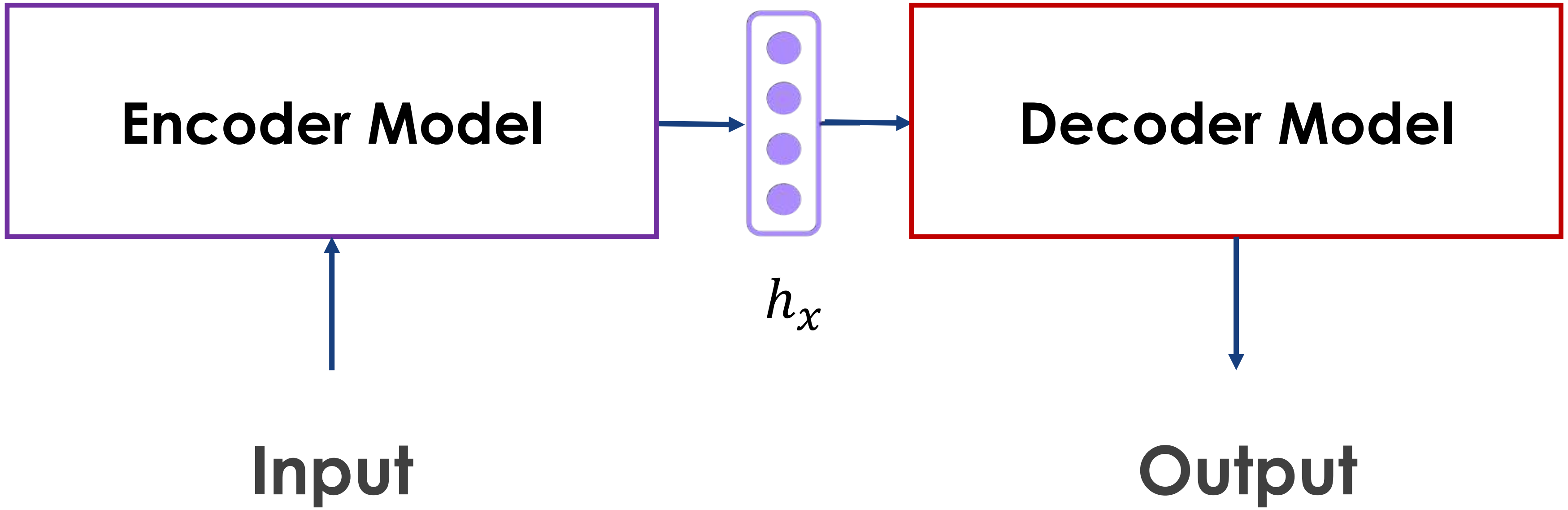
$$P(Y|X) = \prod_{j=1}^{J} P(\boldsymbol{y_j}|\boldsymbol{X}, \boldsymbol{y_1}, \dots, \boldsymbol{y_{i-1}})$$

Next decoder word

Previous decoder context

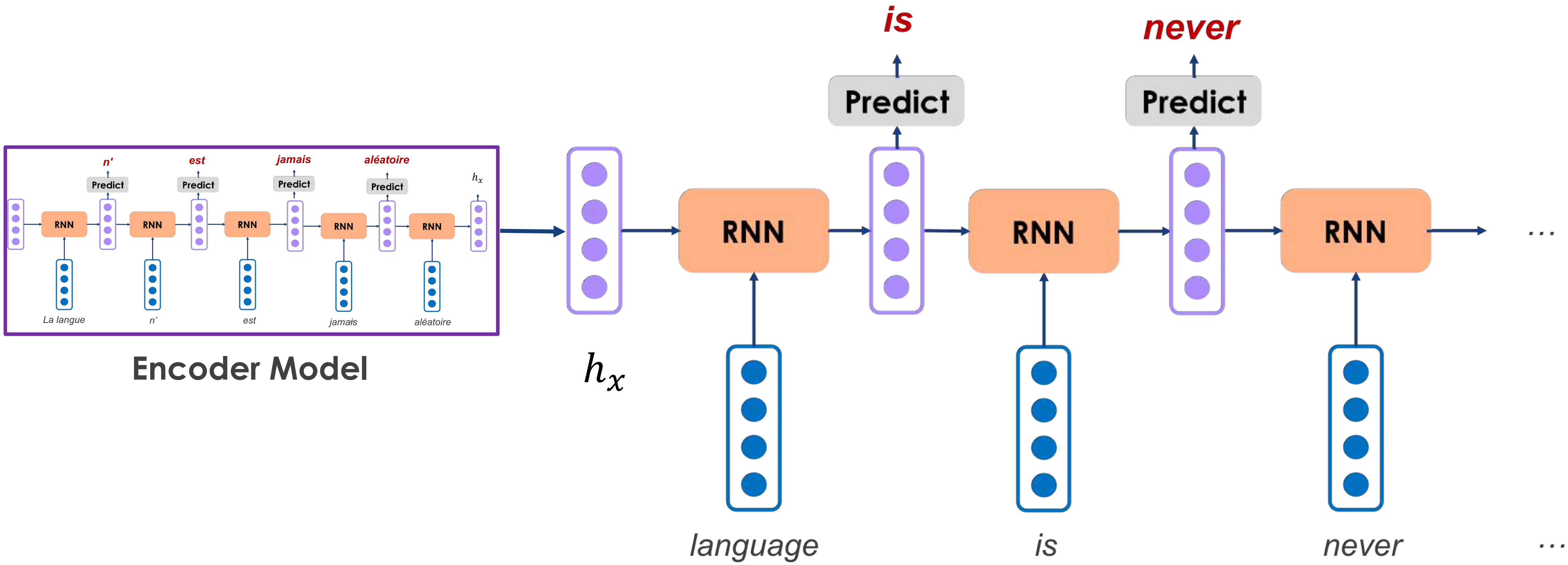
RNN Generation

- Generalized Encode-Decoder Framework



Sequence to Sequence Learning with NN

- Take final hidden state of an encoder model, feed it as the start state of a decoder model (Sutskever et al. 2014)



Sequence to Sequence Learning with NN

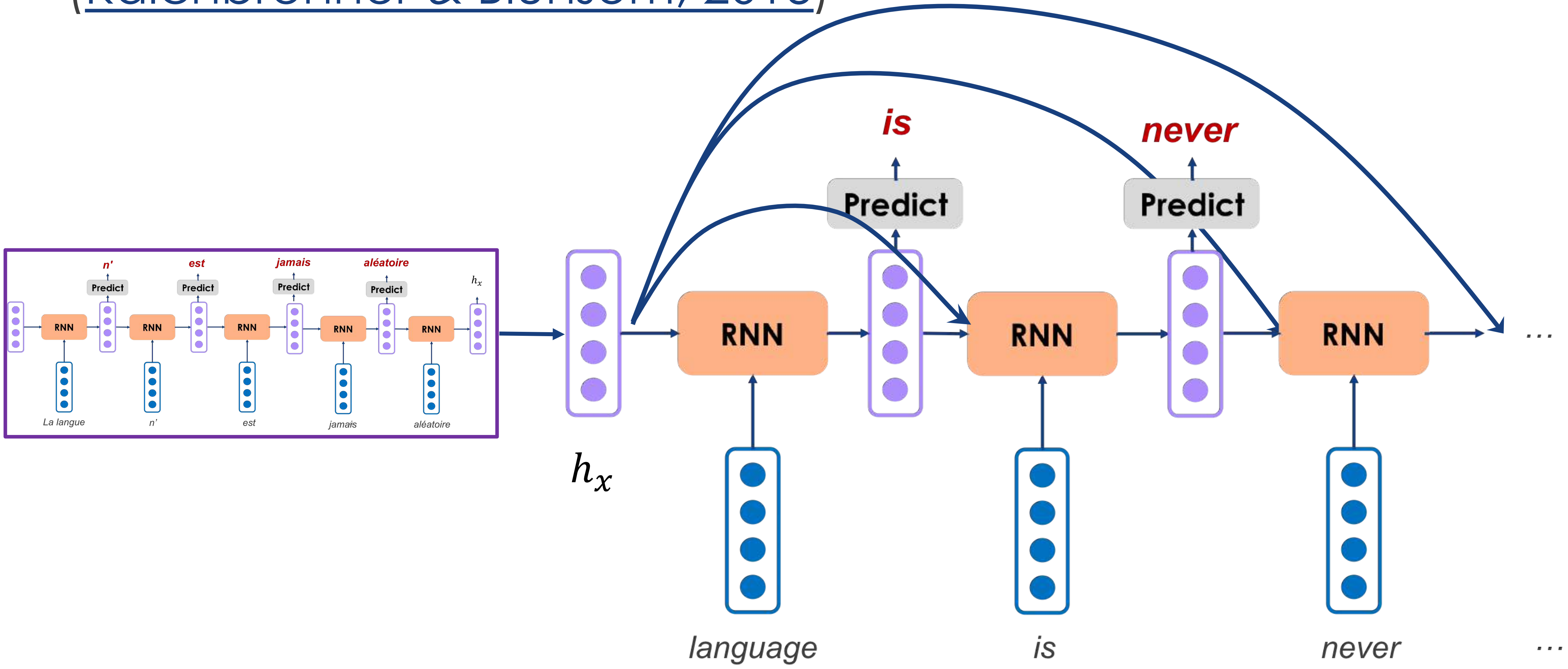
- Take final hidden state of an encoder model, feed it as the start state of a decoder model (Sutskever et al. 2014)

- RNNs deal naturally with undefined encoding input lengths

- But we’re depending on a single hidden state to squeeze information of the inputs to feed to the decoder

Recurrent Continuous Translation Models

- Add the encoded hidden state at every decoder time step ([Kalchbrenner & Blunsom, 2013](#))



Recurrent Continuous Translation Models

- Add the encoded hidden state at every decoder time step (Kalchbrenner & Blunsom, 2013)
- Having the encoded hidden state force fed to every decoder timestep is too overwhelming
- Still, too much depend on that one hidden encoder state

Greedy Decoding

- Generally, we want to find the most probable output given the input
- Simple approximation is to pick the highest probability word at each time step, `torch.max(predictions, 1)`
- Simple causes problem…
  - Often generate “easy” words first
  - Prefers common phrases to one rare word

Beam Search

- Better approximation is to predict k-best outputs at each time step

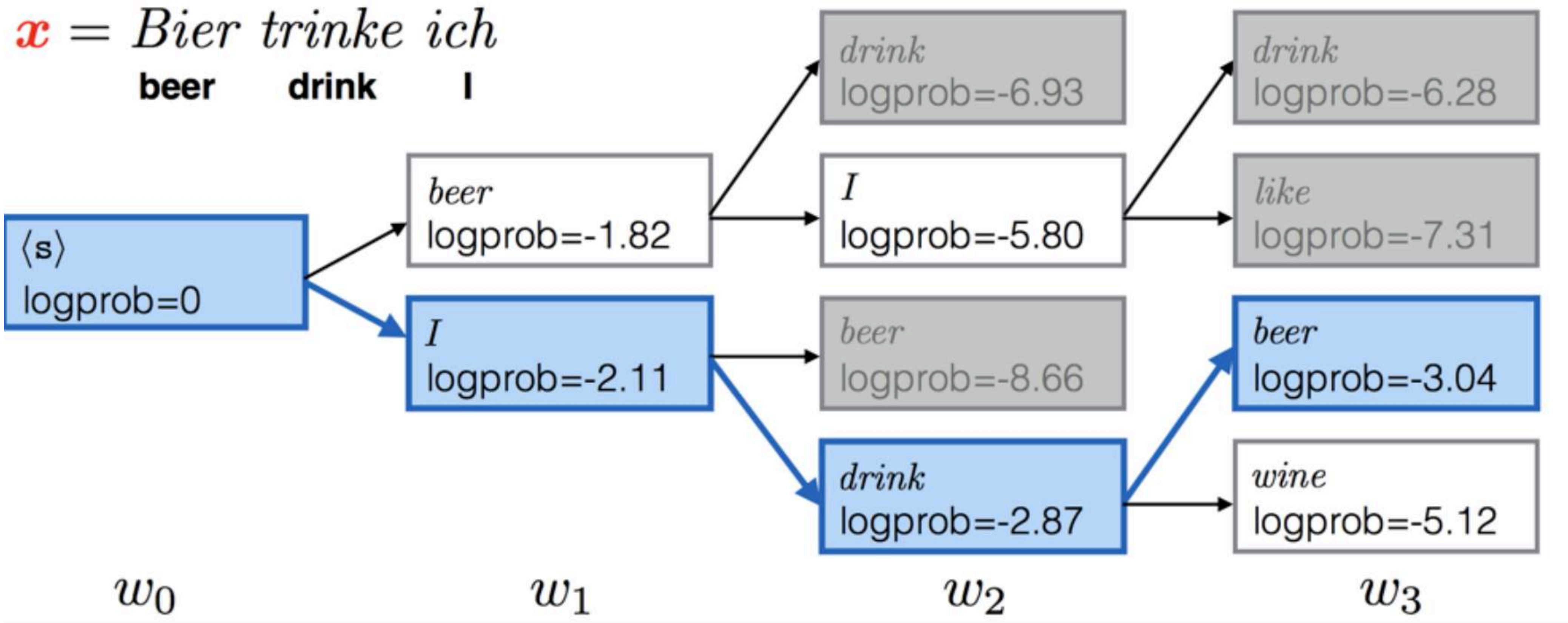


Figure and example from (Dyer, 2018)

Environment Setup

Open Anaconda Navigator.

Go to the PyTorch installation page, copy the command as per configuration: https://pytorch.org/get-started/locally/

Fire up the terminal in Anaconda Navigator.

Start a Jupyter Notebook.

Download http://bit.ly/ANLP-Session6Gen

Import the .ipynb to the Jupyter Notebook

Summary

Gated RNN + Generation Knowledge Checklist

- **Gated Recurrent Neural Net**
  - Always use GRU or LSTM, never vanilla RNN
  - When gradient explodes, clip it, even if it doesn't still clip it
  - Bi-directional GRU/LSTM produces reasonable results

- **Conditioned Generation**
  - Encode inputs into a hidden state vector/matrix, then generating outputs stepwise in an RNN
  - Pairs of conditions and target generations are necessary
  - When possible, always do beam search

Fin