# Neural Networks and Deep Learning
# Lecture 9

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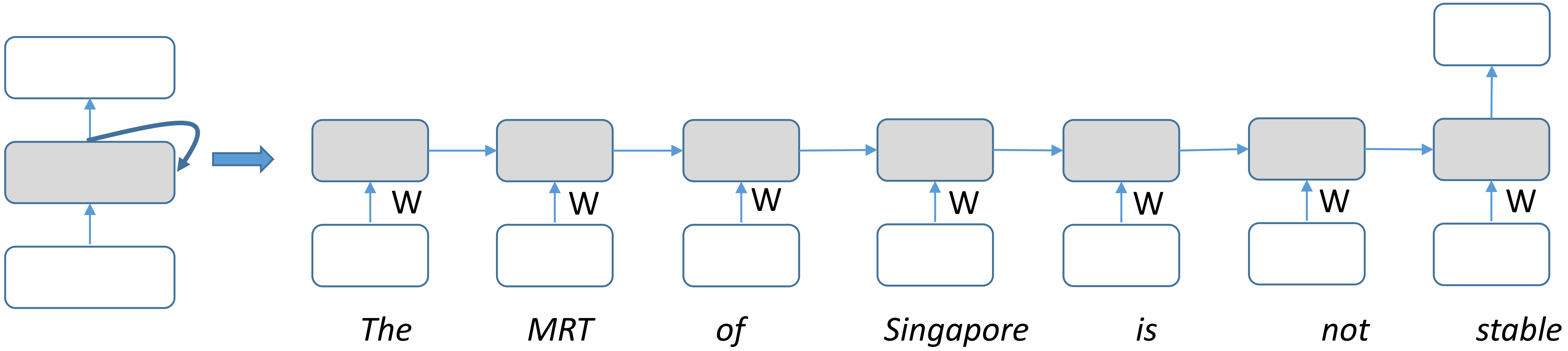
# Administrative

- Assignment 2 is ready
  - Due date: 2 Apr 2018 (Week 11), 17:00
- Remedial session?

# Recap

- RNN
  - processes sequential data by applying the same transformation recurrently
    - Tied weights
  - Hidden feature from position/time t summarizes history
  - Inputs of any length



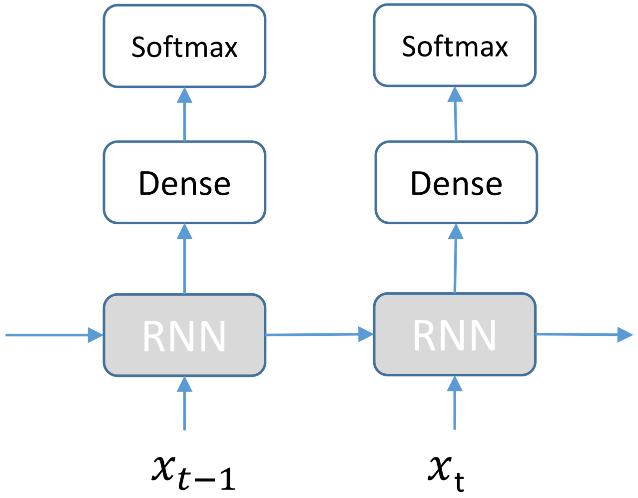
# Recap

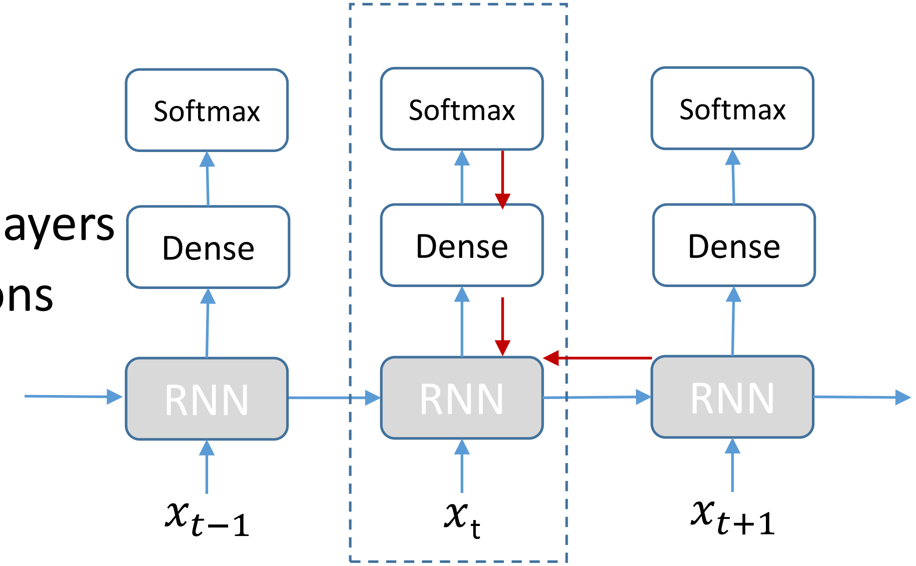
- Vanilla RNN for language modelling
  - Given a corpus D of text (e.g. sentences), model the probability of a sentence (i.e. a sequence of words)
    - $P(x_1, x_2, \dots, x_n)$, $x_i$ represents a word
  - $P(x_1, x_2, \dots, x_n) = \prod_t P(x_t | x_{t-1}, x_{t-2}, \dots, x_1)$
    - $logP(x_1, x_2, \dots, x_n) = \sum_t logP(x_t | x_{t-1}, x_{t-2}, \dots, x_1)$
  - For sentences from the training corpus, we train the RNN parameters to maximize the log-likelihood
    - → minimize negative log-likelihood -$\sum_t logP(x_t | x_{t-1}, x_{t-2}, \dots, x_1)$
    - → minimize the cross-entropy loss $-(l_t == k) \log P(x_t = k | x_{t-1}, x_{t-2}, \dots, x_1)$ for all t
      - $l_t$ is the ground truth word at position t, k is the predicted word
    - → a classification problem
      - Given $x_{t-1}, x_{t-2}, \dots, x_1$, predict $x_t$
      - *The MRT of Singapore* → *is*

# Recap

- Back-propagation through time for training
  - forward
    - $h_t = f(h_{t-1}, x_t|\theta)$
    - $o_t = Vh_t + c$
    - $y_t = softmax(o_t)$
  - Backward
    - Like BP for MLP for each position
    - Hidden layer aggregates gradients from top and right layers
    - Gradients of parameters are aggregated across positions
  - Gradient exploding or vanishing
    - W is multiplied repeatedly

| | $x_t$ |
|---|---|
| One-hot | [0, 1, 0, 0, …,0] |
| WordVector | [0.1, -1.2, 0.5, 0.3, …,-0.1] |



# Intended learning outcomes

01

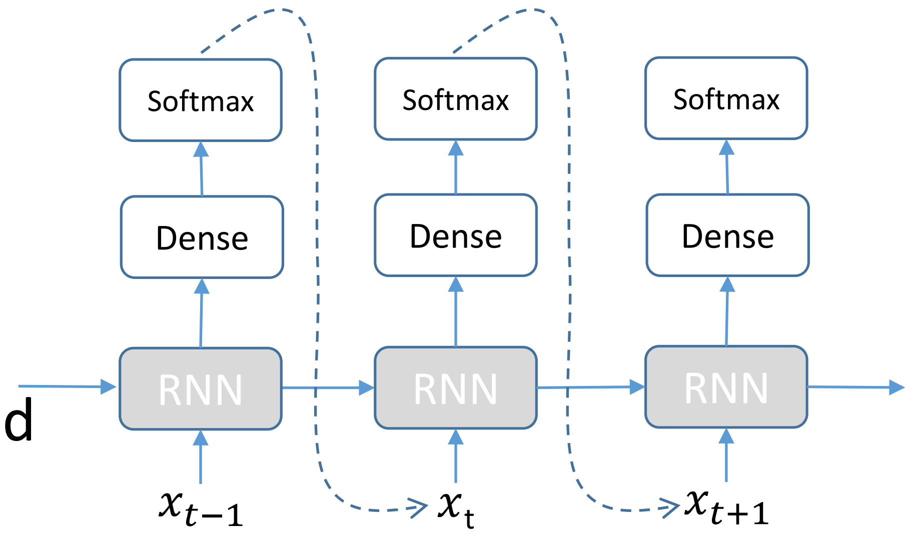
Implement the BP and inference of RNN

02

Compare vanilla RNN, GRU and LSTM

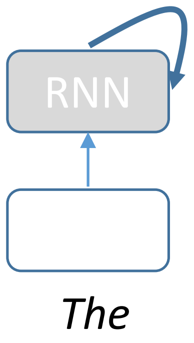
# Inference

- Input some seeding words
  - A special word for the starting of a sentence
    - START
  - Or a few words, “The MRT of”
- Generate the rest words one by one
  - The output from position (or timestamp) t-1 is used as the input of position t, i.e. $x_t$
  - Until a special word for the ending of a sentence
    - END (EOS)



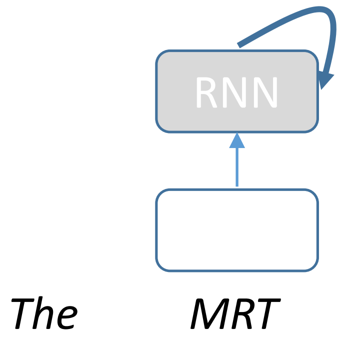
# Inference

- Example
  - Input “The MRT of”



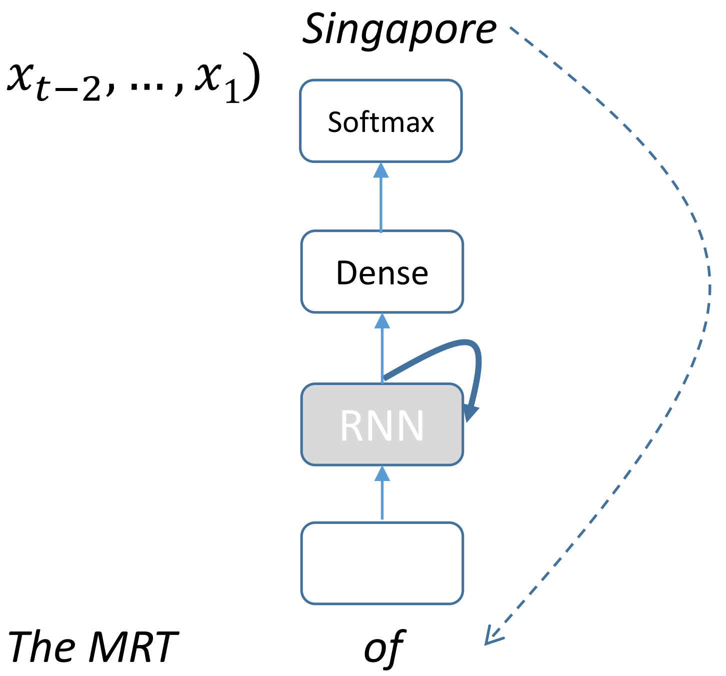
# Inference

- Example
    - Input “The MRT of”



# Inference

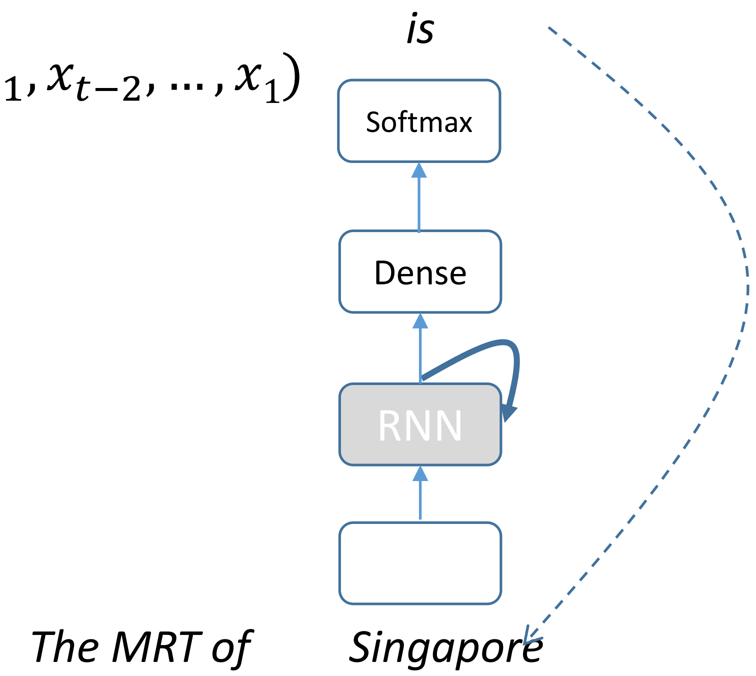
- Example
  - Input “The MRT of”
  - Greedy search
    - Simple, P$(x_t|x_{t-1}, x_{t-2}, \ldots, x_1)$




Singapore: 0.8
MRT : 0.1
Is : 0.05
Stable : 0.04
…

# Inference

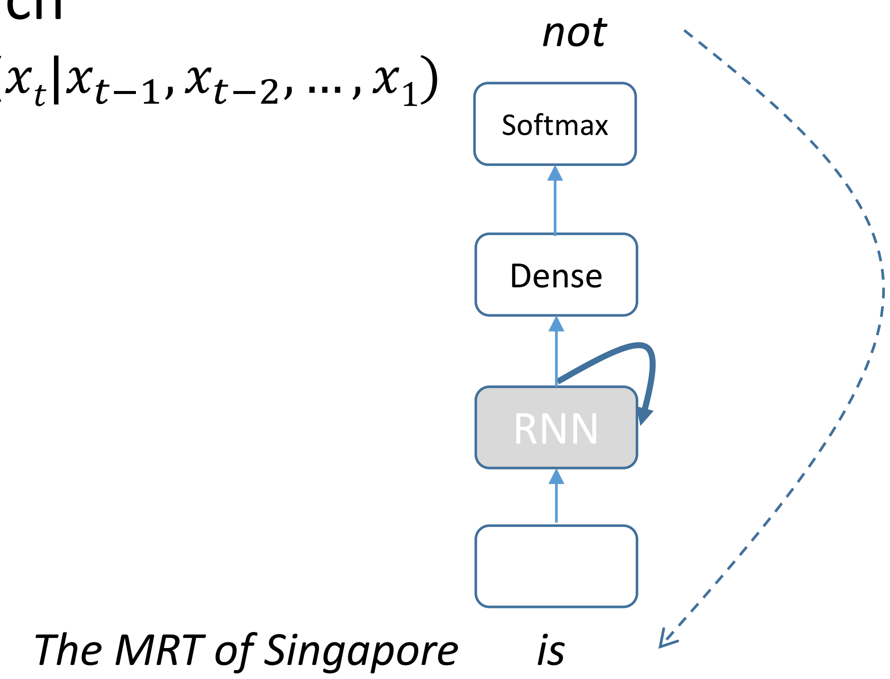
- Example
  - Input "The MRT of"
  - Greedy search
    - Simple, P($x_t|x_{t-1}, x_{t-2}, \ldots, x_1$)




Is : 0.9
Singapore: 0.05
MRT : 0.025
Stable : 0.01
…

# Inference

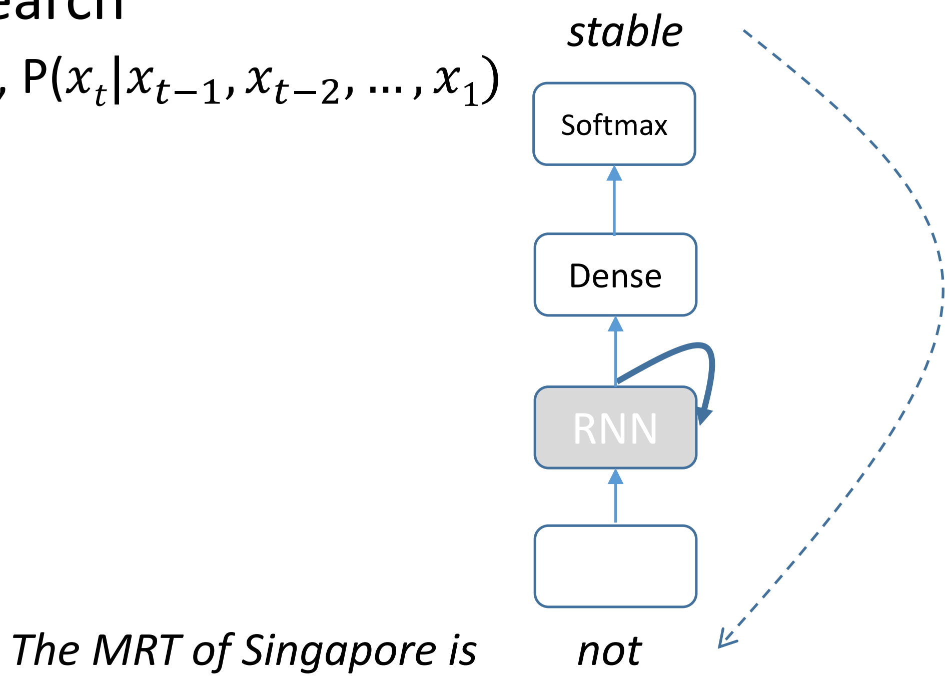
- Example
  - Input “The MRT of”
  - Greedy search
    - Simple, $P(x_t|x_{t-1}, x_{t-2}, \dots, x_1)$




Not : 0.6
Stable : 0.3
Singapore: 0.05
MRT : 0.025
…

# Inference

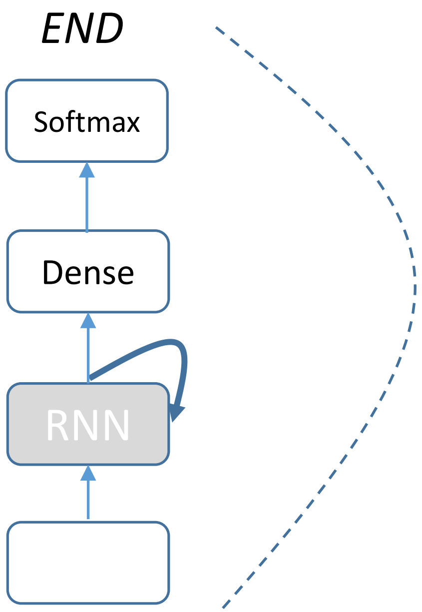
- Example
  - Input “The MRT of”
  - Greedy search
    - Simple, $P(x_t | x_{t-1}, x_{t-2}, \ldots, x_1)$




Stable : 0.8
Singapore: 0.1
MRT : 0.025
Not : 0.001
…

# Inference

- Example
  - Input "The MRT of"
  - Greedy search
    - Simple, P($x_t|x_{t-1}, x_{t-2}, \ldots, x_1$)

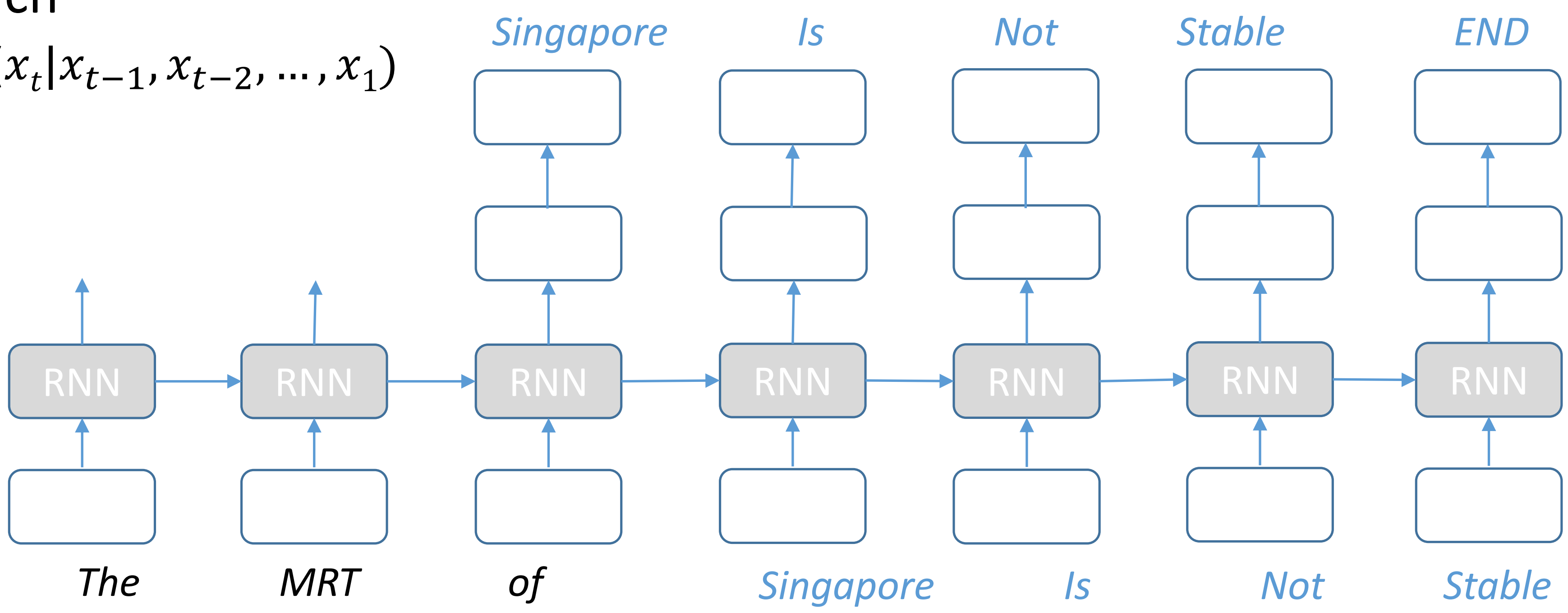



*The MRT of Singapore is not* *stable*

END : 0.7
MRT : 0.1
Is : 0.05
Stable : 0.04
…

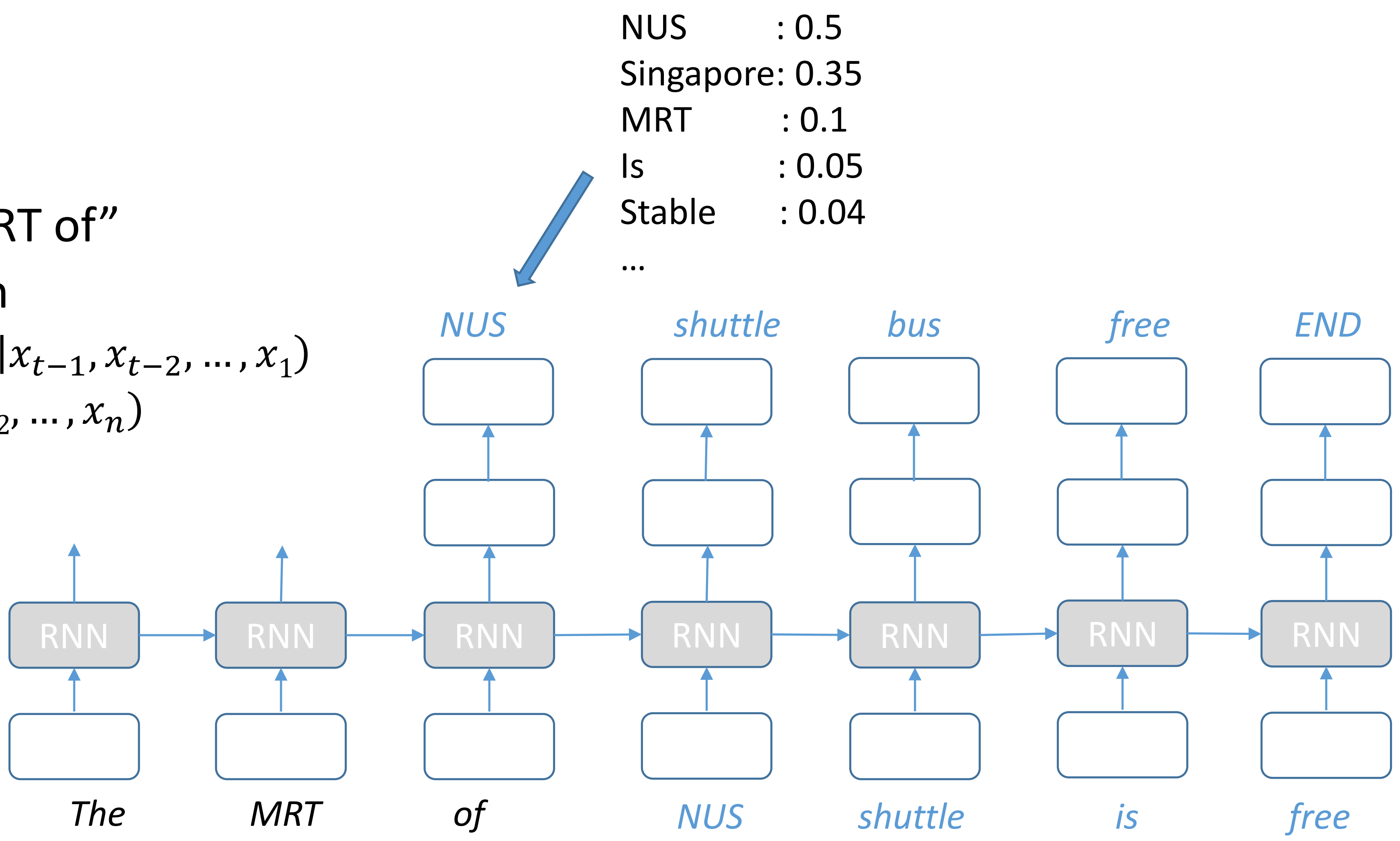
# Inference

- Example
  - Input “The MRT of”
  - Greedy search
    - Simple, P($x_t|x_{t-1}, x_{t-2}, \ldots, x_1$)
    - **?**



# Inference

- Example
  - Input “The MRT of”
  - Greedy search
    - Simple, $P(x_t|x_{t-1}, x_{t-2}, \dots, x_1)$
    - NOT $P(x_1, x_2, \dots, x_n)$

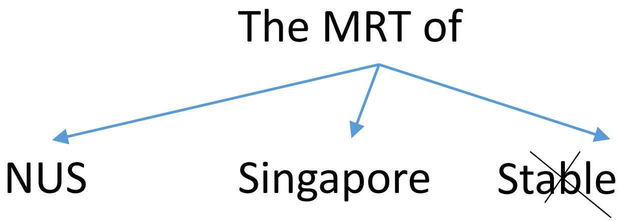


# Inference

- Beam search
  - Suppose we have the top-K assignments of $(x_1, x_2, \ldots x_t)_i$ (i=1…k) for position 1 to t.
    - Sorted by $P(x_1, x_2, \ldots x_t)$
  - To select the words for $x_{t+1,}$
    - For each word $w_j$ from the vocabulary V
      - For each top-K assignment $(x_1, x_2, \ldots x_t)_i$
        - Compute $P_{ij}=P((x_1, x_2, \ldots x_t)_i, x_{t+1}=w_j) = P(x_{t+1} = w_j \mid (x_1, x_2, \ldots x_t)_i) * P(x_1, x_2, \ldots x_t)_i$
    - Sort $P_{ij}$ to keep the top-K assignments
- How to set K
  - 2-5 is suggested [13]

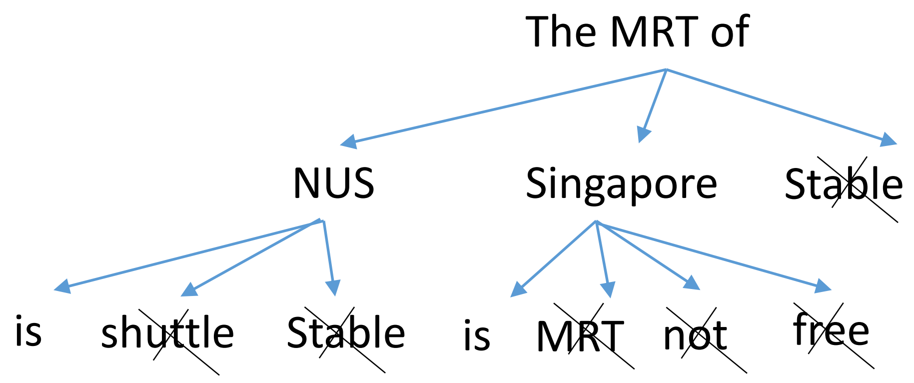
# Inference

- Beam search
  - K=2



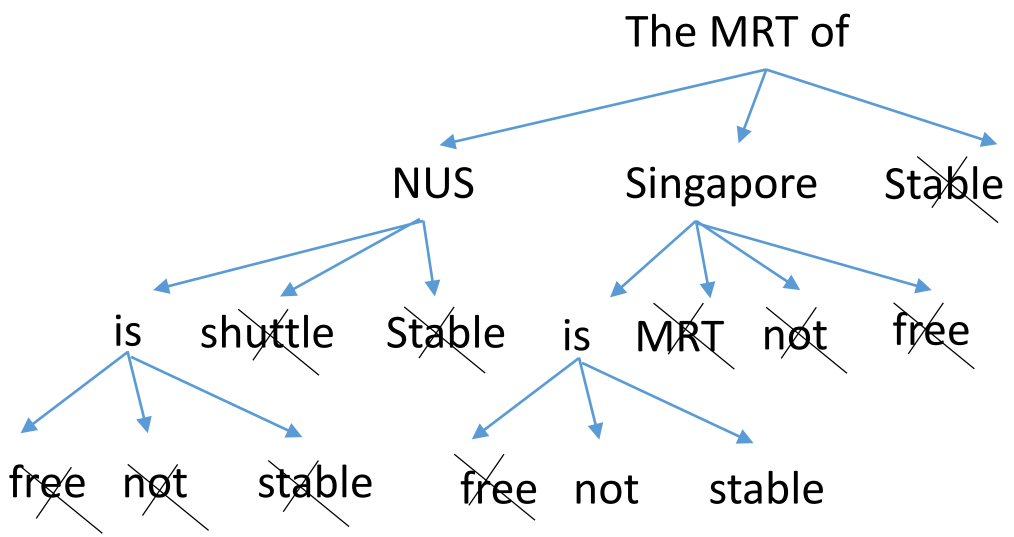
# Inference

- Beam search
  - K=2



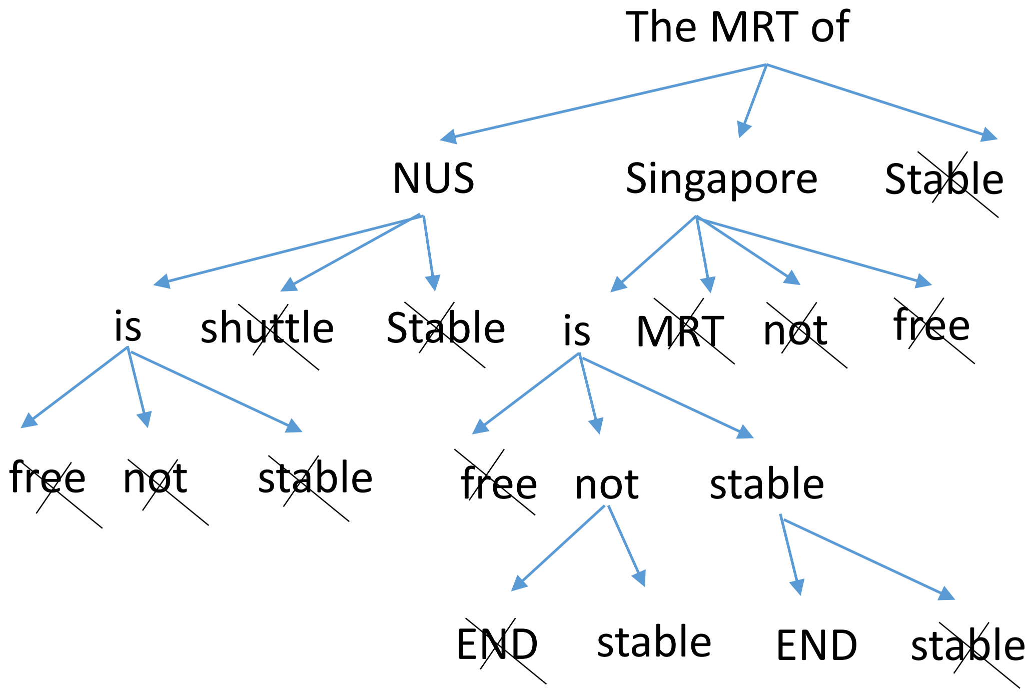
# Inference

- Beam search
  - K=2



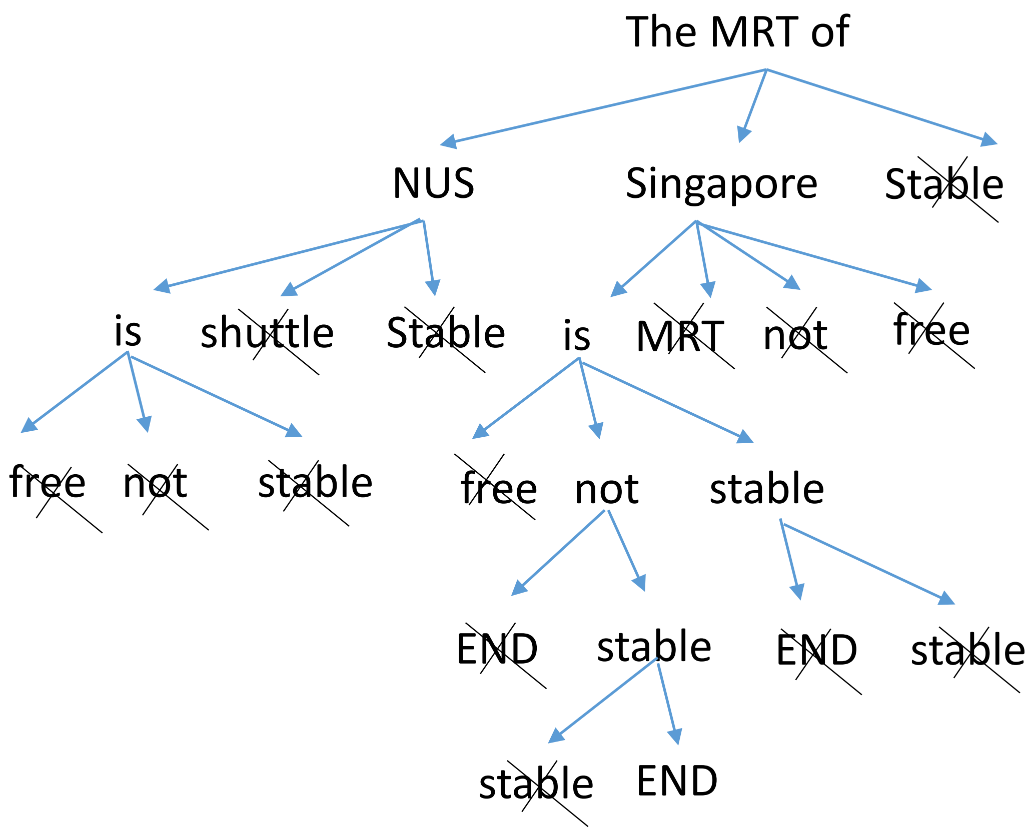
# Inference

- Beam search
  - K=2



# Inference

- Beam search
  - K=2



# Inference

- Beam search code from
  - https://gist.github.com/udibr/67be473cf053d8c38730

```python
def beamsearch(predict=keras_rnn_predict,
               k=1, maxsample=400, use_unk=False, oov=oov, empty=empty, eos=eos):
    """return k samples (beams) and their NLL scores, each sample is a sequence of labels,
    all samples starts with an `empty` label and end with `eos` or truncated to length of `maxsample`.
    You need to supply `predict` which returns the label probability of each sample.
    `use_unk` allow usage of `oov` (out-of-vocabulary) label in samples
    """

    live_k = 1 # samples that did not yet reached eos
    live_samples = [[empty]]
    live_scores = [0]

    while live_k                  :
        # for every possible live sample calc prob for every possible label
        probs = predict(live_samples, empty=empty)

        # total score for every sample is sum of -log of word prb
        cand_scores = np.array(live_scores)[:,None] - np.log(probs)
        if not use_unk and oov is not None:
            cand_scores[:,oov] = 1e20
        cand_flat = cand_scores.flatten()

        # find the best (lowest) scores we have from all possible samples and new words
        ranks_flat = cand_flat.argsort()[:(k-dead_k)]
        live_scores = cand_flat[ranks_flat]

        # append the new words to their appropriate live sample
        voc_size = probs.shape[1]
        live_samples = [live_samples[r//voc_size]+[r%voc_size] for r in ranks_flat]
```

Input->RNN->Dense->Softmax

$P(x_t \mid x_1, x_2, \ldots x_{t-1})$

$-\log P(x_1, x_2, \ldots x_{t-1}) - \log P(x_t \mid x_1, x_2, \ldots x_{t-1})$

# Char-RNN

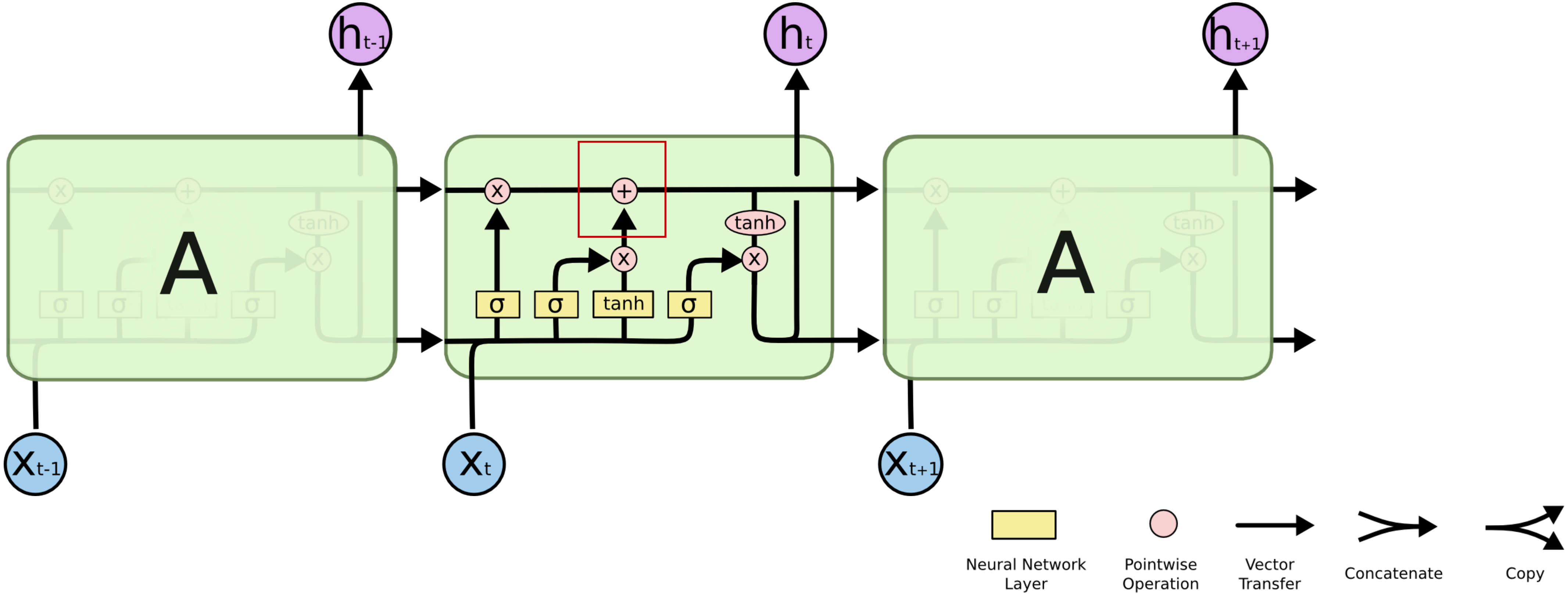
- https://gist.github.com/karpathy/d4dee566867f8291f086
- https://github.com/tensorflow/models/blob/master/tutorials/rnn/ptb/ptb_word_lm.py

# LSTM, GRU and Bi-directional RNN

# For gradient vanishing

- Adding gates to the RNN layer
  - Gate controls the information flow

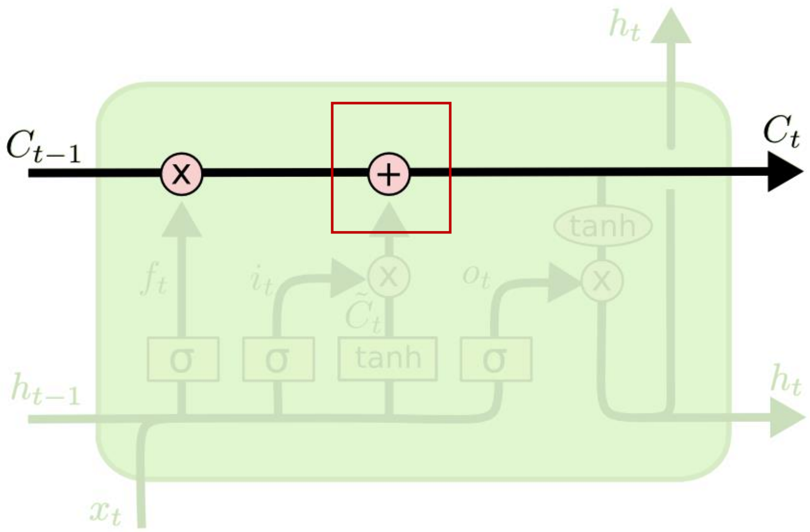
# LSTM




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

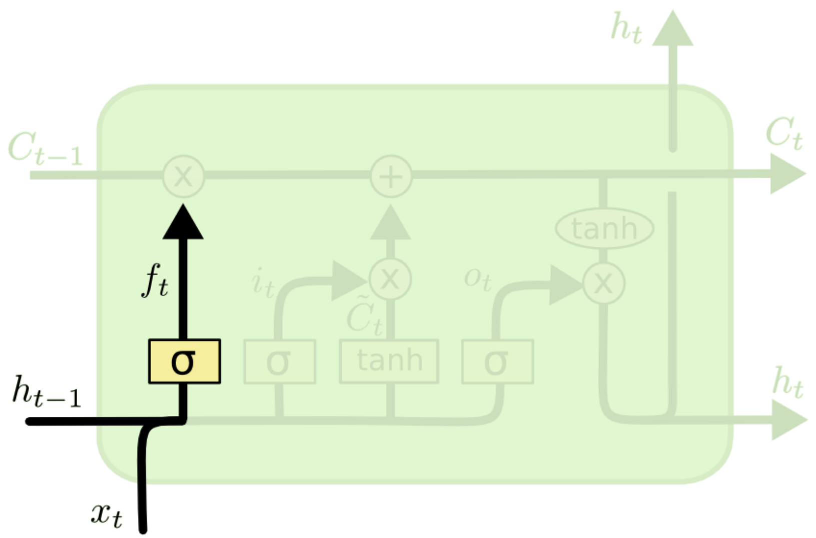
# LSTM

- Leaky unit
  - $C_t$ is a linear combination of $C_{t-1}$ and other input
  - Easy to back-propagate gradients



# LSTM

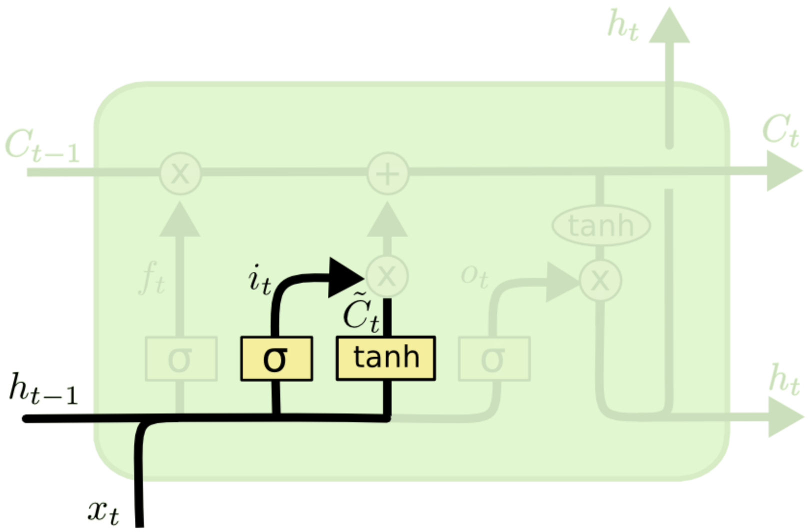
- Forget gate
  - To control the information flow about the cell state




$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

# LSTM

- Input gate
  - Decide how much information from the input can be added into the cell state

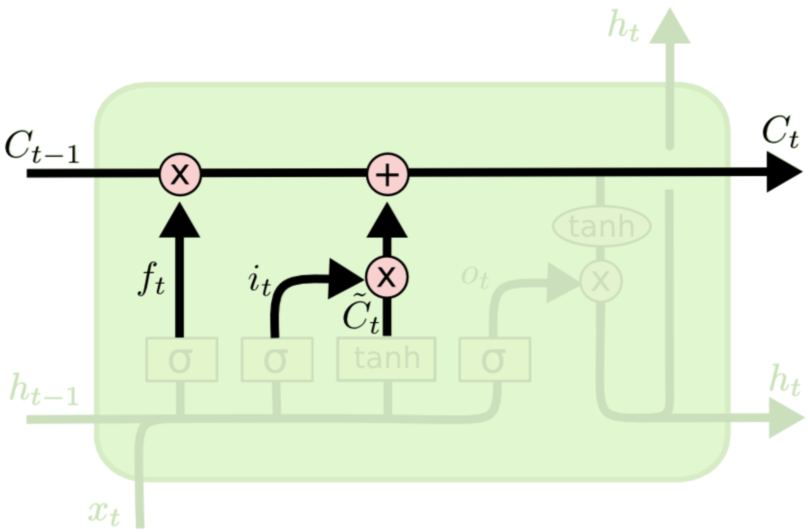



$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

# LSTM

- Cell state
  - Tanh (not sigmoid)?

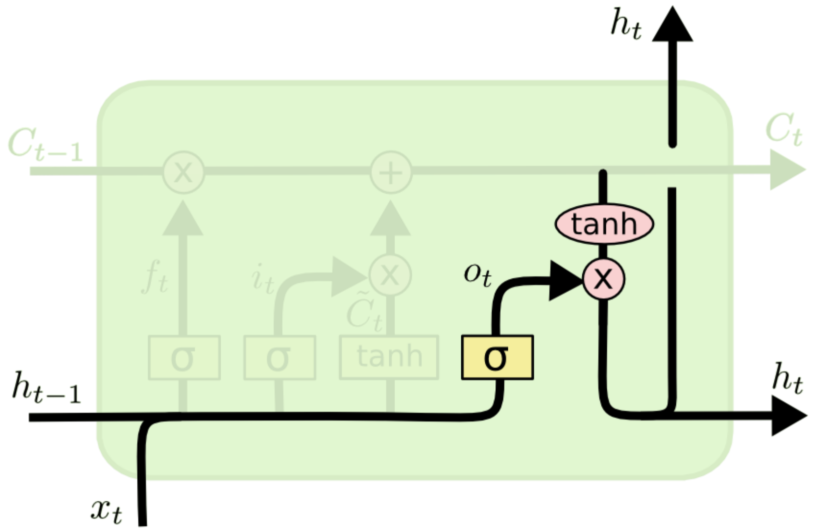



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Forget gate and input gate are (0, 1). Their sum may not be 1, like $\gamma$ and (1- $\gamma$ )
$C_t$ is not computed using affine transformation like
$C_t = WC_{t-1} + \cdots$, hence we do not have $\frac{\partial L}{\partial C_{t-k}} = (W^T)^k \frac{\partial L}{\partial C_t}$
Then, gradient vanishing/exploding is prevented.

# LSTM

- Output gate
  - Determine the information flows out of the unit




$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t]\ +\ b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

# LSTM

- Gates + States

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$

$$o_t = \sigma\left(W_o \ [h_{t-1}, x_t] \ + \ b_o\right)$$

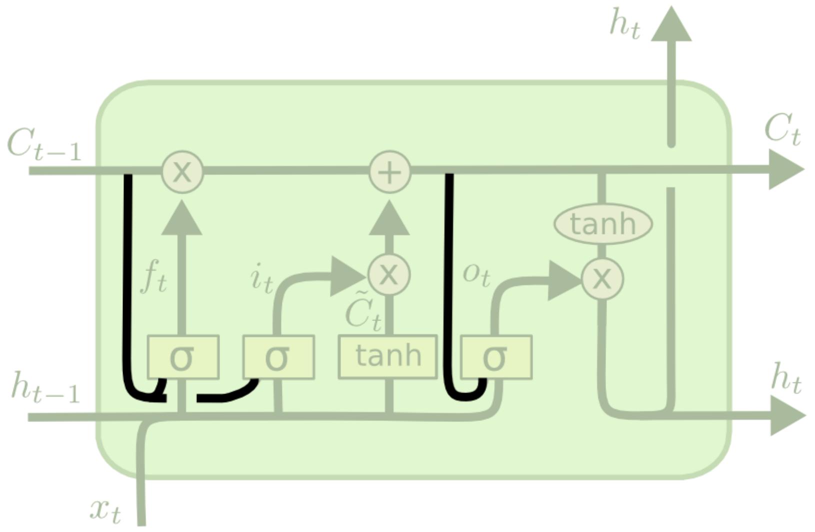
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

$$h_t = o_t * \tanh\left(C_t\right)$$

# LSTM

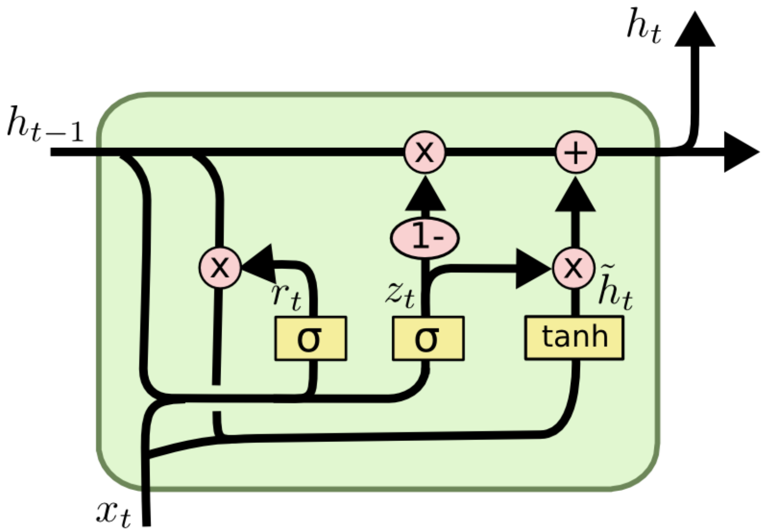
- With peephole
  - Cell state has effect on the gate values




$$f_t = \sigma\left(W_f \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \ + \ b_f\right)$$
$$i_t = \sigma\left(W_i \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \ + \ b_i\right)$$
$$o_t = \sigma\left(W_o \cdot [\boldsymbol{C_t}, h_{t-1}, x_t] \ + \ b_o\right)$$

- Other variants [12]

# GRU




$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$ Update gate

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$ Reset gate

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

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

# LSTM for Char-RNN

Each character is represented by a V-dim one-hot vector

```
from __future__ import print_function
from keras.models import Sequential
from keras.layers import Dense, Activation
from keras.layers import LSTM
from keras.optimizers import RMSprop
from keras.utils.data_utils import get_file
import numpy as np
import random
import sys

path = get_file('nietzsche.txt', origin='https://s3.amazonaws.com/text-datasets/nietzsche.txt')
text = open(path).read().lower()
print('corpus length:', len(text))

chars = sorted(list(set(text)))
print('total chars:', len(chars))
char_indices = dict((c, i) for i, c in enumerate(chars))
indices_char = dict((i, c) for i, c in enumerate(chars))

# cut the text in semi-redundant sequences of maxlen characters
maxlen = 40
step = 3
sentences = []
next_chars = []
for i in range(0, len(text) - maxlen, step):
    sentences.append(text[i: i + maxlen])
    next_chars.append(text[i + maxlen])
print('nb sequences:', len(sentences))
```

Truncate the character stream into sentences

```
X = np.zeros((len(sentences), maxlen, len(chars)), dtype=np.bool)
y = np.zeros((len(sentences), len(chars)), dtype=np.bool)
for i, sentence in enumerate(sentences):
    for t, char in enumerate(sentence):
        X[i, t, char_indices[char]] = 1
    y[i, char_indices[next_chars[i]]] = 1


# build the model: a single LSTM
print('Build model...')
model = Sequential()
model.add(LSTM(128, input_shape=(maxlen, len(chars))))
model.add(Dense(len(chars)))
model.add(Activation('softmax'))

optimizer = RMSprop(lr=0.01)
model.compile(loss='categorical_crossentropy', optimizer=optimizer)
```

https://github.com/fchollet/keras/blob/master/examples/lstm_text_generation.py

```python
# train the model, output generated text after each iteration
for iteration in range(1, 60):
    print()
    print('-' * 50)
    print('Iteration', iteration)
    model.fit(X, y,
              batch_size=128,
              epochs=1)

    start_index = random.randint(0, len(text) - maxlen - 1)

    for diversity in [0.2, 0.5, 1.0, 1.2]:
        print()
        print('----- diversity:', diversity)

        generated = ''
        sentence = text[start_index: start_index + maxlen]
        generated += sentence
        print('----- Generating with seed: "' + sentence + '"')
        sys.stdout.write(generated)

        for i in range(400):
            x = np.zeros((1, maxlen, len(chars)))
            for t, char in enumerate(sentence):
                x[0, t, char_indices[char]] = 1.

            preds = model.predict(x, verbose=0)[0]
            next_index = sample(preds, diversity)
            next_char = indices_char[next_index]

            generated += next_char
            sentence = sentence[1:] + next_char

            sys.stdout.write(next_char)
            sys.stdout.flush()
```

```python
def sample(preds, temperature=1.0):
    # helper function to sample an index from a probability array
    preds = np.asarray(preds).astype('float64')
    preds = np.log(preds) / temperature
    exp_preds = np.exp(preds)
    preds = exp_preds / np.sum(exp_preds)
    probas = np.random.multinomial(1, preds, 1)
    return np.argmax(probas)
```

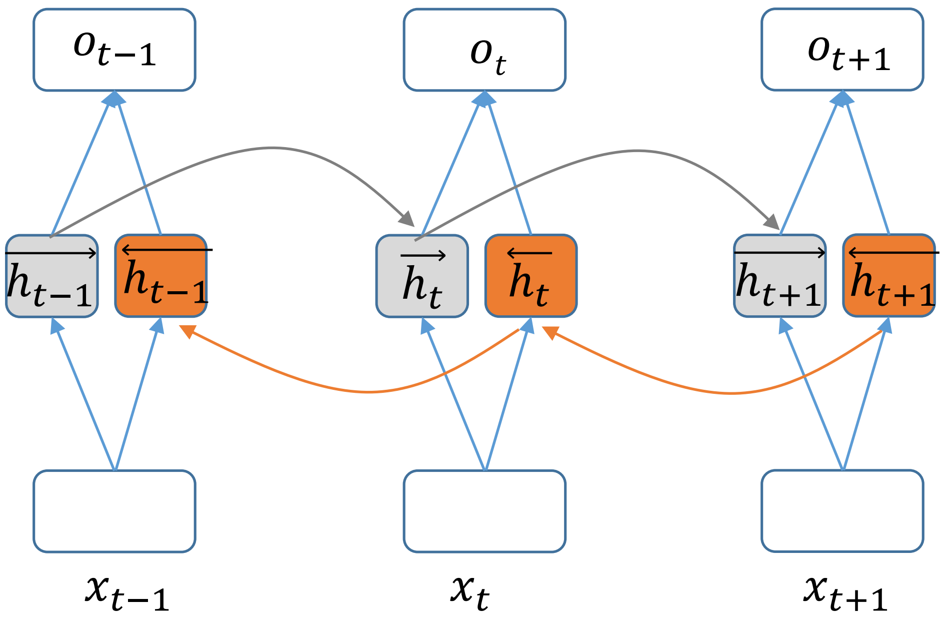
Robust Softmax

Greedy sampling

# Bi-directional RNN

1st RNN: → a, b, c, d, x, x, x
2nd RNN: x, x, x, a, b, c, d ←
Concatenate the hidden features for the same word

- Using vanilla RNN
  - $\overrightarrow{h_t} = \tanh(\vec{U}x_t + \vec{W}\overrightarrow{h_{t-1}} + \vec{b})$
  - $\overleftarrow{h_t} = \tanh(\overleftarrow{U}x_t + \overleftarrow{W}\overleftarrow{h_{t+1}} + \vec{b})$
  - $o_t = V[\overrightarrow{h_t}, \overleftarrow{h_t}] + c$
    - [,] concatenate
- Using LSTM/GRU
  - $\overrightarrow{h_t}$ =LSTM$_{lr}$($\overrightarrow{h_{t-1}}, \overrightarrow{c_{t-1}}, x_t$)
  - $\overleftarrow{h_t}$ =LSTM$_{rl}$ ($\overleftarrow{h_{t+1}}, \overleftarrow{c_{t+1}}, x_t$)
  - $o_t = V[\overrightarrow{h_t}, \overleftarrow{h_t}] + c$
    - [,] concatenate
- Widely used for processing sentences



# Reference


- [1] https://www.quora.com/What-are-differences-between-recurrent-neural-network-language-model-hidden-markov-model-and-n-gram-language-model
- [2] https://code.google.com/archive/p/word2vec/
- [3] https://nlp.stanford.edu/projects/glove/
- [4] Klaus Greff, Rupesh Kumar Srivastava, Jan Koutník, Bas R. Steunebrink, Jürgen Schmidhuber. LSTM: A Search Space Odyssey. https://arxiv.org/abs/1503.04069
- [5] http://web.stanford.edu/class/cs224n/lectures/cs224n-2017-lecture8.pdf
- [6] http://www.deeplearningbook.org/contents/applications.html (12.4.3)
- [7] Quoc V. Le, Navdeep Jaitly, Geoffrey E. Hinton. A Simple Way to Initialize Recurrent Networks of Rectified Linear Units. 2015. arxiv.org/abs/1504.00941v2
- [8] "Layer Normalization" Jimmy Lei Ba, Jamie Ryan Kiros, Geoffrey E. Hinton. https://arxiv.org/abs/1607.06450.
- [9] "Recurrent Dropout without Memory Loss" Stanislau Semeniuta, Aliaksei Severyn, Erhardt Barth. https://arxiv.org/abs/1603.05118
- [10] https://www.tensorflow.org/api_docs/python/tf/contrib/rnn/LayerNormBasicLSTMCell
- [11] https://r2rt.com/non-zero-initial-states-for-recurrent-neural-networks.html
- [12] LSTM: A Search Space Odyssey. Klaus Greff, Rupesh Kumar Srivastava, Jan Koutník, Bas R. Steunebrink, Jürgen Schmidhuber. https://arxiv.org/abs/1503.04069
- [13] https://github.com/karpathy/char-rnn/issues/138#issuecomment-162763435
- https://research.googleblog.com/2016/05/announcing-syntaxnet-worlds-most.html
- https://danijar.com/tips-for-training-recurrent-neural-networks/

- [14] https://github.com/kjw0612/awesome-rnn#image-captioning
- [15] Oriol Vinyals, Alexander Toshev, Samy Bengio, and Dumitru Erhan, Show and Tell: A Neural Image Caption Generator, arXiv:1411.4555 / CVPR 2015
- [16] K. Papineni, S. Roukos, T. Ward, and W. J. Zhu. BLEU: A method for automatic evaluation of machine translation. In ACL, 2002.
- [17] Junhua Mao, Wei Xu, Yi Yang, Jiang Wang, Zhiheng Huang, and Alan L. Yuille, Deep Captioning with Multimodal Recurrent Neural Networks (m-RNN), arXiv:1412.6632 / ICLR 2015
- [18] Jeff Donahue, Lisa Anne Hendricks, Sergio Guadarrama, Marcus Rohrbach, Subhashini Venugopalan, Kate Saenko, and Trevor Darrell, Long-term Recurrent Convolutional Networks for Visual Recognition and Description, arXiv:1411.4389 / CVPR 2015
- [19] Ilya Sutskever, Oriol Vinyals, and Quoc V. Le, Sequence to Sequence Learning with Neural Networks, arXiv:1409.3215 / NIPS 2014
- [20] Dzmitry Bahdanau, KyungHyun Cho, and Yoshua Bengio, Neural Machine Translation by Jointly Learning to Align and Translate, arXiv:1409.0473 / ICLR 2015
- [21] Karl M. Hermann, Tomas Kocisky, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom, Teaching Machines to Read and Comprehend, arXiv:1506.03340 / NIPS 2015
- [22] SQuAD: 100,000+ Questions for Machine Comprehension of Text. Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, Percy Liang. https://arxiv.org/abs/1606.05250
- [23] Ankit Kumar, Ozan Irsoy, Jonathan Su, James Bradbury, Robert English, Brian Pierce, Peter Ondruska, Mohit Iyyer, Ishaan Gulrajani, and Richard Socher, Ask Me Anything: Dynamic Memory Networks for Natural Language Processing, arXiv:1506.07285
- [24] Question Answering Using Deep Learning. https://cs224d.stanford.edu/reports/StrohMathur.pdf
- [25] Shuohang Wang and Jing Jiang. Machine comprehension using match-lstm and answer pointer. arXiv preprint arXiv:1608.07905, 2016
- https://machinelearningmastery.com/how-does-attention-work-in-encoder-decoder-recurrent-neural-networks
- https://sites.google.com/site/deeplearningdialogue/references
- https://blog.acolyer.org/2016/04/21/the-amazing-power-of-word-vectors/