ITCS 6156/8156 Fall 2024
Machine Learning

Recurrent Neural Networks

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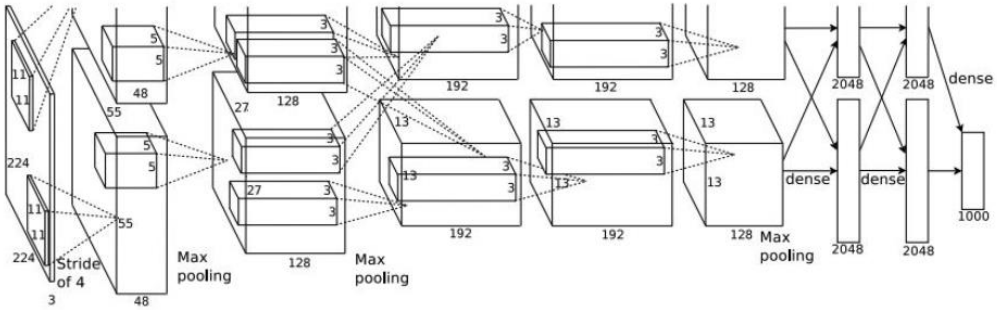
Class Meeting: Tue & Thu, 4:00 PM – 5:15 PM, WWH 130

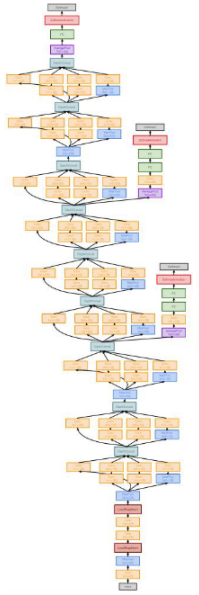
UNIVERSITY OF NORTH CAROLINA CHARLOTTE

Some content in the slides is based on DeepMind's and Dr. Fei-Fei Li's lectures

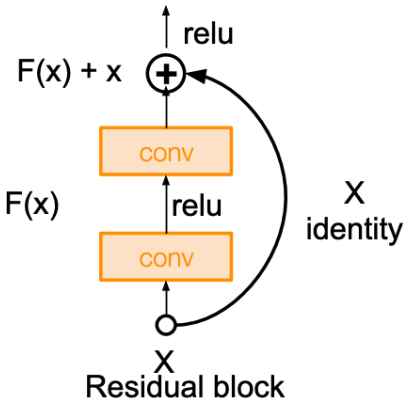
Recap: CNN Architecture

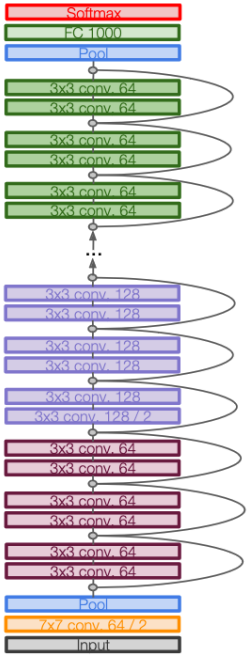


VGG16 VGG19

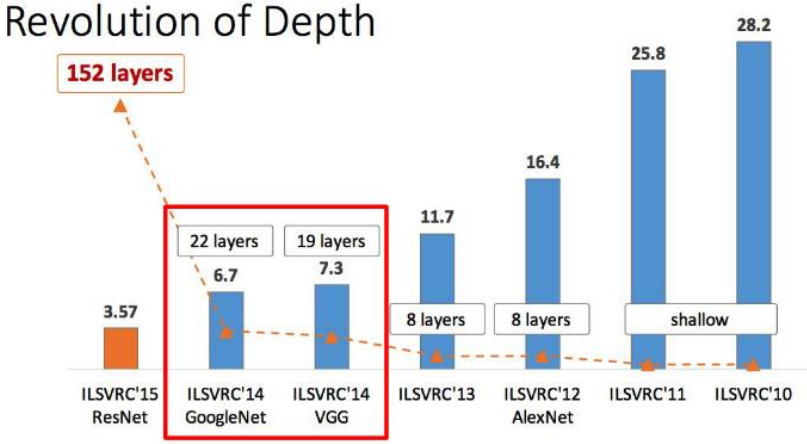


GoogLeNet

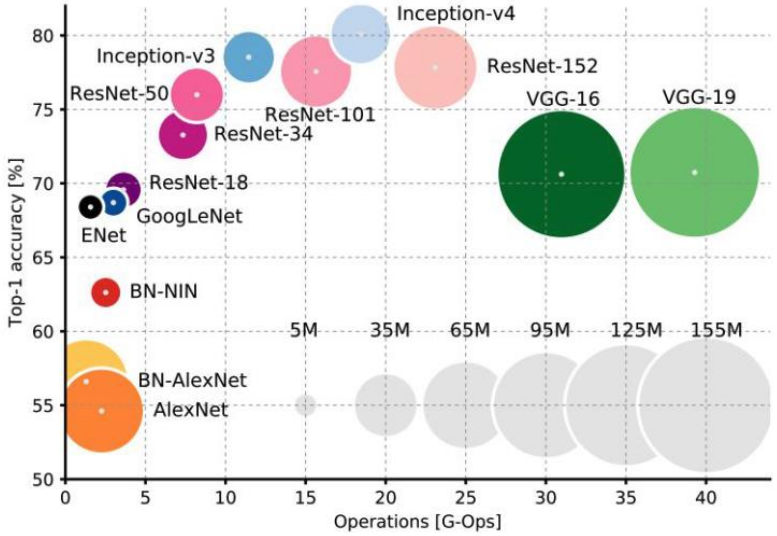




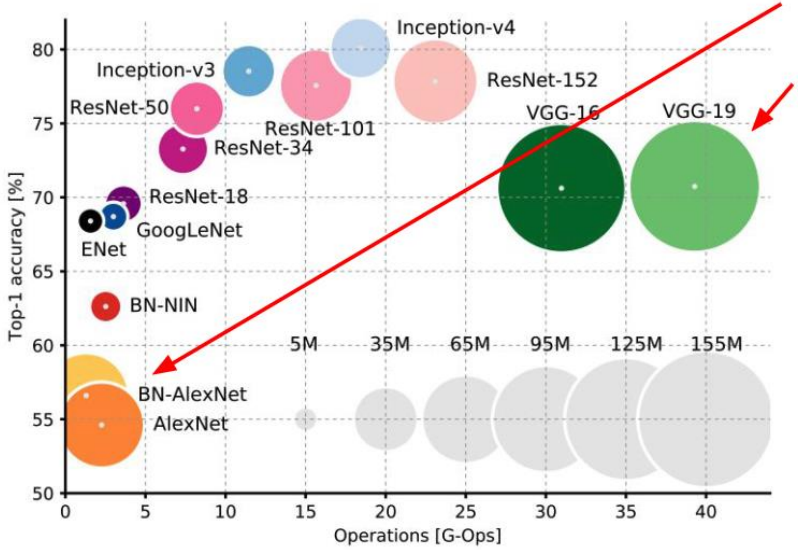
ResNet



Recap: CNN Architecture



Recap: CNN Architecture

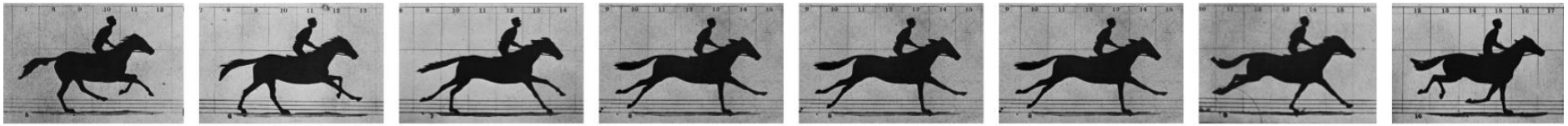


AlexNet and VGG have tons of parameters in the fully connected layers

AlexNet: ~62M parameters

FC6: 256x6x6 -> 4096: 38M params
FC7: 4096 -> 4096: 17M params
FC8: 4096 -> 1000: 4M params
~59M params in FC layers!

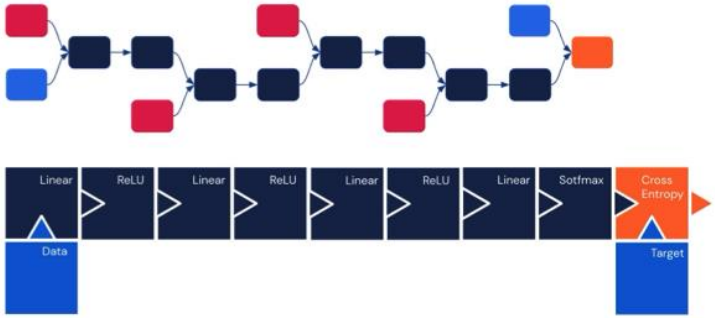
Modeling Sequences

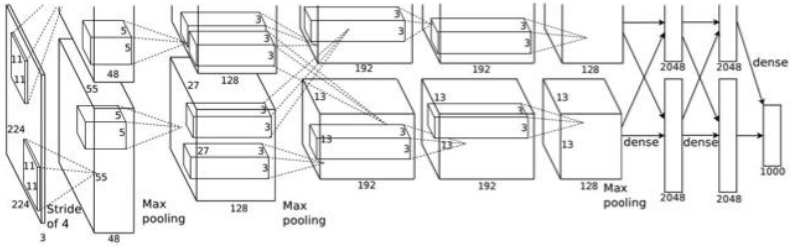


Collections of elements where:

- Elements can be **repeated**
- **Order** matters
- Of **variable** (potentially infinite) length

Models discussed so far don't do well with sequential data.





Modeling Sequences

“Why do we care about sequences?”

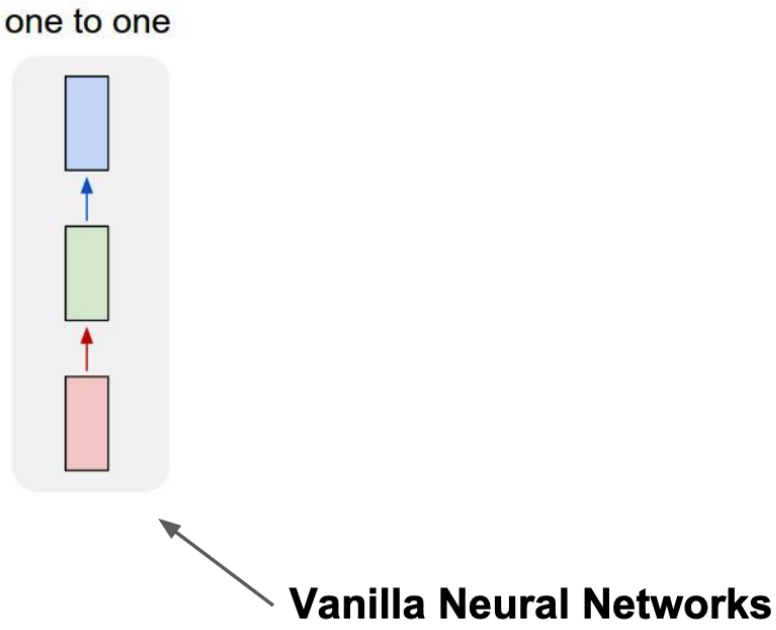
“Why”, “do”, “we”, “care”, “about”, “sequences”, ”?”

“D”, “O” “C”, “A”, “R”, “E” “S”, “E”, “Q”, “U”, “E”, “N”, “C”, “E”, “S”

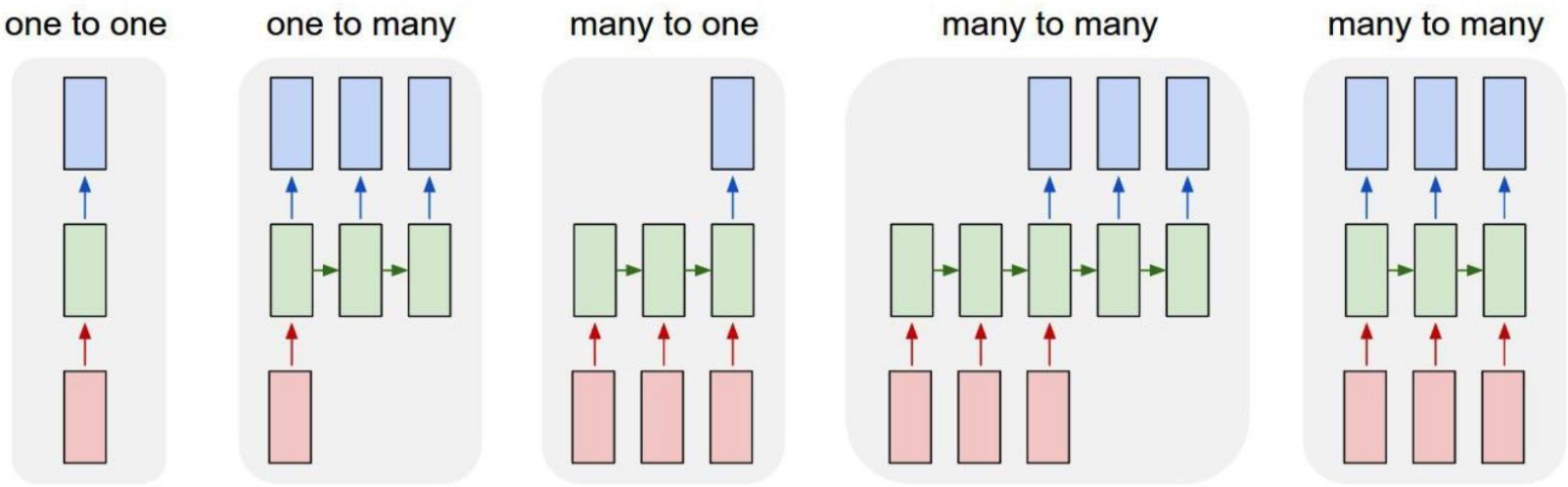
“Why”, “do”, “we”, “care”, “about”, “sequences”, ”?”

“W”, “H”, “Y” “W”, “E” “A”, “B”, “O”, “U”, “T”

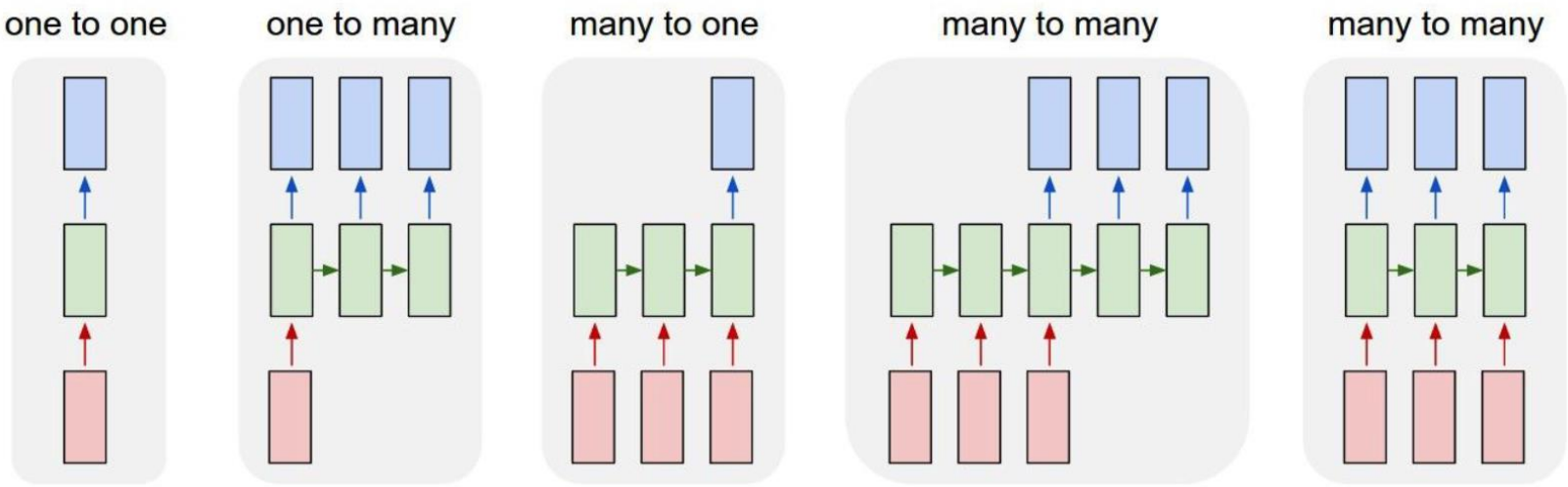
Process Sequence



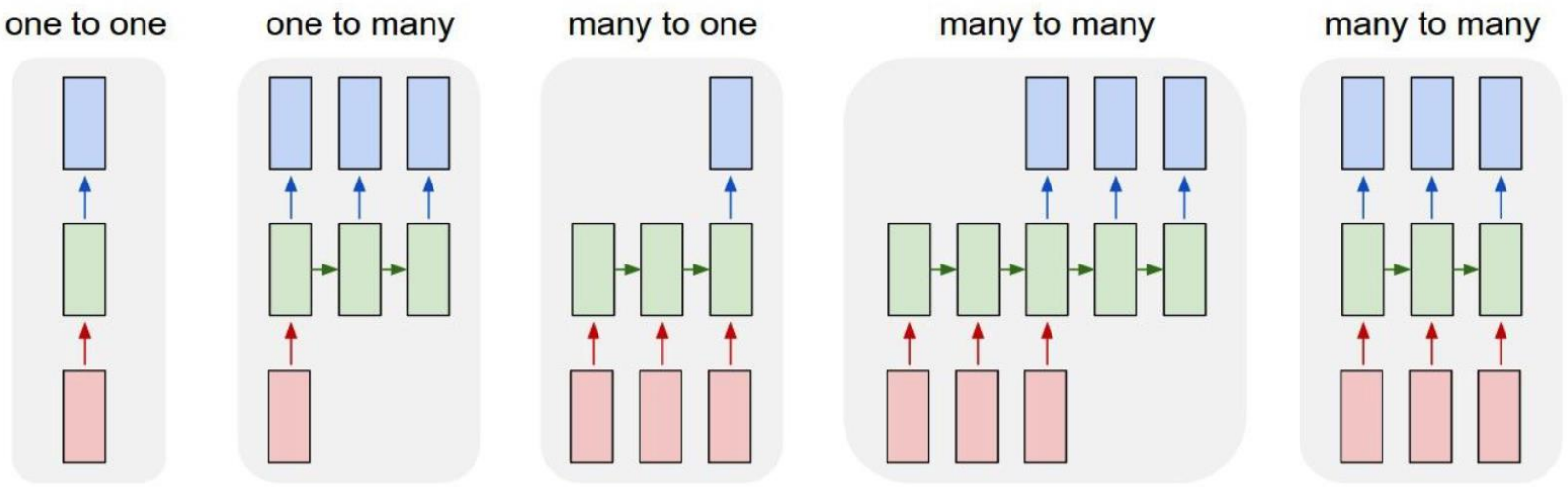
Process Sequence



Process Sequence

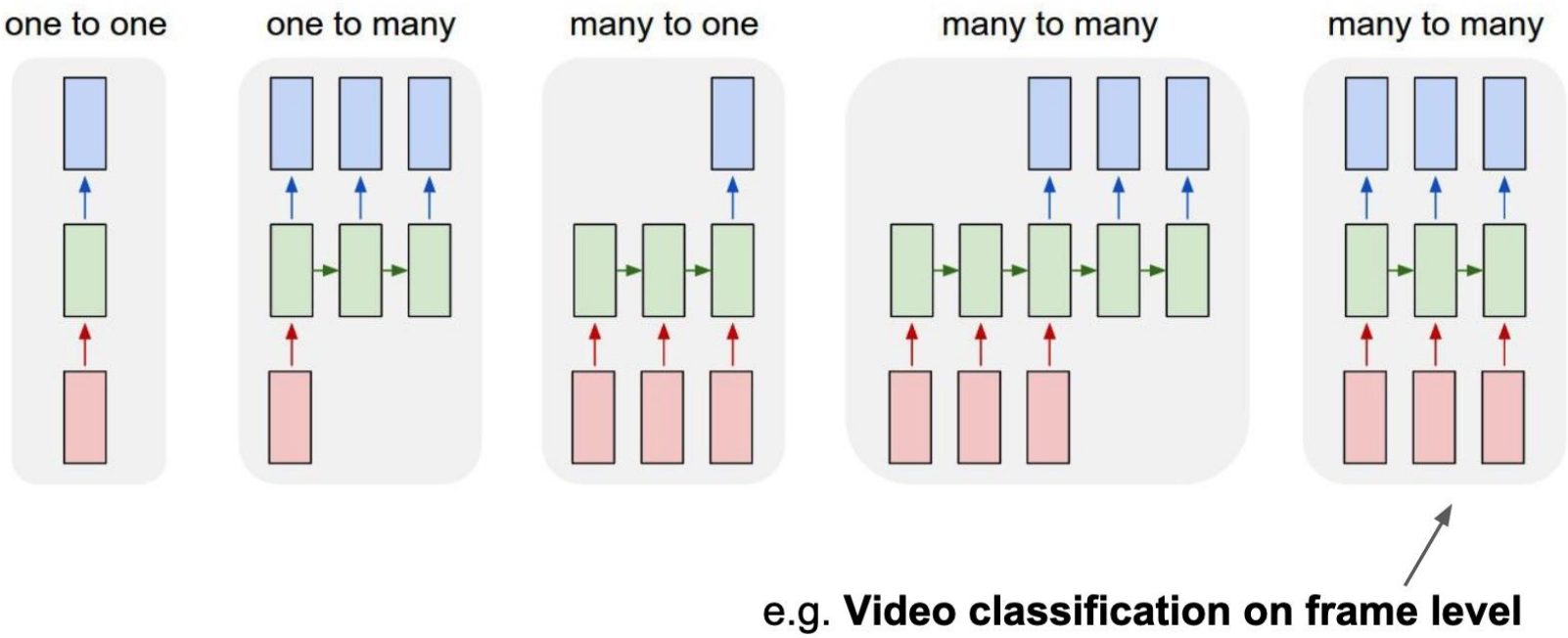


Process Sequence



e.g. **Machine Translation (Chatbots)**
seq of words -> seq of words

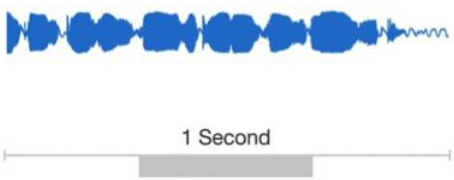
Process Sequence



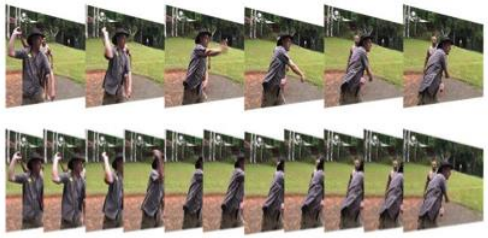
Sequences Are Everywhere

"Sequences really seem to be everywhere! We should learn how to model them. What is the best way to do that? Stay tuned!"

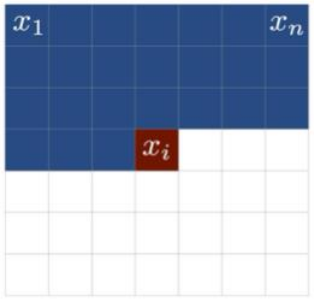
Words, letters



Speech



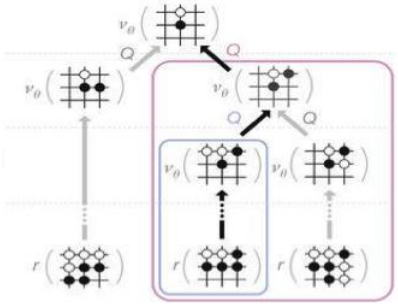
Videos



Images

```
import numpy as np
import matplotlib.pyplot as plt

def forward_backward_prop(w, T):
  hs = [0.5]
  for _ in range(T):
    hs.append(np.tanh(w*hs[-1]))

  dh = 1
  for t in range(T):
    dh = (1-hs[-1-t] ** 2) * w * dh

  return hs[-1], dh

T = 10  # sequence length
wlim = 4  #limit of interval over weights w

results = []
ws = np.linspace(-wlim, wlim, 1000)
for w in ws:
  results.append(forward_backward_prop(w, T))

plt.plot(ws, [r[0] for r in results], label='RNN state')
plt.plot(ws, [r[1] for r in results], label='Gradients')
```

Programs



Decision making

- Sequences are collections of variable length where order matters.
- Sequences are widespread across machine learning applications.
- Not all deep learning models can handle sequential data.

Training Machine Learning Models

	Supervised learning	Sequence modelling
Data	$\{x, y\}_i$	$\{x\}_i$
Model	$y \approx f_\theta(x)$	$p(x) \approx f_\theta(x)$
Loss	$\mathcal{L}(\theta) = \sum_{i=1}^{N} l(f_\theta(x_i), y_i)$	$\mathcal{L}(\theta) = \sum_{i=1}^{N} \log p(f_\theta(x_i))$
Optimisation	$\theta^* = \arg\min_\theta \mathcal{L}(\theta)$	$\theta^* = \arg\max_\theta \mathcal{L}(\theta)$

Modeling p(x)

“Modeling word probabilities is really difficult”

Simplest model:
Assume independence of words

$$p(\mathbf{x}) = \prod_{t=1}^{T} p(x_t)$$

p(“modeling“) × p(“word“) × p(“probabilities“) × p(“is“) × p(“really“) × p(“difficult“)

Word	$p(x_i)$
the	0.049
be	0.028
...	...
really	0.0005
...	...

However:

Most likely 6-word sentence:

“The the the the the the.”

→ Independence assumption does not match sequential structure of language.

Modeling p(x)

More realistic model:

Assume conditional dependence of words

$$p(x_T) = p(x_T | x_1, \ldots, x_{T-1})$$

Modeling word probabilities is really ?

Context | Target

	p(x|context)
difficult	0.01
hard	0.009
fun	0.005
...	...
easy	0.00001

Modeling p(x)

The chain rule

Computing the joint p(**x**) from conditionals

$$p(\mathbf{x}) = \prod_{t=1}^{T} p(x_t | x_1, ..., x_{t-1})$$

Modeling

Modeling **word**

Modeling word **probabilities**

Modeling word probabilities **is**

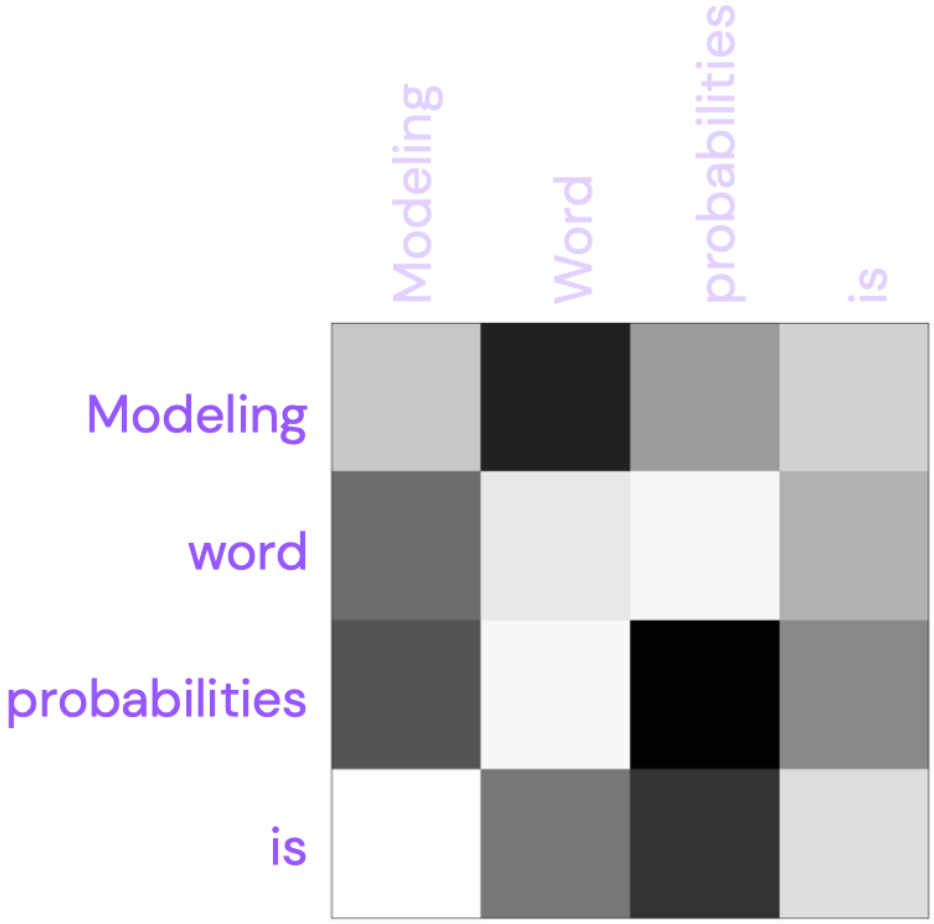
Modeling word probabilities is **really**

Modeling word probabilities is really **difficult**

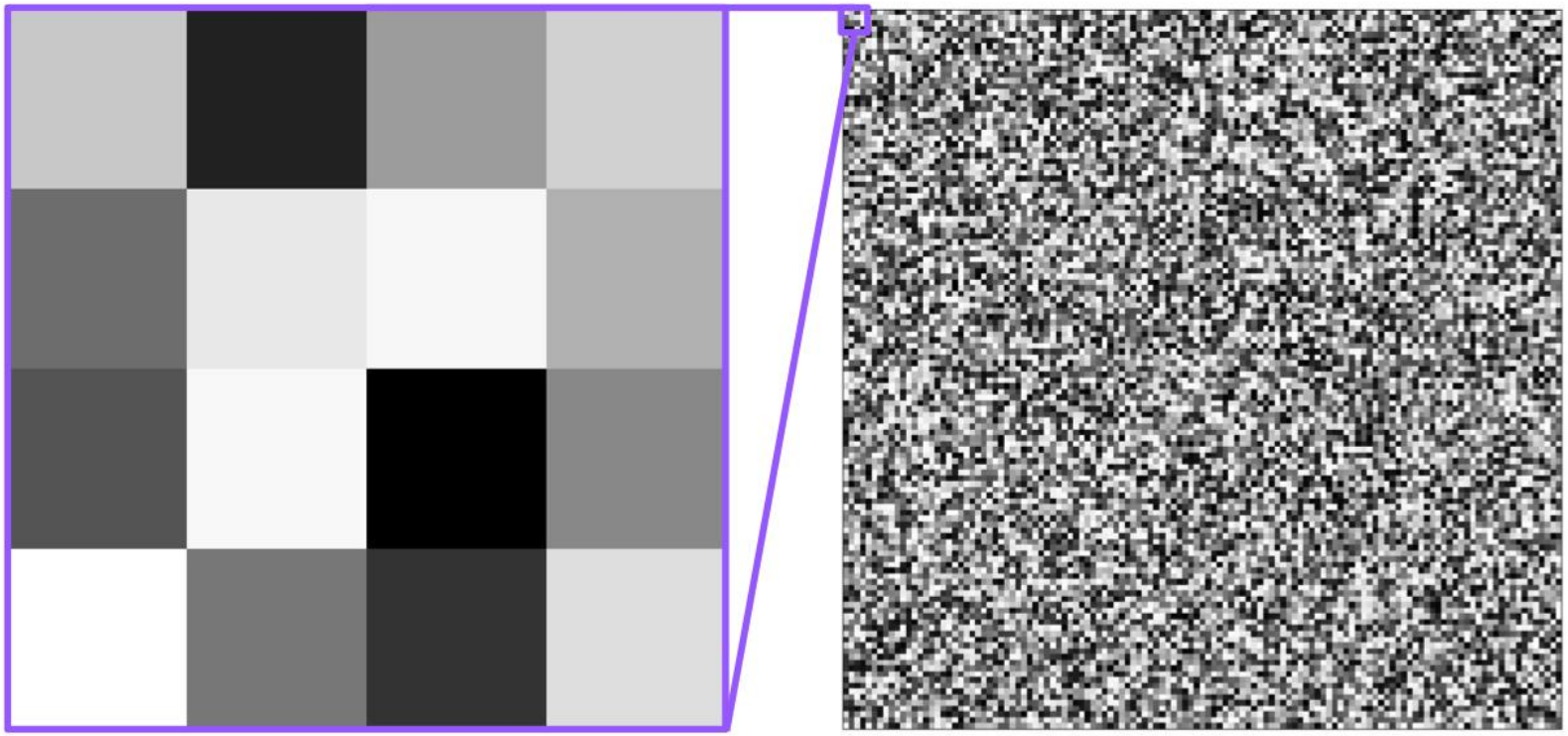
$$p(x_1)$$
$$p(x_2|x_1)$$
$$p(x_3|x_2, x_1)$$
$$p(x_4|x_3, x_2, x_1)$$
$$p(x_5|x_4, x_3, x_2, x_1)$$
$$p(x_6|x_5, x_4, x_3, x_2, x_1)$$

Scalability Issues

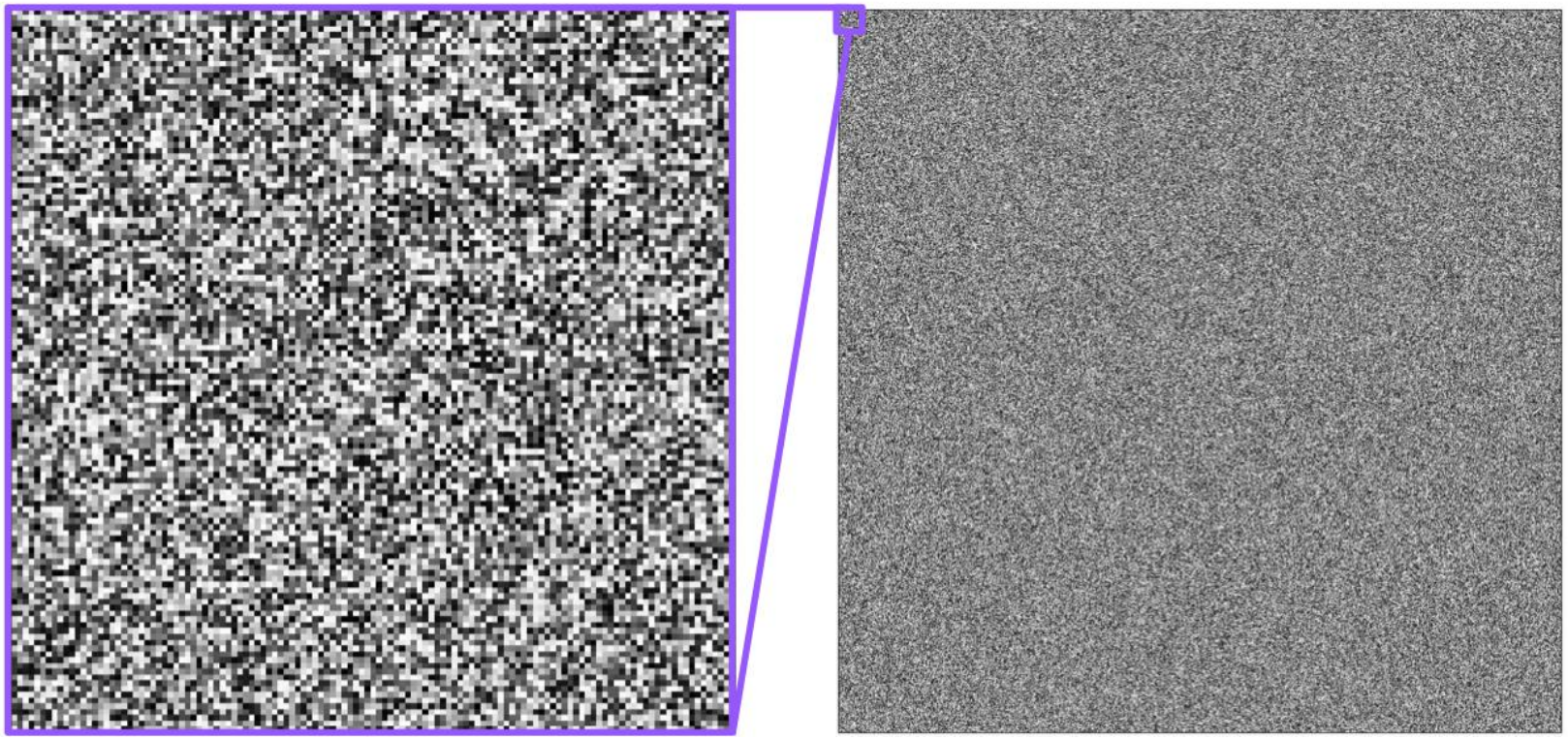
$$p(x_2|x_1)$$



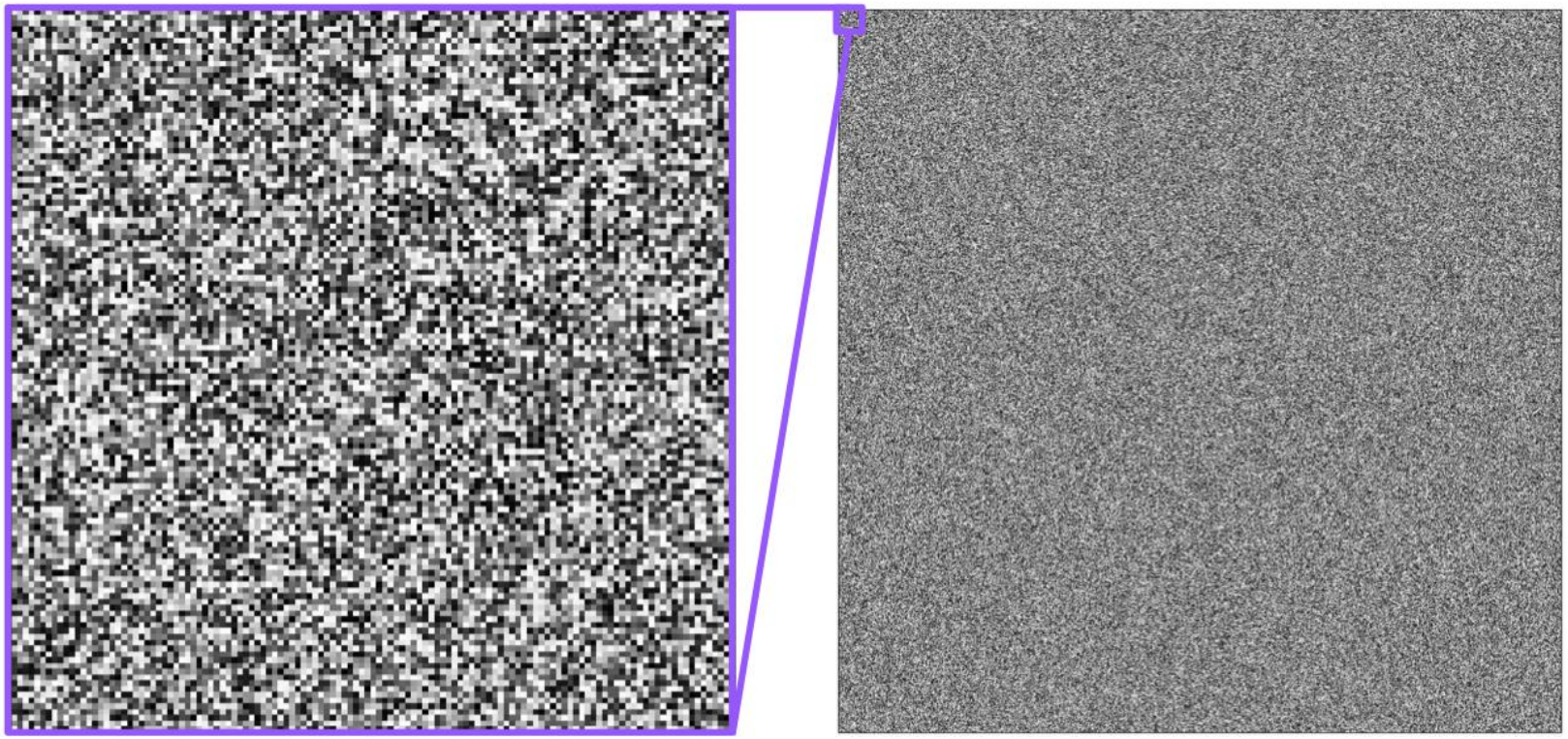
Scalability Issues



Scalability Issues



Scalability Issues



These images are only for context of size N=1!
The table size of larger contexts will grow with **vocabulary**^{N}

Fixing a small context: N-grams

Only condition on N previous words

$$p(\mathbf{x}) \approx \prod_{t=1}^{T} p(x_t | x_{t-N-1}, \ldots, x_{t-1})$$

Modeling

Modeling **word**

Modeling word **probabilities**

word probabilities **is**

probabilities is **really**

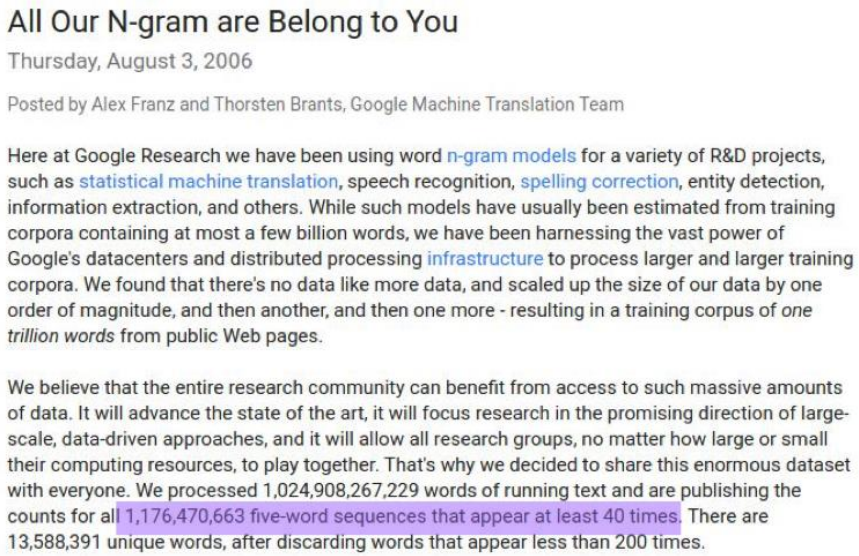
is really **difficult**

$$p(x_1)$$
$$p(x_2|x_1)$$
$$p(x_3|x_2, x_1)$$
$$p(x_4|x_3, x_2)$$
$$p(x_5|x_4, x_3)$$
$$p(x_6|x_5, x_4)$$

Downsides of Using N-grams

1. Doesn't take into account words that are more than N words away

2. Data table is still very, very large



All Our N-gram are Belong to You

Thursday, August 3, 2006

Posted by Alex Franz and Thorsten Brants, Google Machine Translation Team

Here at Google Research we have been using word n-gram models for a variety of R&D projects, such as statistical machine translation, speech recognition, spelling correction, entity detection, information extraction, and others. While such models have usually been estimated from training corpora containing at most a few billion words, we have been harnessing the vast power of Google's datacenters and distributed processing infrastructure to process larger and larger training corpora. We found that there's no data like more data, and scaled up the size of our data by one order of magnitude, and then another, and then one more - resulting in a training corpus of *one trillion words* from public Web pages.

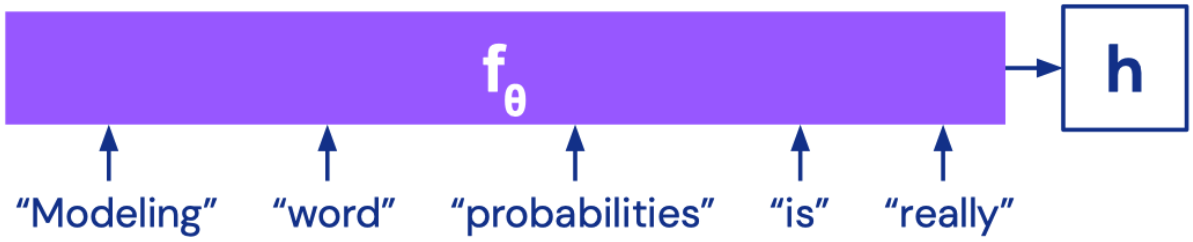
We believe that the entire research community can benefit from access to such massive amounts of data. It will advance the state of the art, it will focus research in the promising direction of large-scale, data-driven approaches, and it will allow all research groups, no matter how large or small their computing resources, to play together. That's why we decided to share this enormous dataset with everyone. We processed 1,024,908,267,229 words of running text and are publishing the counts for all 1,176,470,663 five-word sequences that appear at least 40 times. There are 13,588,391 unique words, after discarding words that appear less than 200 times.

- Modeling probabilities of sequences scales badly given the non-independent structure of their elements.

Learning to Model Word Probabilities

- Can this probability estimation be learned from data in a more efficient way?

1. Vectorising the context



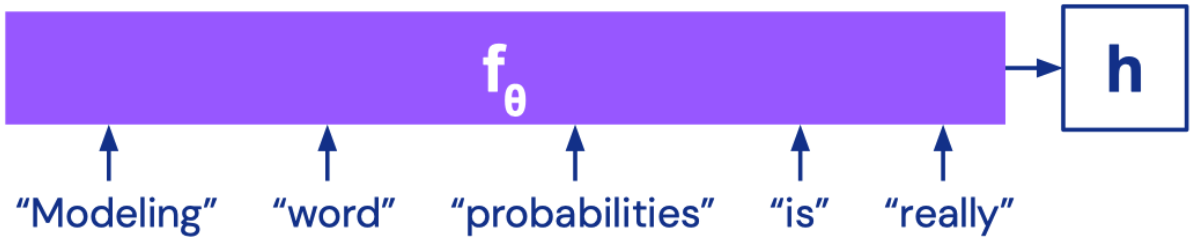
f_θ summarises the context in **h** such that:

$$p(x_t|x_1, \ldots, x_{t-1}) \approx p(x_t|h)$$

Learning to Model Word Probabilities

- Can this probability estimation be learned from data in a more efficient way?

1. Vectorising the context



Desirable properties for f_θ:

Order matters

Variable length

Differentiable

Pairwise encoding

Preserves long-term

N-grams

$$p(\mathbf{x}) \approx \prod_{t=1}^{T} p(x_t | x_{t-N-1}, ..., x_{t-1})$$

Modeling $p(x_1)$

Modeling **word** $p(x_2|x_1)$

Modeling word **probabilities** $p(x_3|x_2, x_1)$

word probabilities **is** $p(x_4|x_3, x_2)$

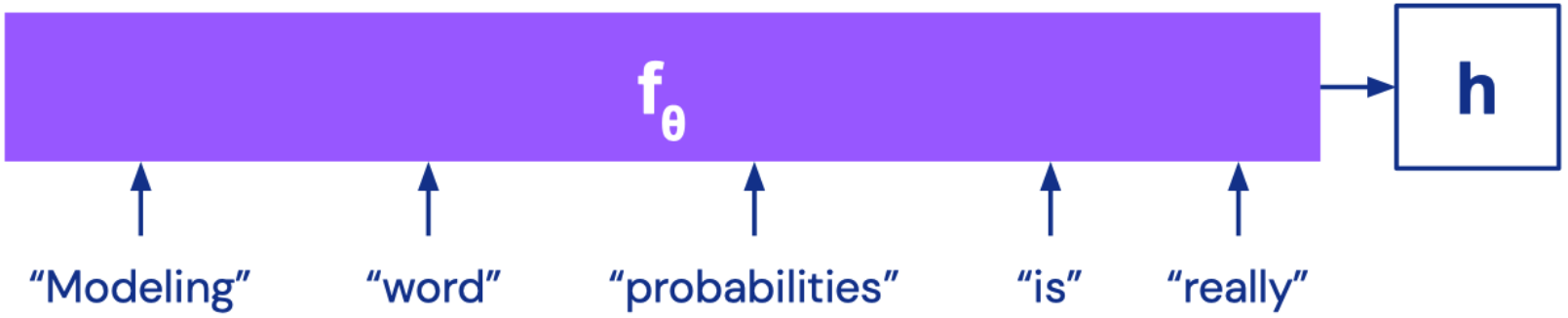
probabilities is **really** $p(x_5|x_4, x_3)$

is really **difficult** $p(x_6|x_5, x_4)$

f_θ concatenates the N last words

	N-gram
Order matters	✔
Variable length	✘
Differentiable	✘
Pairwise encoding	✔
Preserves long-term	✘

Addition



	N-gram	Addition
Order matters	✓	✗
Variable length	✗	✓
Differentiable	✗	✓
Pairwise encoding	✓	✗
Preserves long-term	✗	✓

- N-grams and simple aggregation do not meet the requirements for modeling sequences.

Learning to Model Word Probabilities

Modeling conditional probabilities

Desirable properties for g_θ :

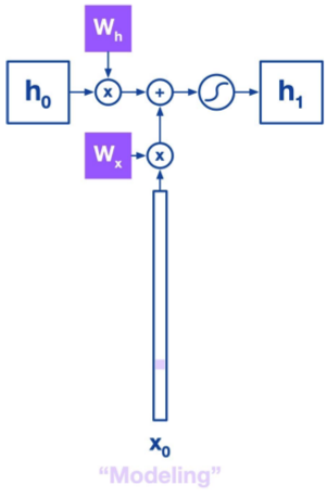
Individual changes can have large effects (non-linear/deep)

Returns a probability distribution

Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs)

Persistent state variable **h** stores information from the context observed so far.



$$\mathbf{h}_t = \tanh(\mathbf{W}_h \mathbf{h}_{t-1} + \mathbf{W}_x \mathbf{x}_t)$$

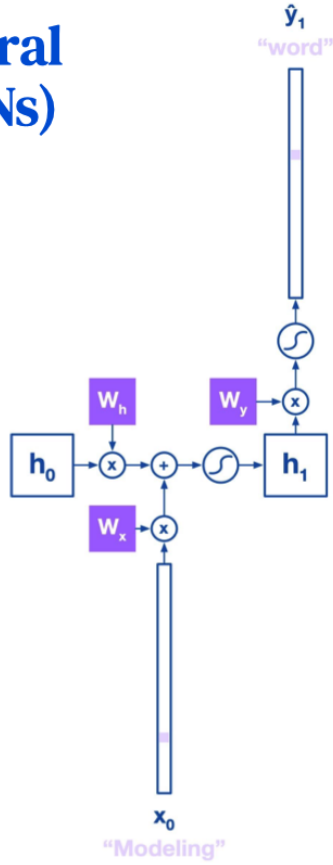
Word representation

Words are indexed and represented as 1-hot vectors

Large Vocabulary of possible words $|V|$

Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs)



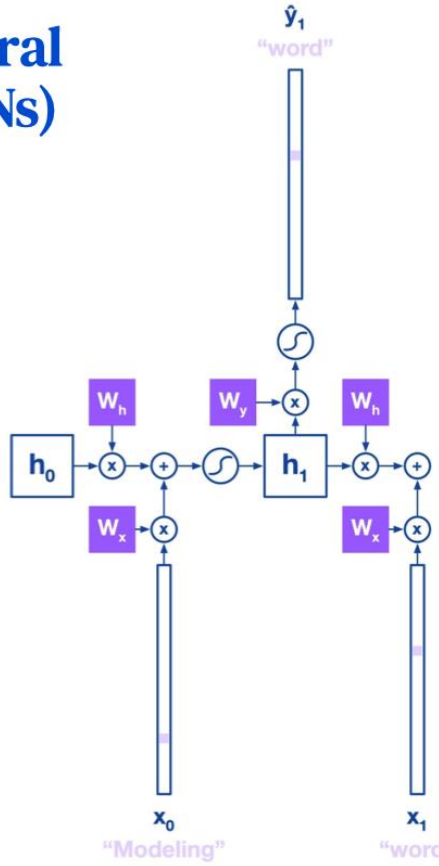
RNNs predict the target **y** (the next word) from the state **h.**

$$p(\mathbf{y_{t+1}}) = softmax(\mathbf{W}_y \mathbf{h}_t)$$

Softmax ensures we obtain a distribution over all possible words.

Recurrent Neural Networks (RNNs)

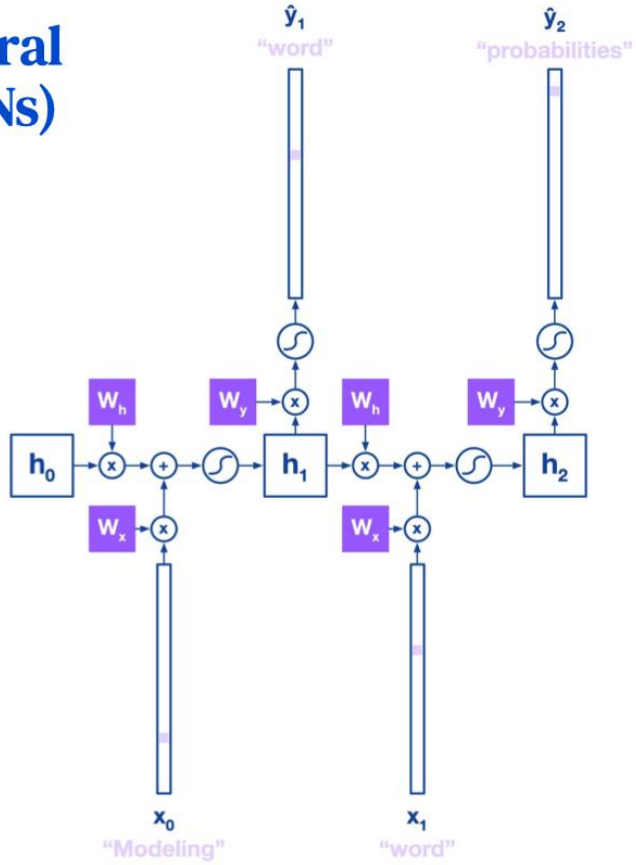
Recurrent Neural Networks (RNNs)



Input next word in sentence x_1

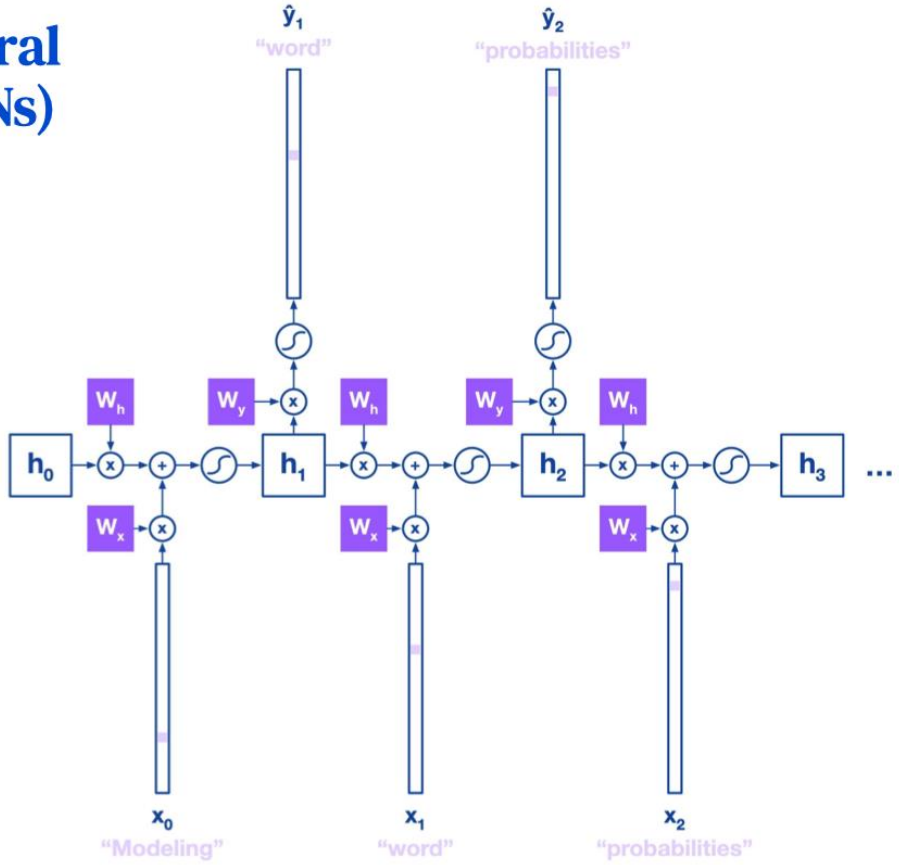
Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs)



Recurrent Neural Networks (RNNs)

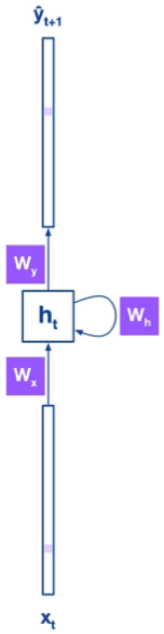
Recurrent Neural Networks (RNNs)



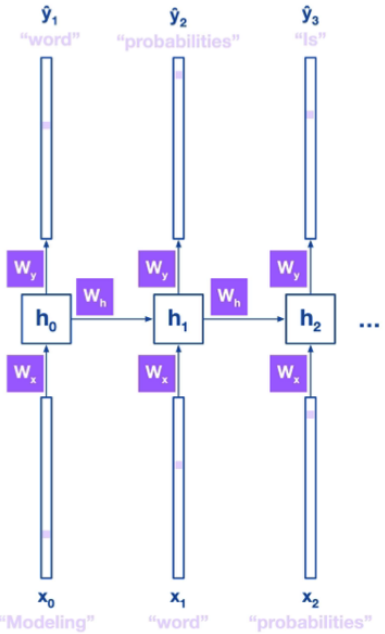
Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs)

Weights are shared over time steps



RNN



RNN rolled out over time

Loss: Cross Entropy

Next word prediction is essentially a classification task where the number of classes is the size of the vocabulary.

As such we use the cross-entropy loss:

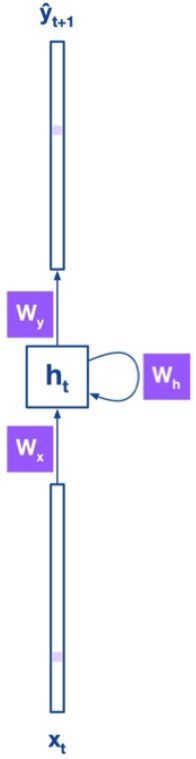
For one word:

$$\mathcal{L}_\theta(\mathbf{y}, \hat{\mathbf{y}})_t = -\mathbf{y}_t \log \hat{\mathbf{y}}_t$$

For the sentence:

$$\mathcal{L}_\theta(\mathbf{y}, \hat{\mathbf{y}}) = -\sum_{t=1}^{T} \mathbf{y}_t \log \hat{\mathbf{y}}_t$$

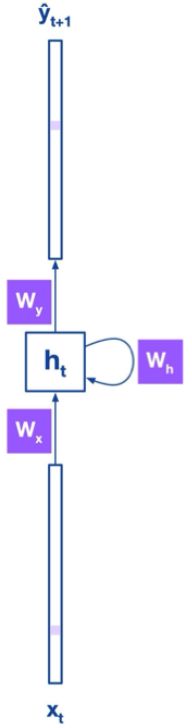
With parameters $\theta = \{\mathbf{W}_y, \mathbf{W}_x, \mathbf{W}_h\}$



Differentiating

Parameters: $\mathbf{W}_y$, $\mathbf{W}_x$ and $\mathbf{W}_h$

$$\mathbf{h}_t = \tanh(\mathbf{W}_h\mathbf{h}_{t-1} + \mathbf{W}_x\mathbf{x}_t)$$
$$p(\mathbf{x}_{t+1}) = softmax(\mathbf{W}_y\mathbf{h}_t)$$
$$\mathcal{L}_\theta(\mathbf{y}, \hat{\mathbf{y}})_t = -\mathbf{y}_t \log \hat{\mathbf{y}}_t$$



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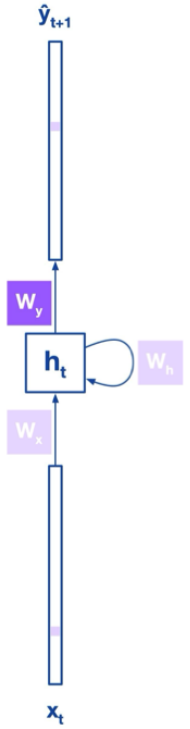

$\mathbf{W}_y$:

$$\frac{\partial \mathcal{L}_{\theta,t}}{\partial \mathbf{W}_y} = \frac{\partial \mathcal{L}_{\theta,t}}{\partial \hat{\mathbf{y}}_t}\frac{\partial \hat{\mathbf{y}}_t}{\partial \mathbf{W}_y}$$
$$= (\mathbf{y}_t - \hat{\mathbf{y}}_t)\mathbf{h}_t$$

Differentiating

Parameters: $\mathbf{W_y}$, $\mathbf{W_x}$ and $\mathbf{W_h}$

$$\mathbf{h}_t = \tanh(\mathbf{W}_h\mathbf{h}_{t-1} + \mathbf{W}_x\mathbf{x}_t)$$
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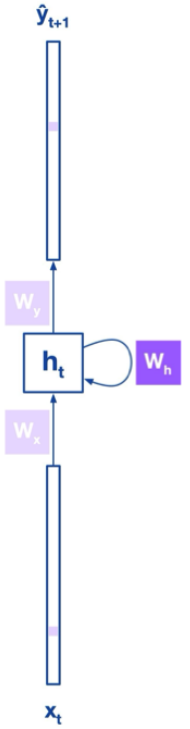
$$\mathcal{L}_\theta(\mathbf{y}, \hat{\mathbf{y}})_t = -\mathbf{y}_t \log \hat{\mathbf{y}}_t$$



$\mathbf{W_h}$:

$$\frac{\partial \mathcal{L}_{\theta,t}}{\partial \mathbf{W}_h} = \frac{\partial \mathcal{L}_{\theta,t}}{\partial \hat{\mathbf{y}}_t} \frac{\partial \hat{\mathbf{y}}_t}{\partial \mathbf{h}_t} \frac{\partial \mathbf{h}_t}{\partial \mathbf{W}_h}$$

Differentiating

Parameters: $\mathbf{W_y}$, $\mathbf{W_x}$ and $\mathbf{W_h}$

$$\mathbf{h}_t = \tanh(\mathbf{W}_h\mathbf{h}_{t-1} + \mathbf{W}_x\mathbf{x}_t)$$
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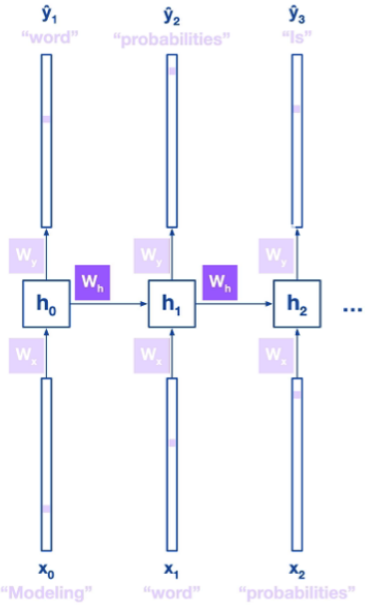

$\mathbf{W_h}$:

$$\frac{\partial \mathcal{L}_{\theta,t}}{\partial \mathbf{W}_h} = \frac{\partial \mathcal{L}_{\theta,t}}{\partial \hat{\mathbf{y}}_t} \frac{\partial \hat{\mathbf{y}}_t}{\partial \mathbf{h}_t} \frac{\partial \mathbf{h}_t}{\partial \mathbf{W}_h}$$

Differentiating

Back propagating through time

$$
\begin{aligned}
\frac{\partial \mathbf{h}_t}{\partial \mathbf{W}_h} &= \frac{\partial \mathbf{h}_t}{\partial \mathbf{W}_h} + \frac{\partial \mathbf{h}_t}{\partial \mathbf{h}_{t-1}} \frac{\partial \mathbf{h}_{t-1}}{\partial \mathbf{W}_h} \\
&= \frac{\partial \mathbf{h}_t}{\partial \mathbf{W}_h} + \frac{\partial \mathbf{h}_t}{\partial \mathbf{h}_{t-1}} \left[\frac{\partial \mathbf{h}_{t-1}}{\partial \mathbf{W}_h} + \frac{\partial \mathbf{h}_{t-1}}{\partial \mathbf{h}_{t-2}} \frac{\partial \mathbf{h}_{t-2}}{\partial \mathbf{W}_h} \right] \\
&\dots \\
&= \sum_{k=1}^{t} \frac{\partial \mathbf{h}_t}{\partial \mathbf{h}_k} \frac{\partial \mathbf{h}_k}{\partial \mathbf{W}_h}
\end{aligned}
$$

Differentiating

$$\mathbf{h}_t = \tanh(\mathbf{W}_h \mathbf{h}_{t-1} + \mathbf{W}_x \mathbf{x}_t)$$
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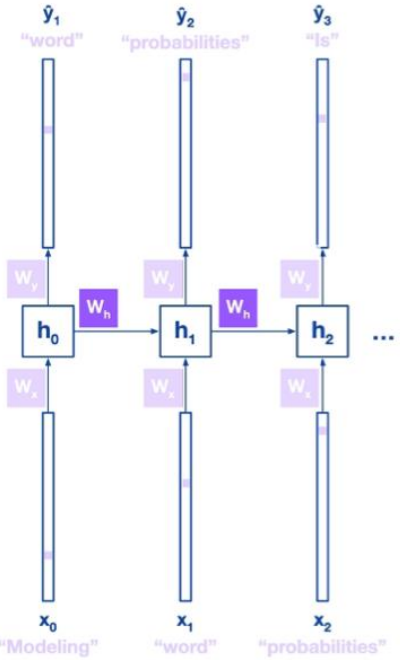


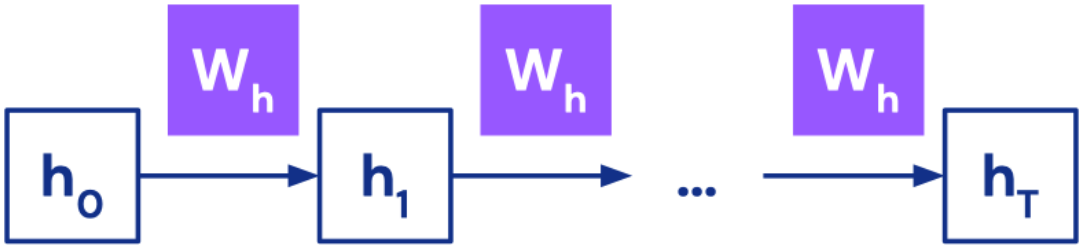
$$\frac{\partial \mathcal{L}_{\theta,t}}{\partial \mathbf{W}_h} = \frac{\partial \mathcal{L}_{\theta,t}}{\partial \hat{\mathbf{y}}_t} \frac{\partial \hat{\mathbf{y}}_t}{\partial \mathbf{h}_t} \frac{\partial \mathbf{h}_t}{\partial \mathbf{W}_h}$$

$$= \sum_{k=1}^{t} \frac{\partial \mathcal{L}_{\theta,t}}{\partial \hat{\mathbf{y}}_t} \frac{\partial \hat{\mathbf{y}}_t}{\partial \mathbf{h}_t} \frac{\partial \mathbf{h}_t}{\partial \mathbf{h}_k} \frac{\partial \mathbf{h}_k}{\partial \mathbf{W}_h}$$

$$\frac{\partial \mathbf{h}_t}{\partial \mathbf{W}_h} = \sum_{k=1}^{t} \frac{\partial \mathbf{h}_t}{\partial \mathbf{h}_k} \frac{\partial \mathbf{h}_k}{\partial \mathbf{W}_h}$$

Vanishing Gradients

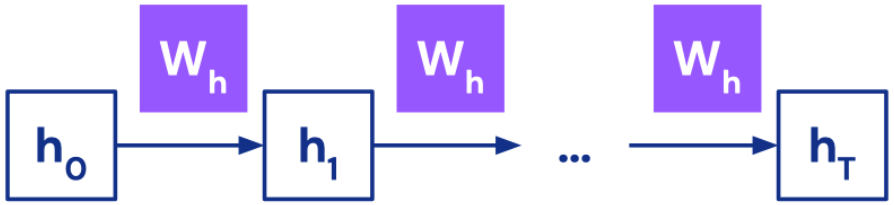
A simple example



$$\mathbf{h}_t = \mathbf{W}_h \mathbf{h}_{t-1} \qquad \mathbf{h}_t \to \infty \text{ if } |\mathbf{W}_h| > 1$$
$$\mathbf{h}_t = (\mathbf{W}_h)^t \mathbf{h}_0 \qquad \mathbf{h}_t \to 0 \text{ if } |\mathbf{W}_h| < 1$$

Vanishing Gradients

A simple example



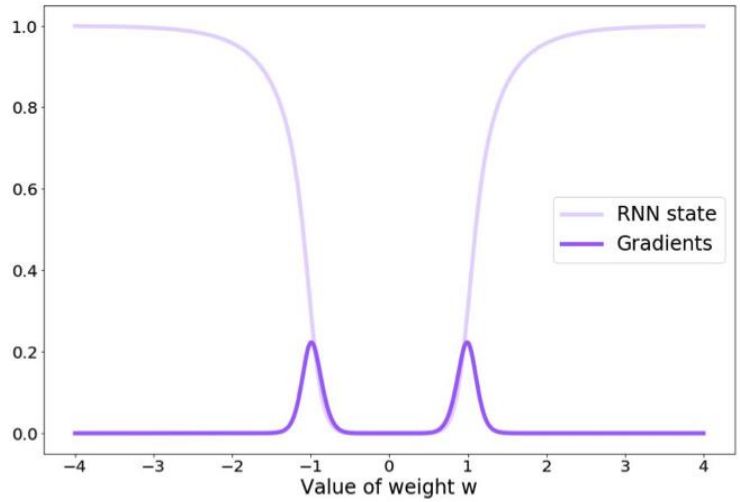
But RNNs bound h with a tanh!

$$\mathbf{h}_t = \mathbf{W}_h \mathbf{h}_{t-1} \rightarrow \mathbf{h}_t = \tanh(\mathbf{W}_h \mathbf{h}_{t-1})$$

Vanishing Gradients

$$\mathbf{h}_t = \tanh(\mathbf{W}_h \mathbf{h}_{t-1})$$

```python
import numpy as np
import matplotlib.pyplot as plt

def forward_backward_prop(w, T):
  hs = [0.5]
  for _ in range(T):
    hs.append(np.tanh(w*hs[-1]))

  dh = 1
  for t in range(T):
    dh = (1-hs[-1-t] ** 2) * w * dh

  return hs[-1], dh

T = 10  # sequence length
wlim = 4  #limit of interval over weights w

results = []
ws = np.linspace(-wlim, wlim, 1000)
for w in ws:
  results.append(forward_backward_prop(w, T))

plt.plot(ws, [r[0] for r in results], label='RNN state')
plt.plot(ws, [r[1] for r in results], label='Gradients')
```



$$\frac{\partial \mathbf{h}_t}{\partial \mathbf{h}_{t-T}} = (1 - \tanh^2(\mathbf{W}_h \mathbf{h}_{t-1}))\mathbf{W}_h \frac{\partial \mathbf{h}_{t-1}}{\partial \mathbf{h}_{t-T}}$$

Properties of RNNs

	N-gram	Addition	RNN
Order matters	✓	✗	✓
Variable length	✗	✓	✓
Differentiable	✗	✓	✓
Pairwise encoding	✓	✗	✗
Preserves long-term	✗	✓	✗

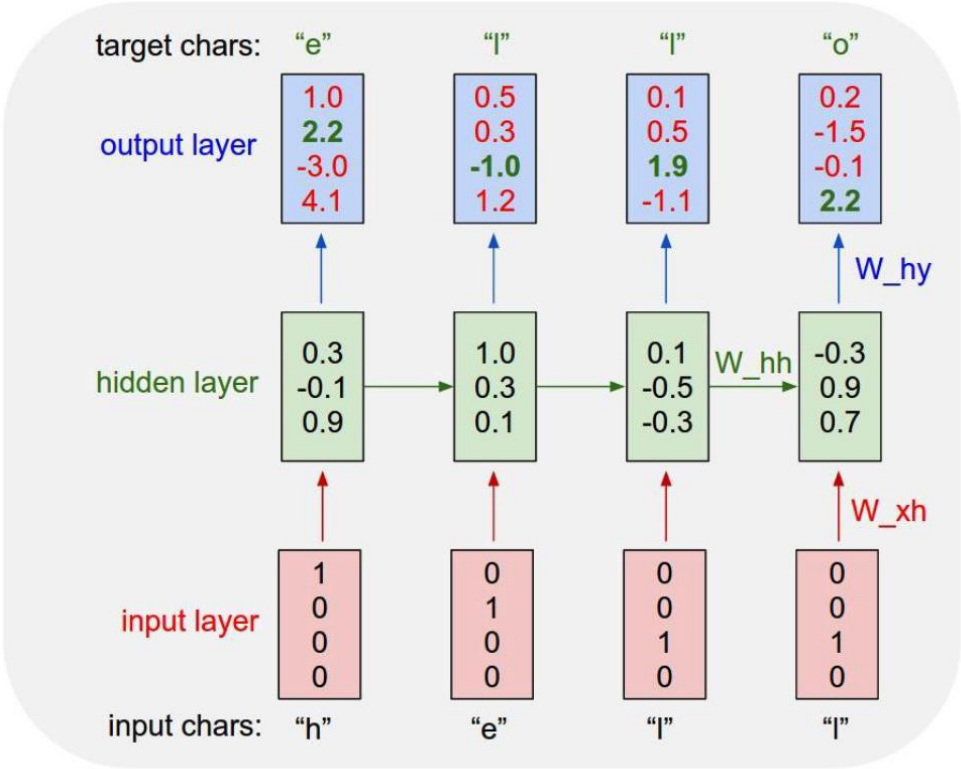
- Recurrent neural networks can model sequences of variable length and can be trained via back-propagation.
- They do, however suffer from the vanishing gradients problem, which stops them from capturing long-term dependencies.

Example: Character-level Language Model

Example: Character-level Language Model

Vocabulary:
[h,e,l,o]

Example training sequence:
“hello”

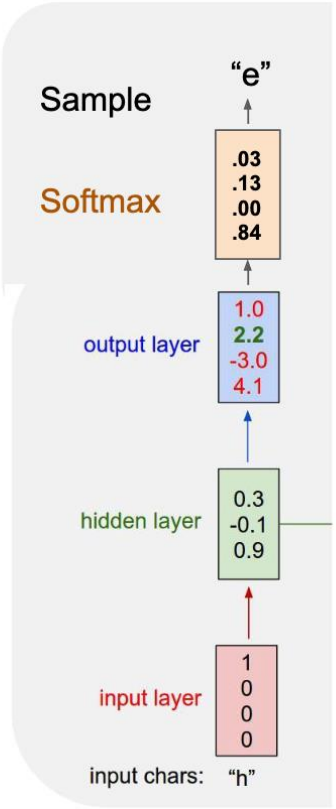


Example: Character-level Language Model

Example: Character-level Language Model Sampling

Vocabulary:
[h,e,l,o]

At test-time sample characters one at a time, feed back to model



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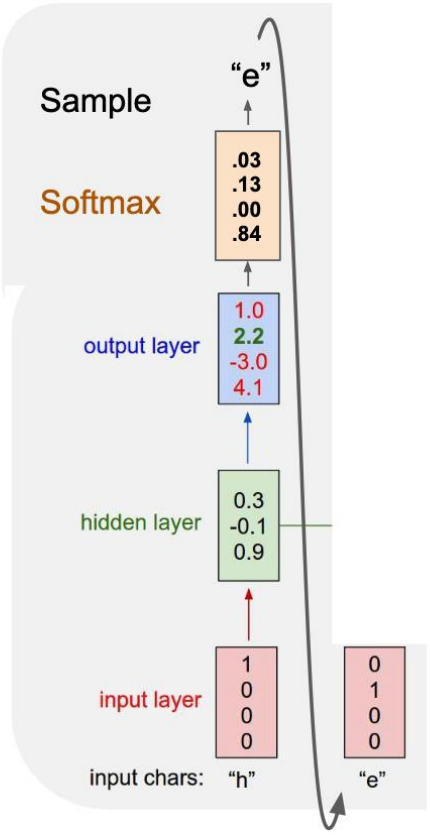

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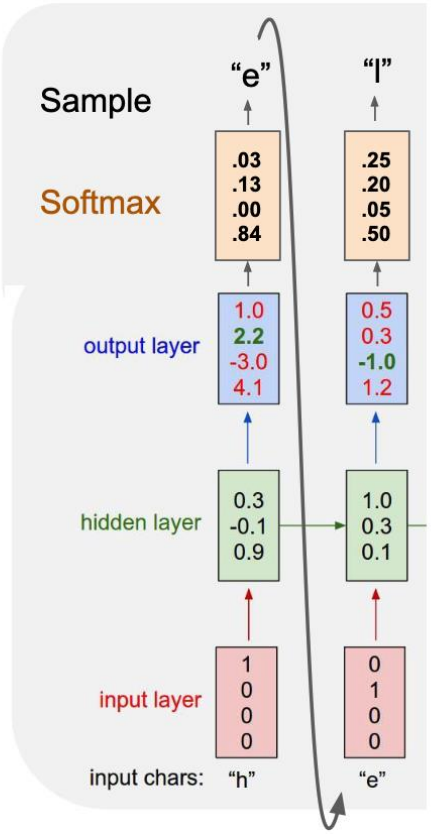

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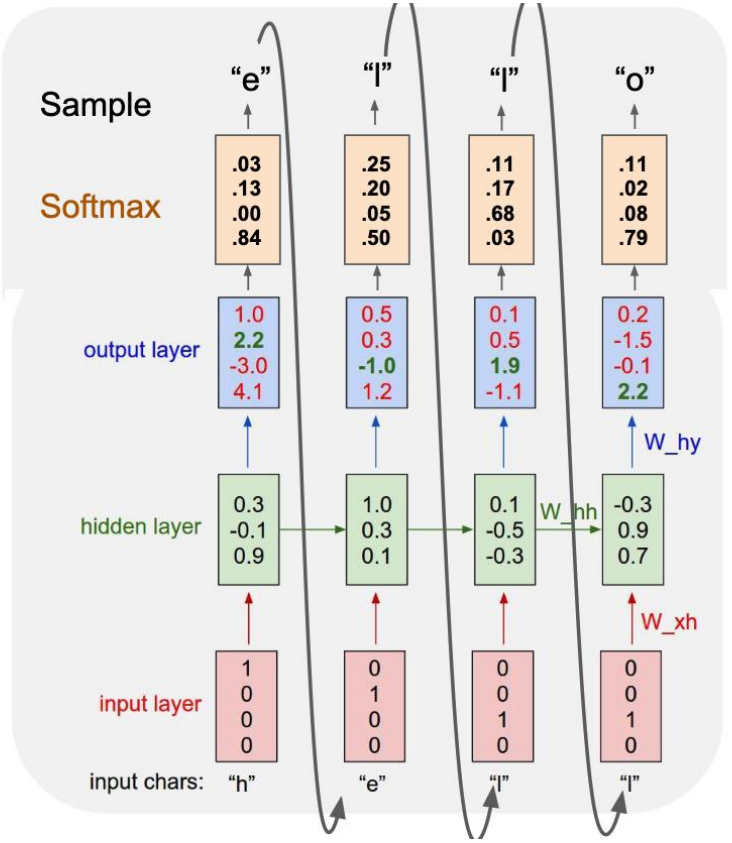
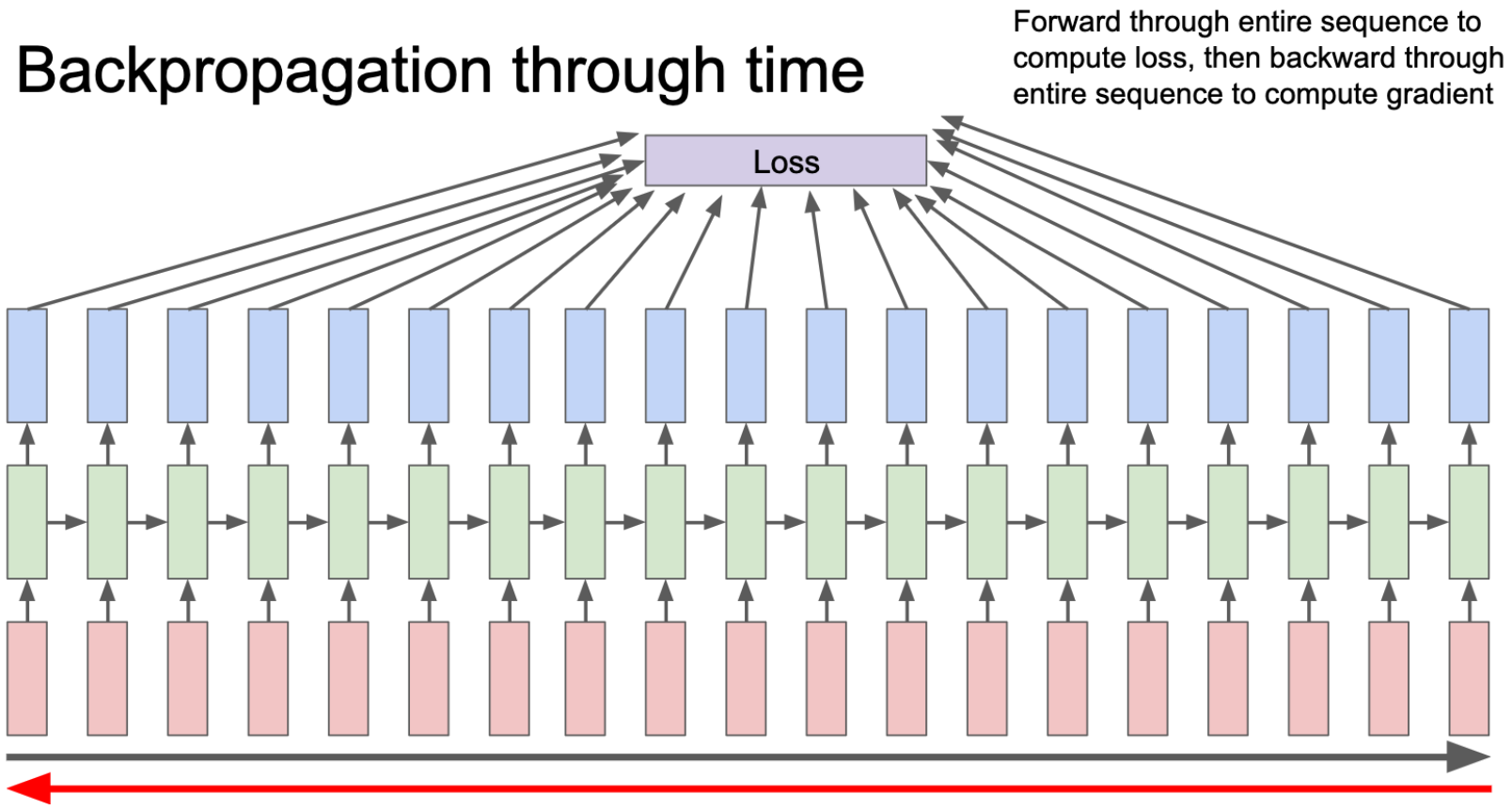
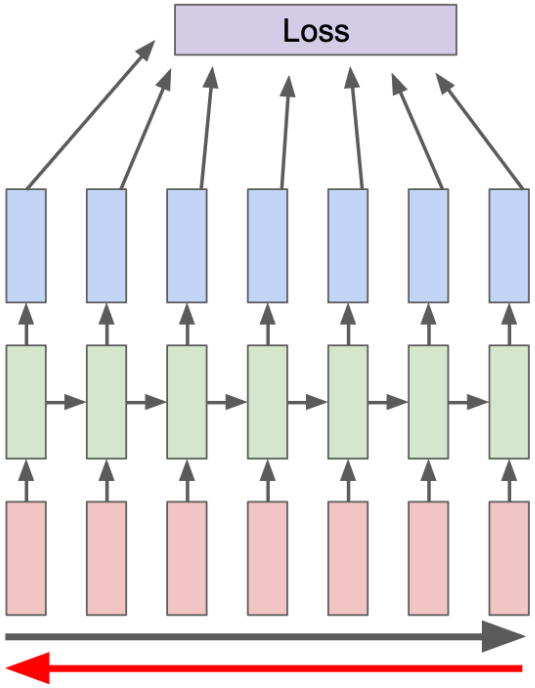


Backpropagation Through Time



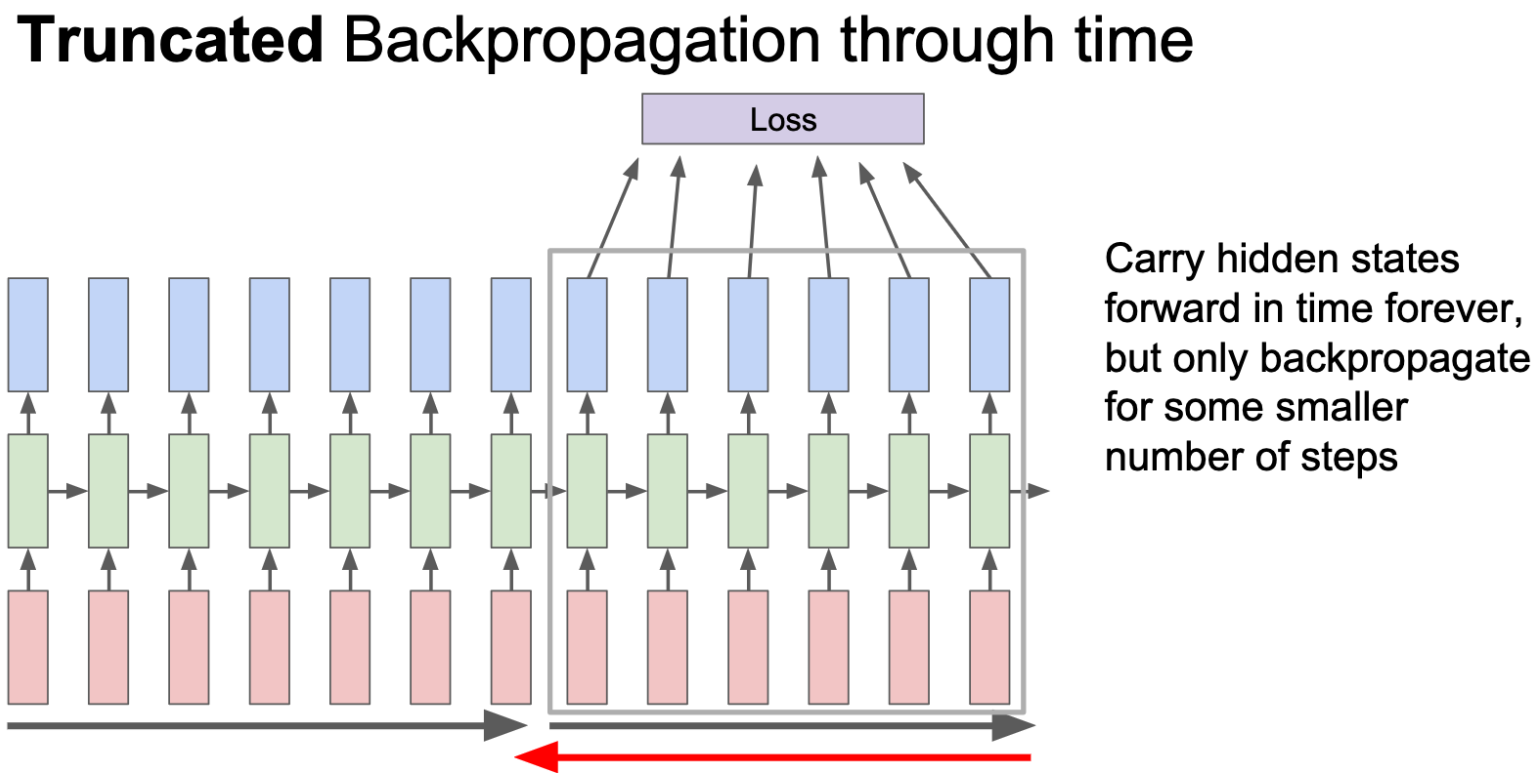
Truncated Backpropagation Through Time

Truncated Backpropagation through time

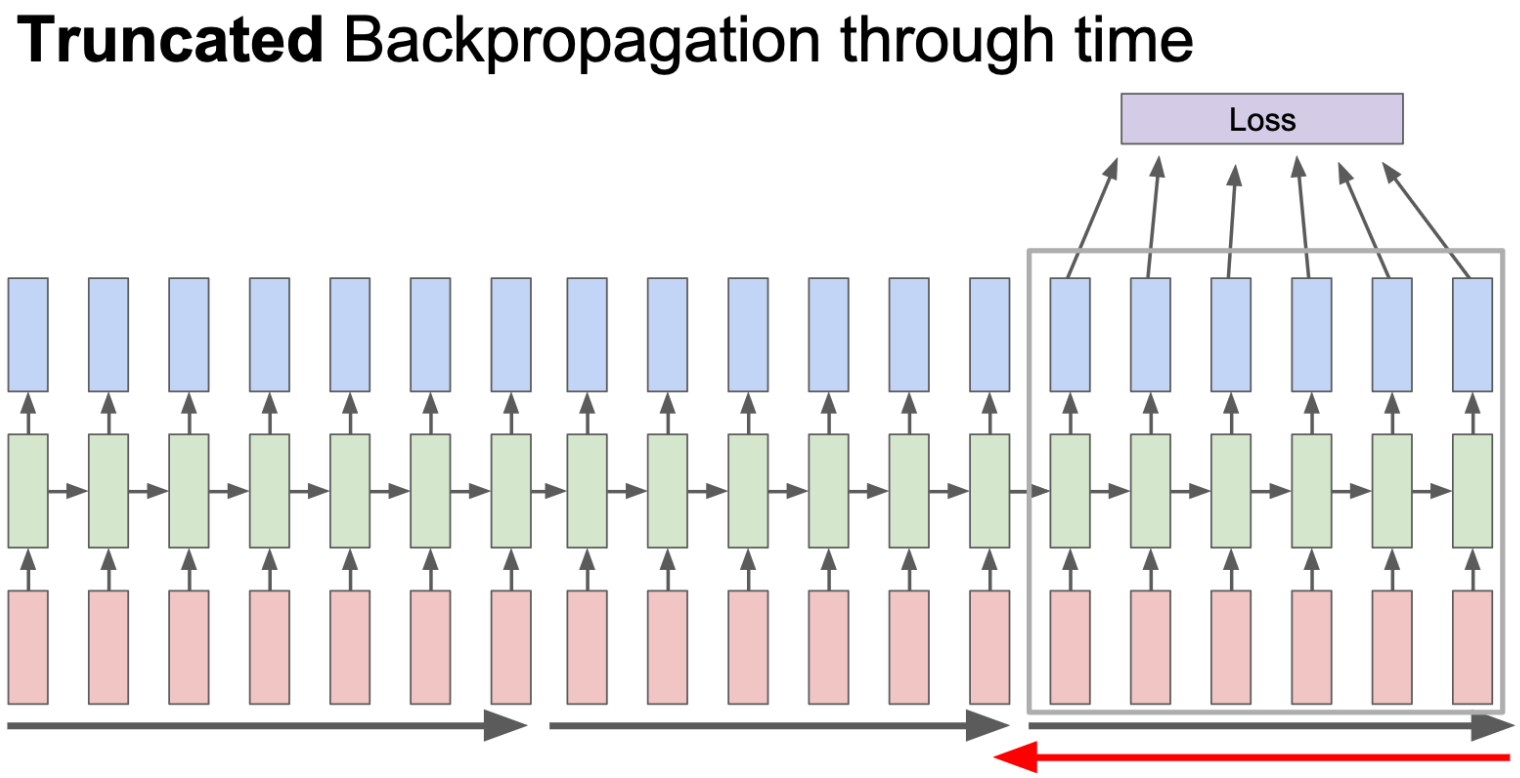


Run forward and backward through chunks of the sequence instead of whole sequence

Truncated Backpropagation Through Time



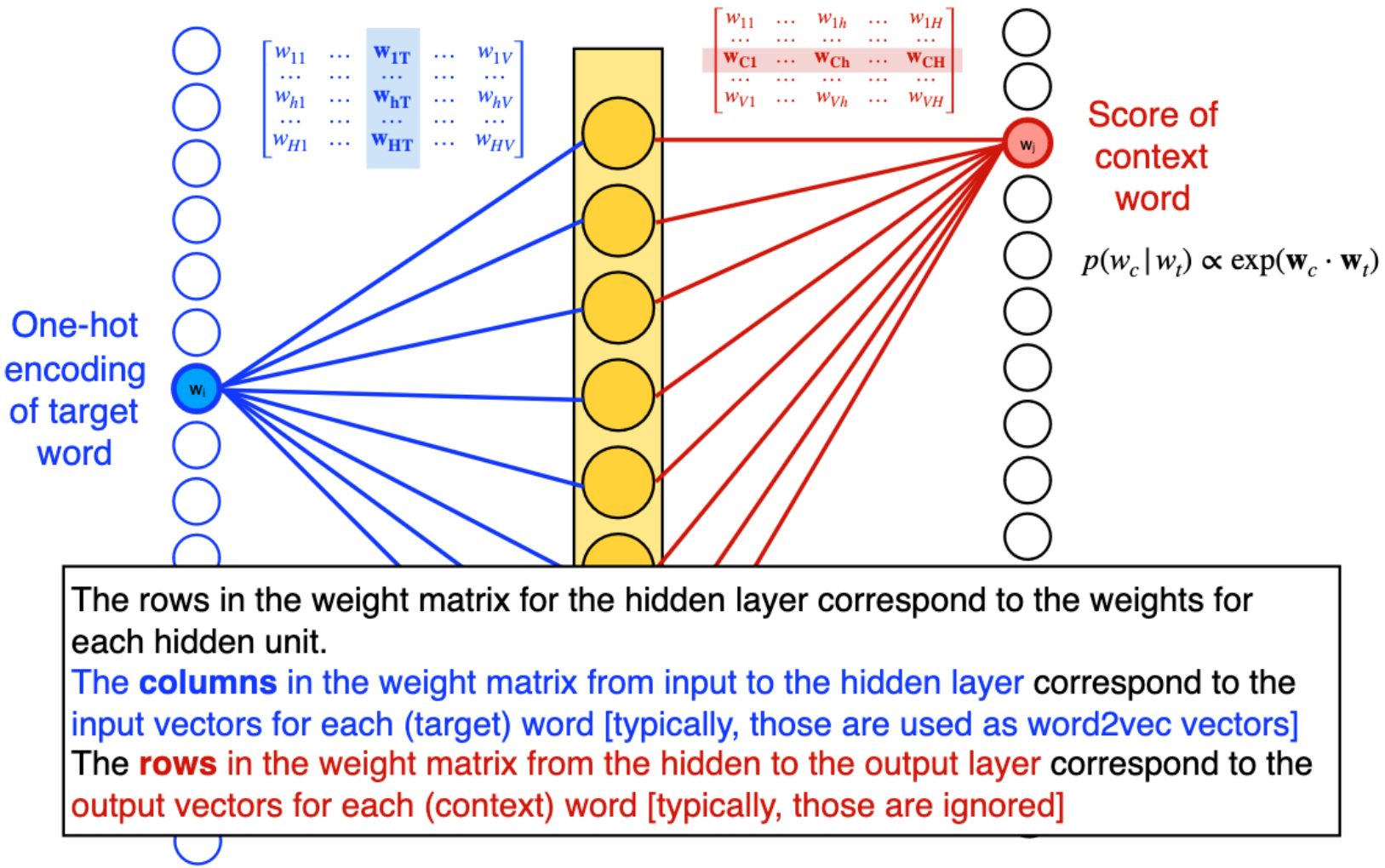
Truncated Backpropagation Through Time



Word Embedding

- Can we represent words as vectors in space?

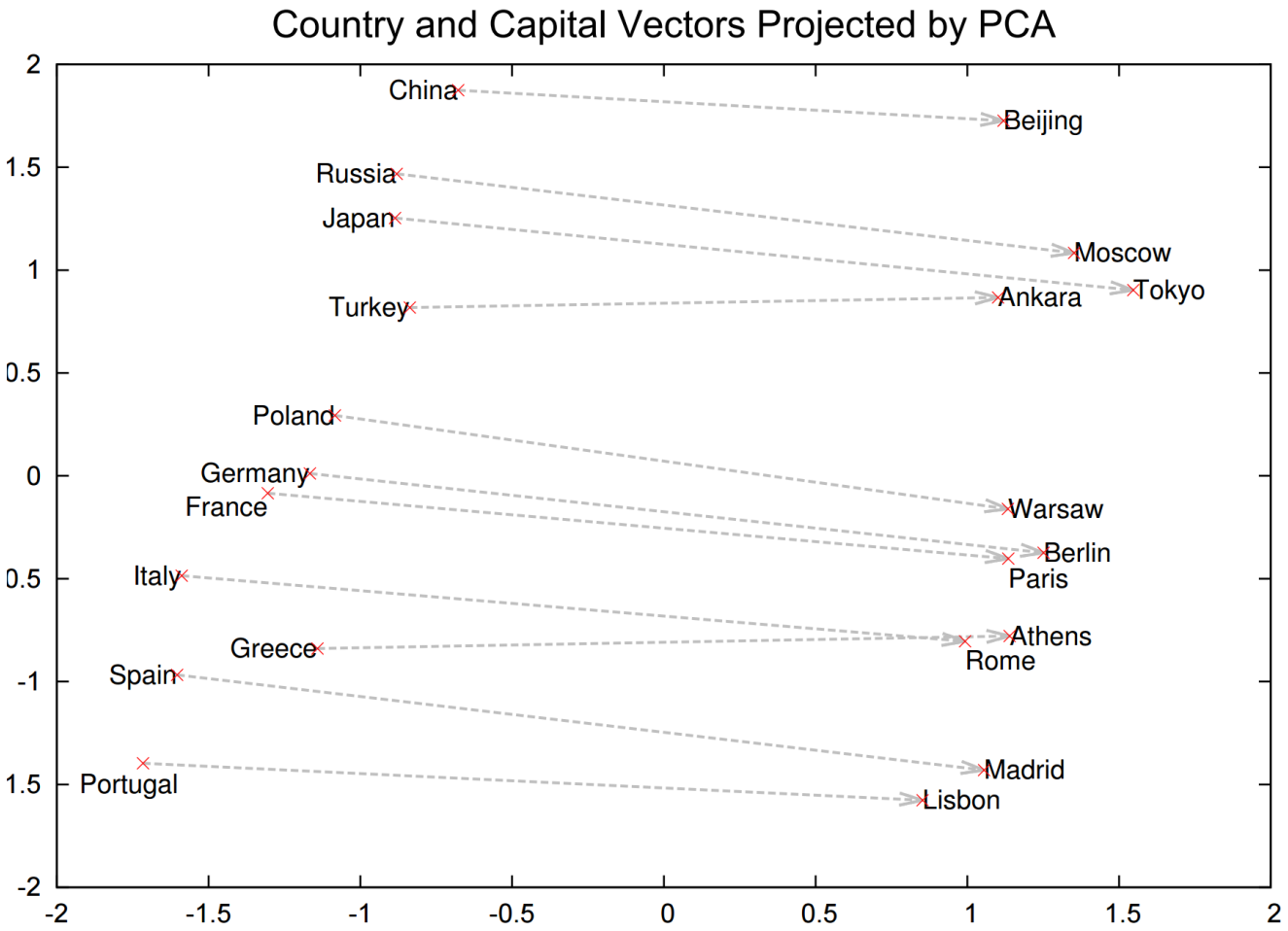
Word Embedding



The rows in the weight matrix for the hidden layer correspond to the weights for each hidden unit.
The **columns** in the weight matrix from input to the hidden layer correspond to the input vectors for each (target) word [typically, those are used as word2vec vectors]
The **rows** in the weight matrix from the hidden to the output layer correspond to the output vectors for each (context) word [typically, those are ignored]

Word Embedding

- Word Analogies:



Long-term Dependencies are Important

... Finally, Tim was planning to visit France on the final week of his journey. He was quite excited to try the local delicacies and had lots of recommendations for good restaurants and exhibitions. His first stop was, of course, the capital where he would meet his long-time Friend Jean-Pierre. In order to arrive for breakfast he took the early 5 AM train from London to ...

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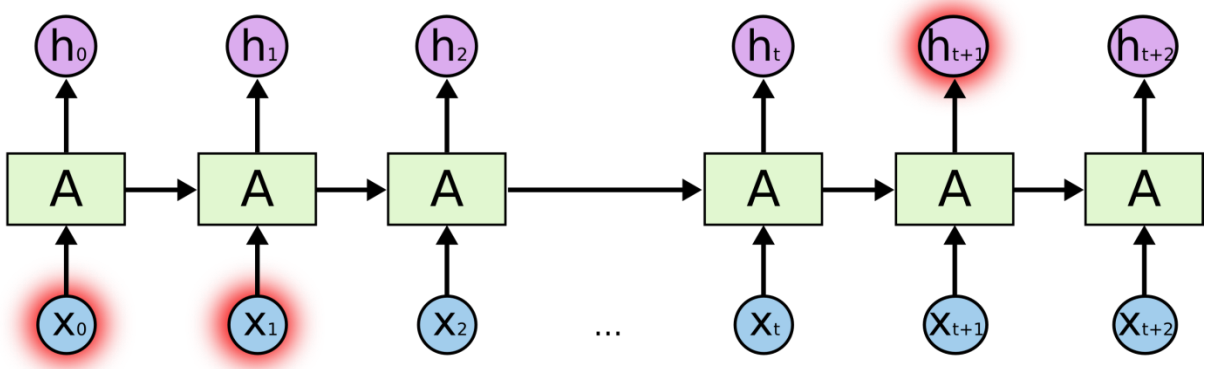
PARIS!

Long Distance Dependencies

- It is very difficult to train RNNs to retain information over many time steps
- This make is very difficult to learn RNNs that handle long-distance dependencies, such as subject-verb agreement.



An Extra Note Page

We need a note page to maintain long-term memory.

When we review books with a fix-sized page for note, we can have a strategy:

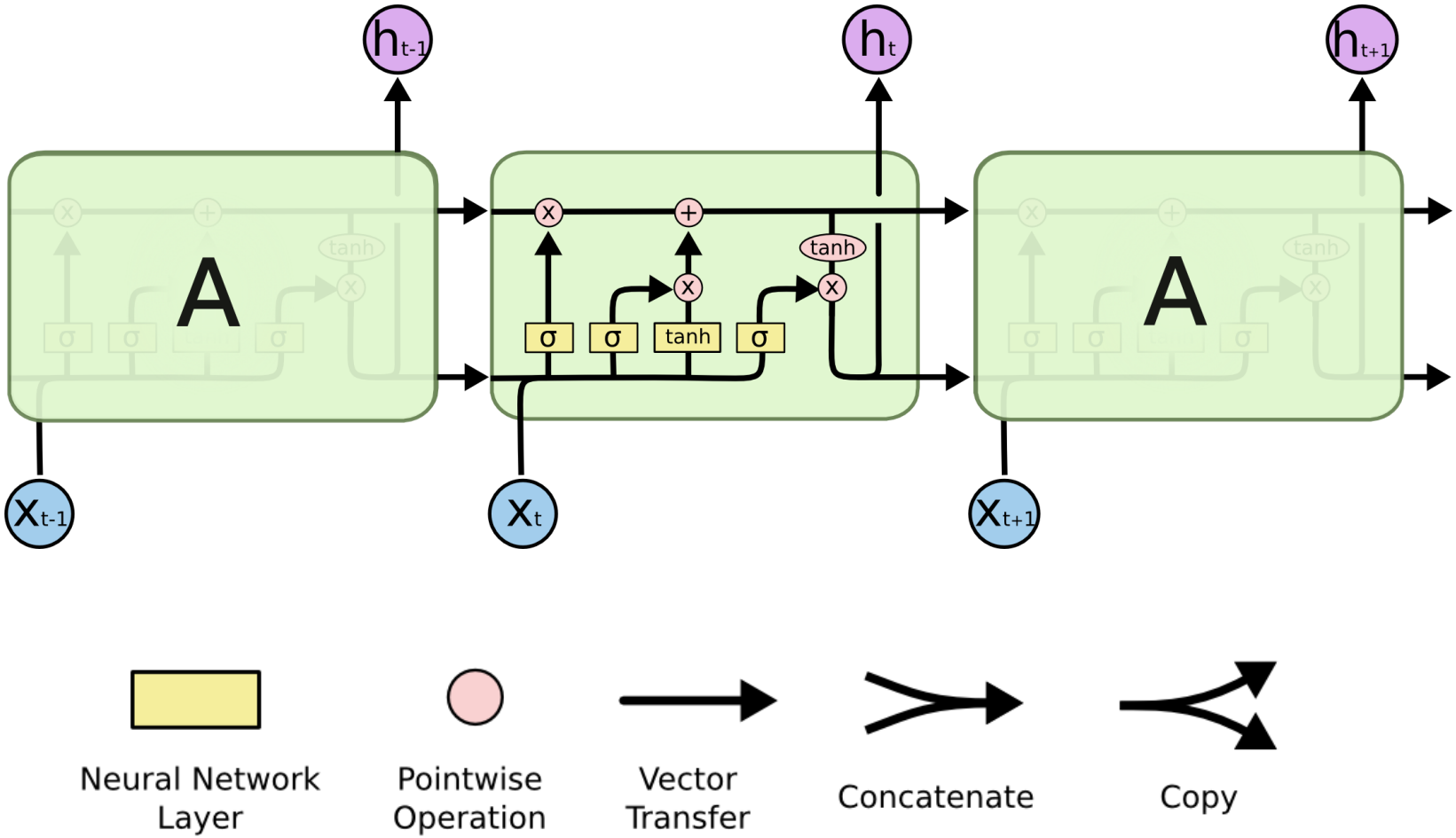
- Note down important concepts;
- Erase everything that is not important anymore;
- Note down new important concepts.

Long Short-Term Memory (LSTM) networks

- LSTM networks, add additional gating units in each memory cell.
  - Forget gate
  - Input gate
  - Output gate

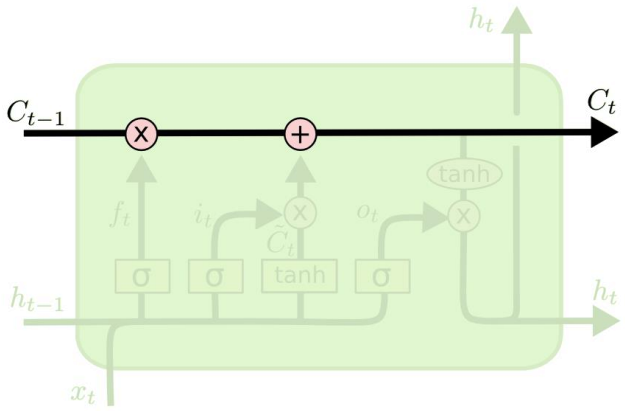
- Prevents vanishing/exploding gradient problem and allows network to retain state information over longer periods of time.

LSTM Network Architecture



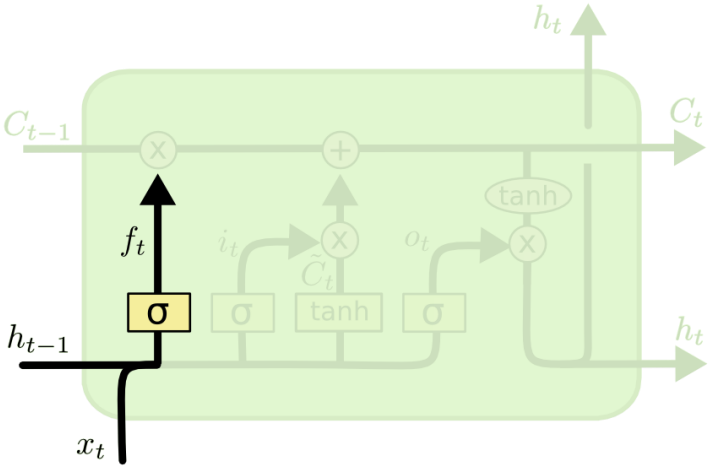
Cell State

- Maintains a vector C_t that is the same dimensionality as the hidden state, h_t
- Information can be added or deleted from this state vector via the forget and input gates.



Forget Gate

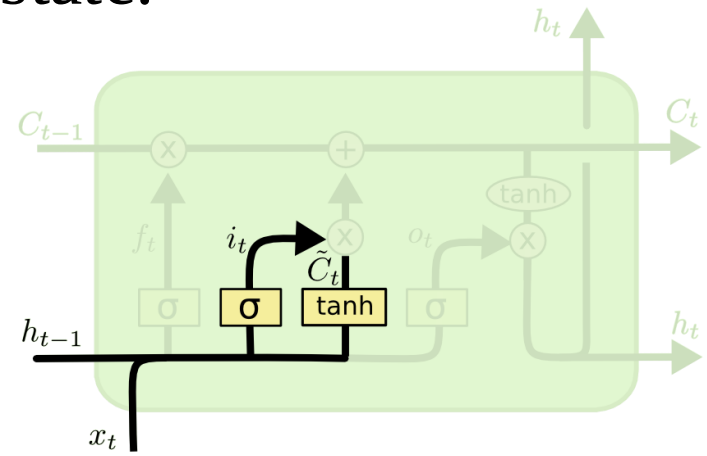
- Forget gate computes a 0-1 value using a logistic sigmoid output function from the input, x_t, and the current hidden state, h_t:
- Multiplicatively combined with cell state, "forgetting" information where the gate outputs something close to 0.



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

Input Gate

- First, determine which entries in the cell state to update by computing 0-1 sigmoid output.
- Then determine what amount to add/subtract from these entries by computing a tanh output (valued –1 to 1) function of the input and hidden state.

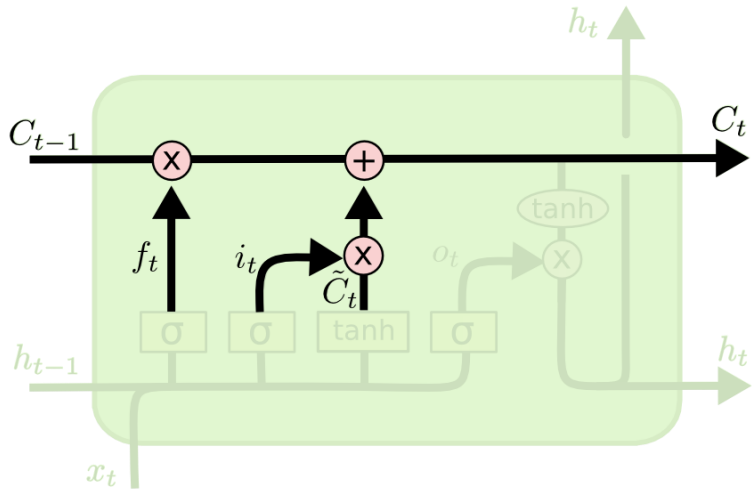


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

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

Updating the Cell State

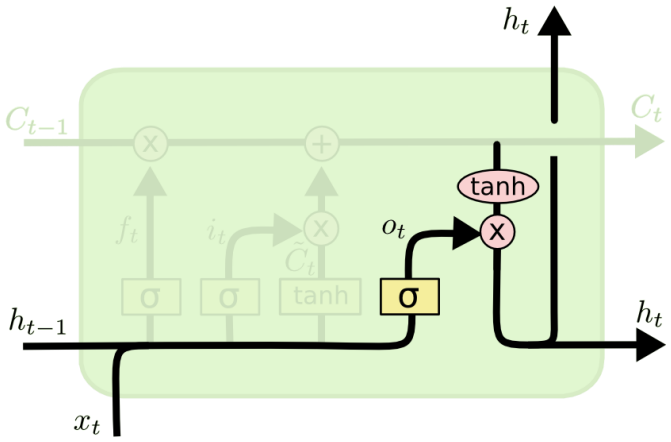
- Cell state is updated by using component-wise vector multiply to "forget" and vector addition to "input" new information.



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

Output Gate

- Hidden state is updated based on a "filtered" version of the cell state, scaled to –1 to 1 using tanh.
- Output gate computes a sigmoid function of the input and current hidden state to determine which elements of the cell state to "output".

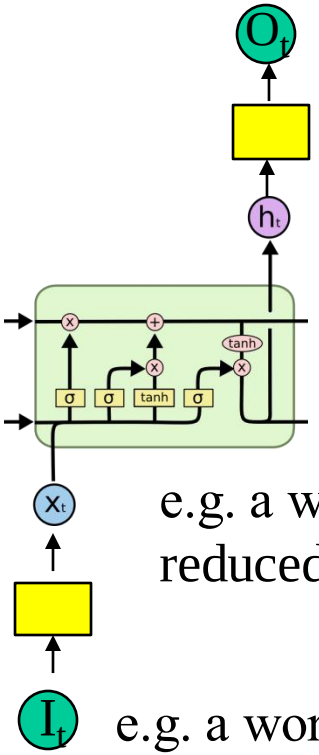


$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right)$$

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

Overall Network Architecture

- Single or multilayer networks can compute LSTM inputs from problem inputs and problem outputs from LSTM outputs.



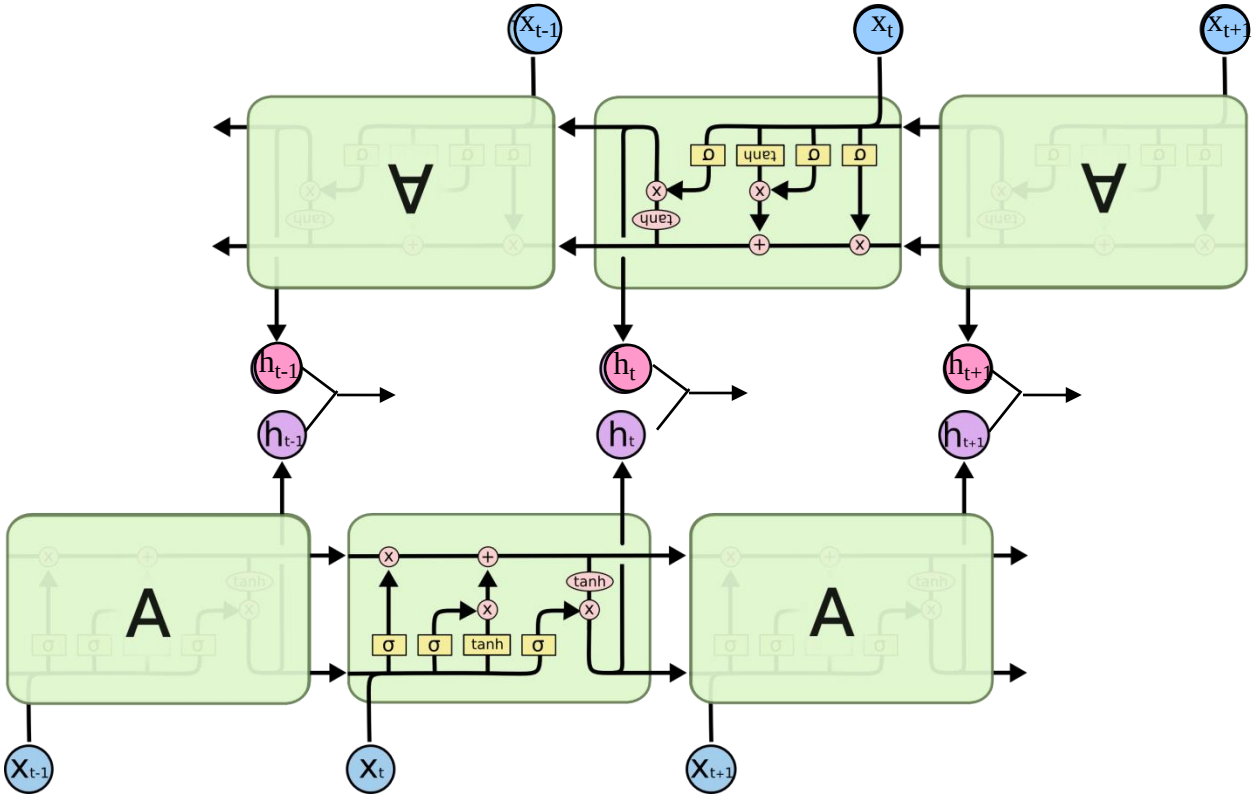
e.g. a word as a "one hot" vector

e.g. a word "embedding" with reduced dimensionality

e.g. a word as a "one hot" vector

Bi-directional LSTM (Bi-LSTM)

- Separate LSTMs process sequence forward and backward and hidden layers at each time step are concatenated to form the cell output.



Multilayer RNNs/LSTMs

Multilayer RNNs

$$h_t^l = \tanh W^l \begin{pmatrix} h_t^{l-1} \\ h_{t-1}^l \end{pmatrix}$$

$h \in \mathbb{R}^n$ $\quad W^l \ [n \times 2n]$

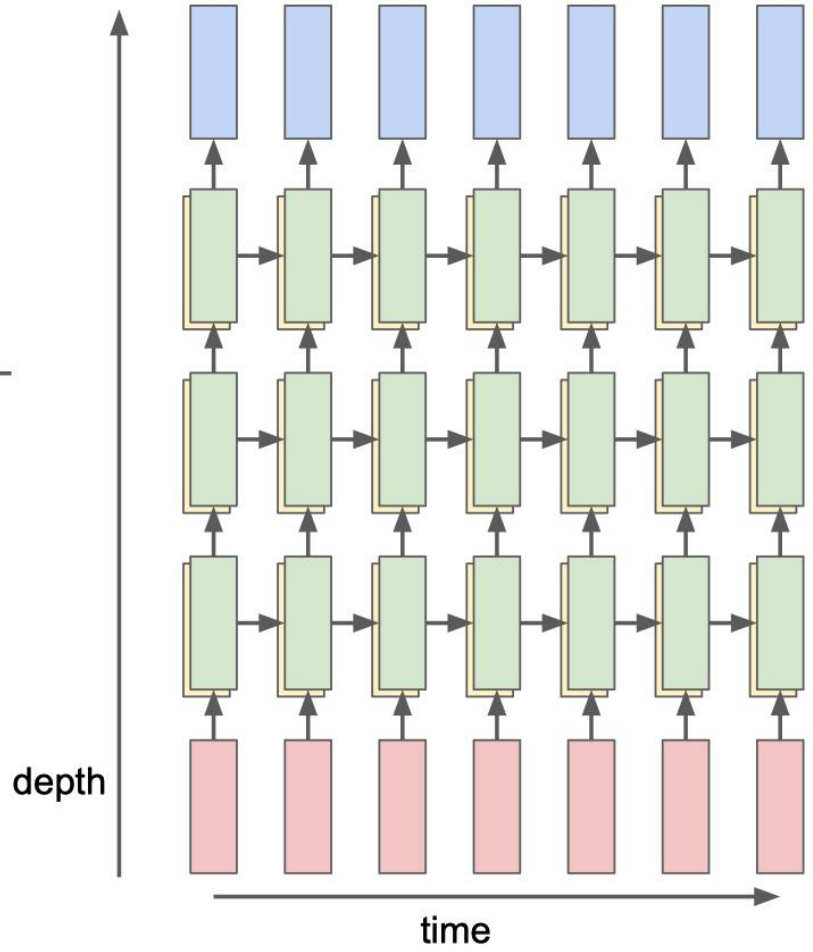
LSTM:

$W^l \ [4n \times 2n]$

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \text{sigm} \\ \text{sigm} \\ \text{sigm} \\ \tanh \end{pmatrix} W^l \begin{pmatrix} h_t^{l-1} \\ h_{t-1}^l \end{pmatrix}$$

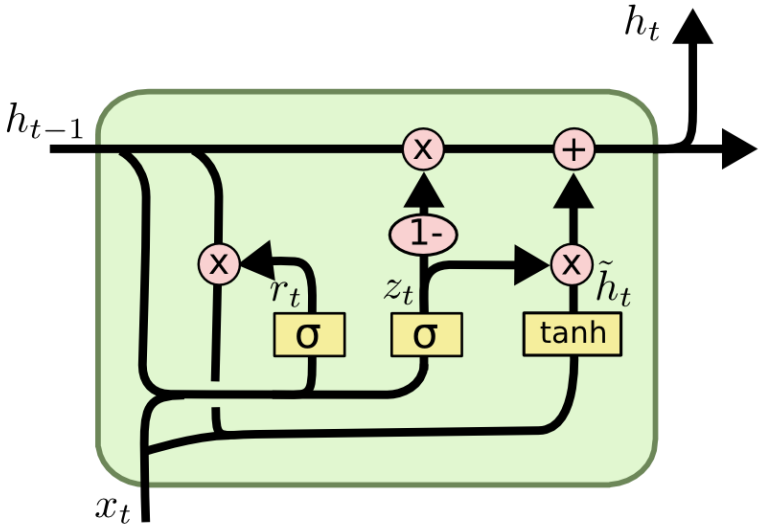
$$c_t^l = f \odot c_{t-1}^l + i \odot g$$

$$h_t^l = o \odot \tanh(c_t^l)$$



Gated Recurrent Unit (GRU)

- Alternative RNN to LSTM that uses fewer gates (Cho, et al., 2014)
  - Combines forget and input gates into "update" gate.
  - Eliminates cell state vector



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

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

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

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

GRU vs. LSTM

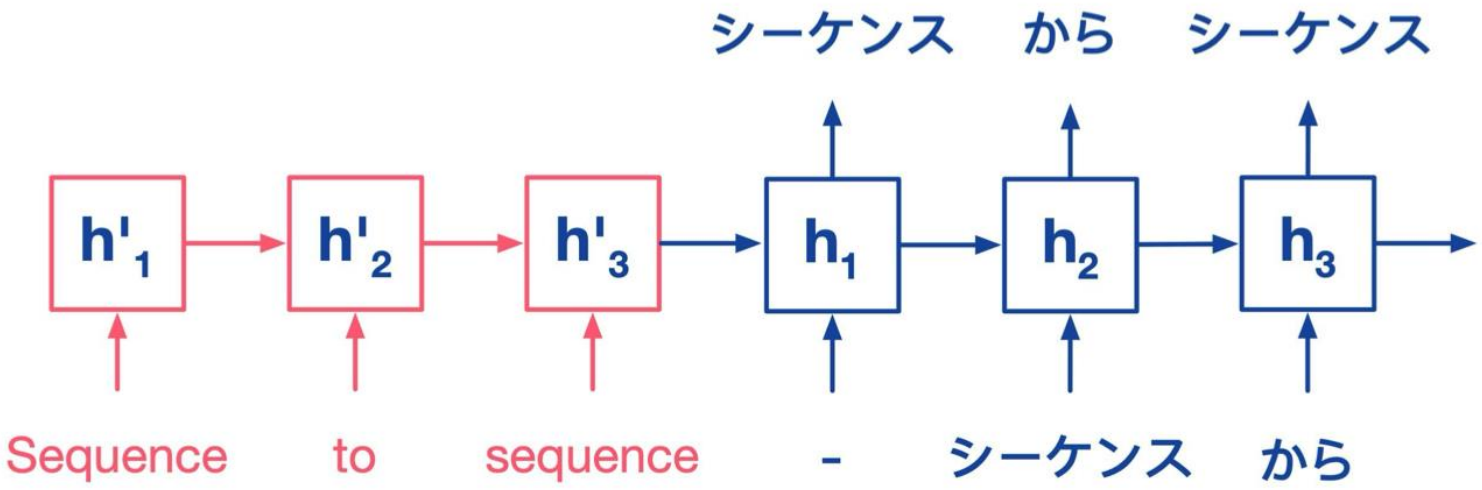
- GRU has significantly fewer parameters and trains faster.
- Experimental results comparing the two are still inconclusive, many problems they perform the same, but each has problems on which they work better.

Conclusions of LSTM

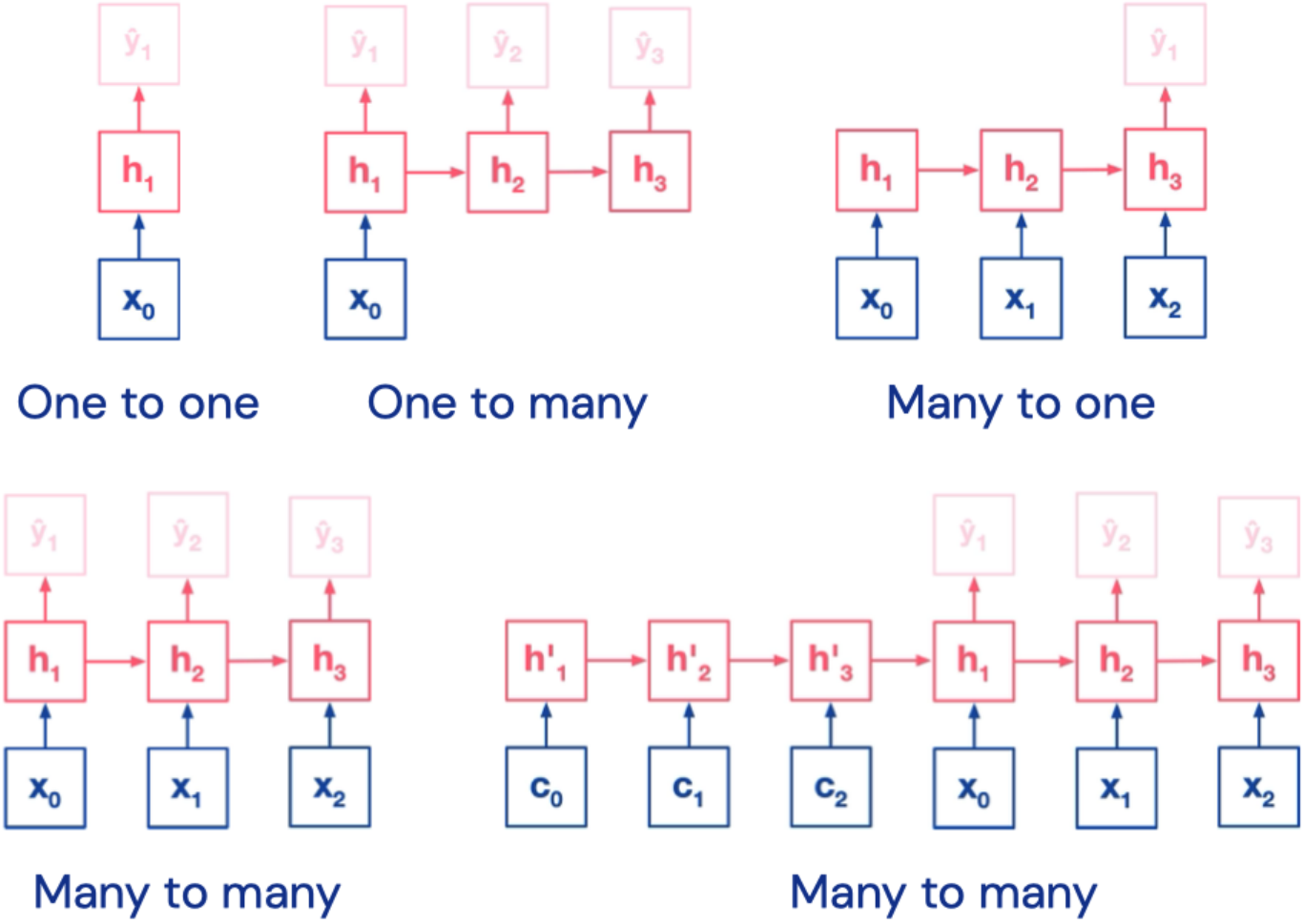
- By adding “gates” to an RNN, we can prevent the vanishing/exploding gradient problem.
- Trained LSTMs/GRUs can retain state information longer and handle long-distance dependencies.

Natural Language as Sequences

Sequence-to-sequence models



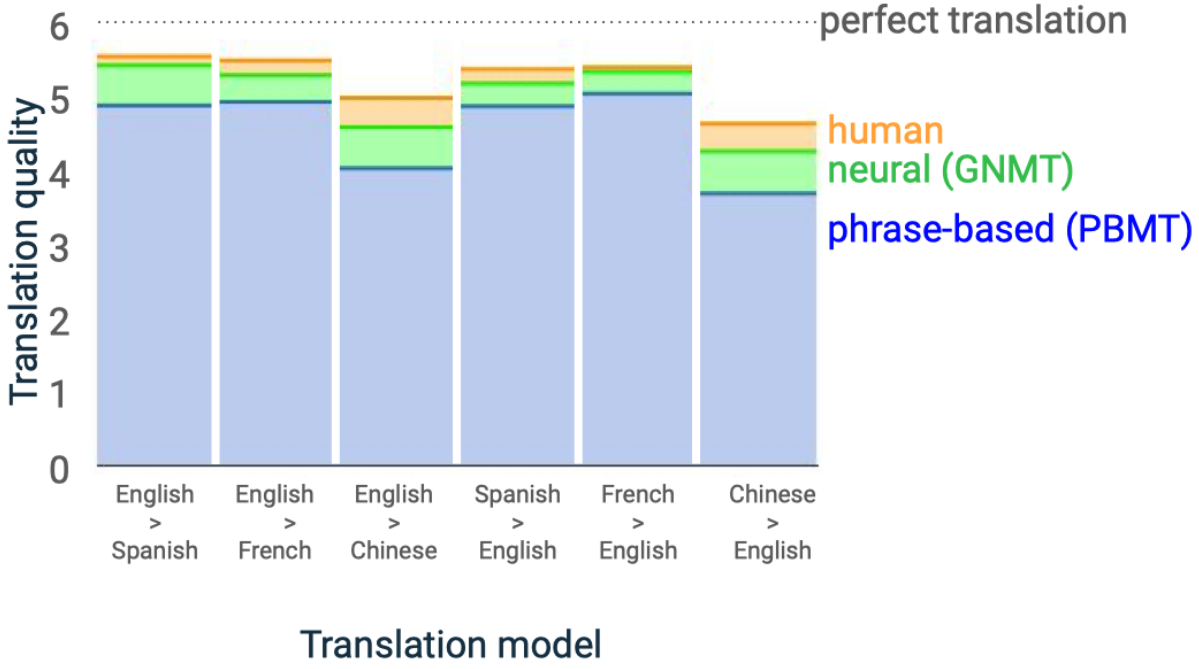
Flexible Sequence Mappings



Seq2seq has a wide range of applications

1. **MT** [Kalchbrenner et al, EMNLP 2013][Cho et al, EMLP 2014][Sutskever & Vinyals & Le, NIPS 2014][Luong et al, ACL 2015][Bahdanau et al, ICLR 2015]
2. **Image captions** [Mao et al, ICLR 2015][Vinyals et al, CVPR 2015][Donahue et al, CVPR 2015][Xu et al, ICML 2015]
3. **Speech** [Chorowsky et al, NIPS DL 2014][Chan et al, arxiv 2015]
4. **Parsing** [Vinyals & Kaiser et al, NIPS 2015]
5. **Dialogue** [Shang et al, ACL 2015][Sordoni et al, NAACL 2015][Vinyals & Le, ICML DL 2015]
6. **Video Generation** [Srivastava et al, ICML 2015]
7. **Geometry** [Vinyals & Fortunato & Jaitly, NIPS 2015]

Google Neural Machine Translation



Closes gap between old system and human-quality translation by 58% to 87%.

Image Captioning

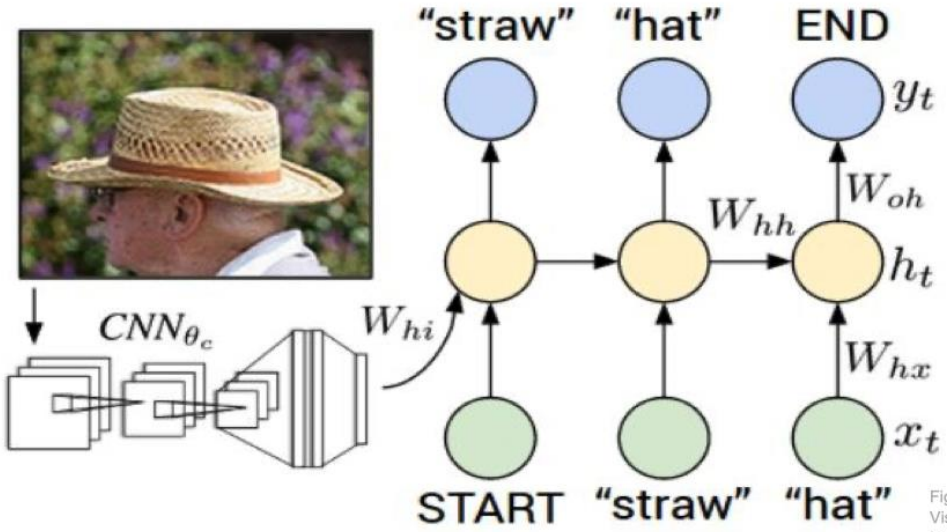


Figure from Karpathy et a, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015; figure copyright IEEE, 2015. Reproduced for educational purposes.

Explain Images with Multimodal Recurrent Neural Networks, Mao et al.
Deep Visual-Semantic Alignments for Generating Image Descriptions, Karpathy and Fei-Fei
Show and Tell: A Neural Image Caption Generator, Vinyals et al.
Long-term Recurrent Convolutional Networks for Visual Recognition and Description, Donahue et al.
Learning a Recurrent Visual Representation for Image Caption Generation, Chen and Zitnick

Image Captioning

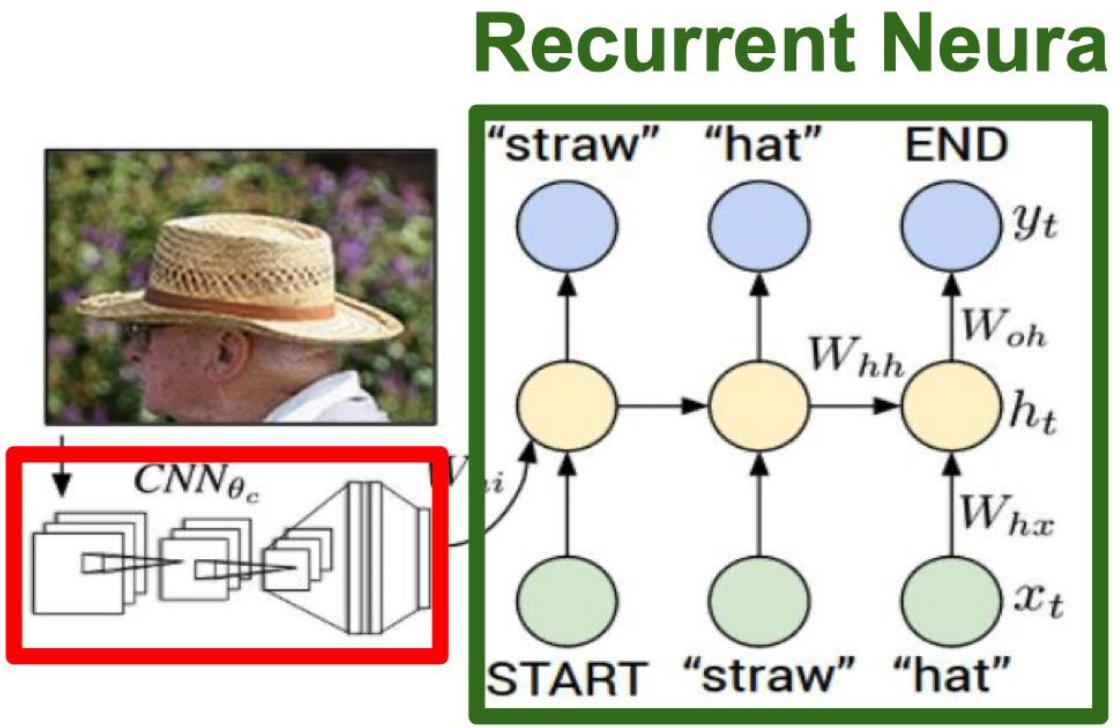
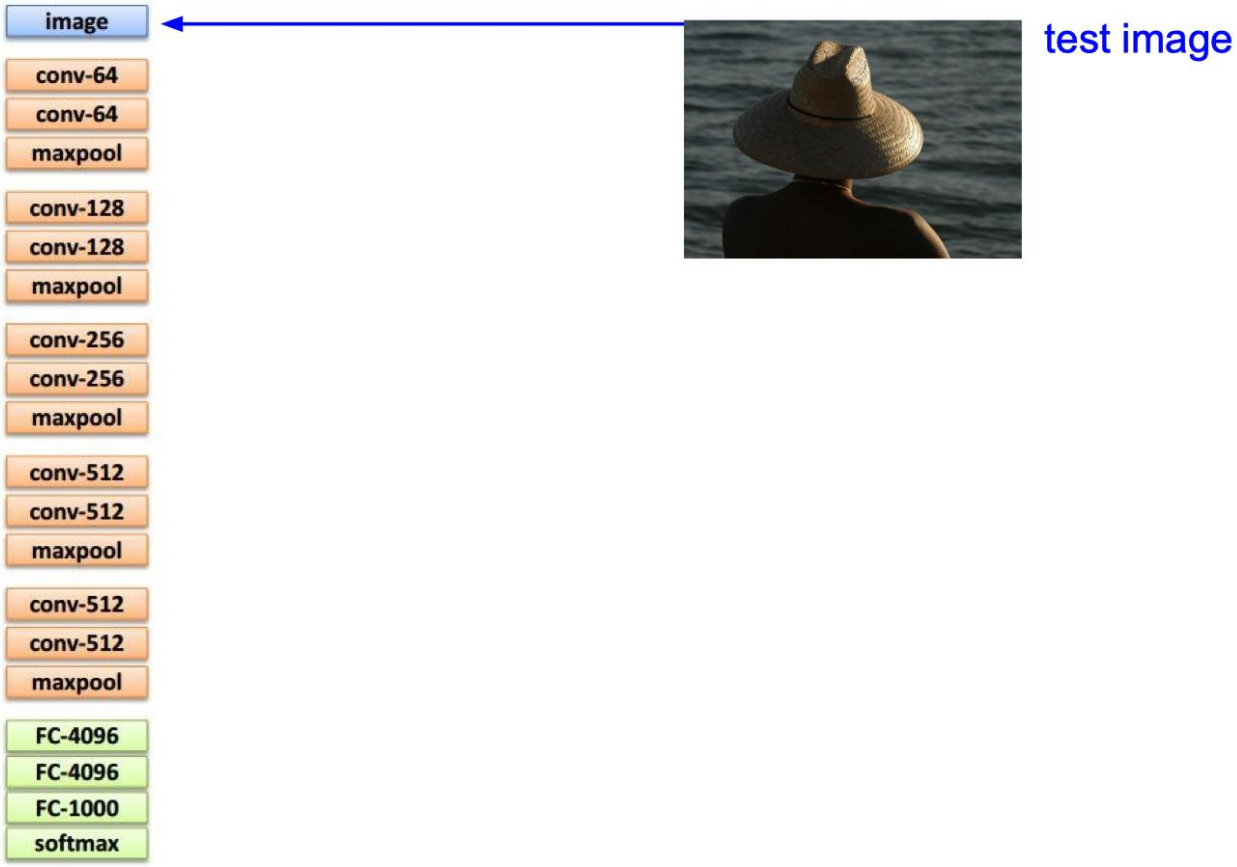


Image Captioning

This image is CC0 public domain

test image

Image Captioning



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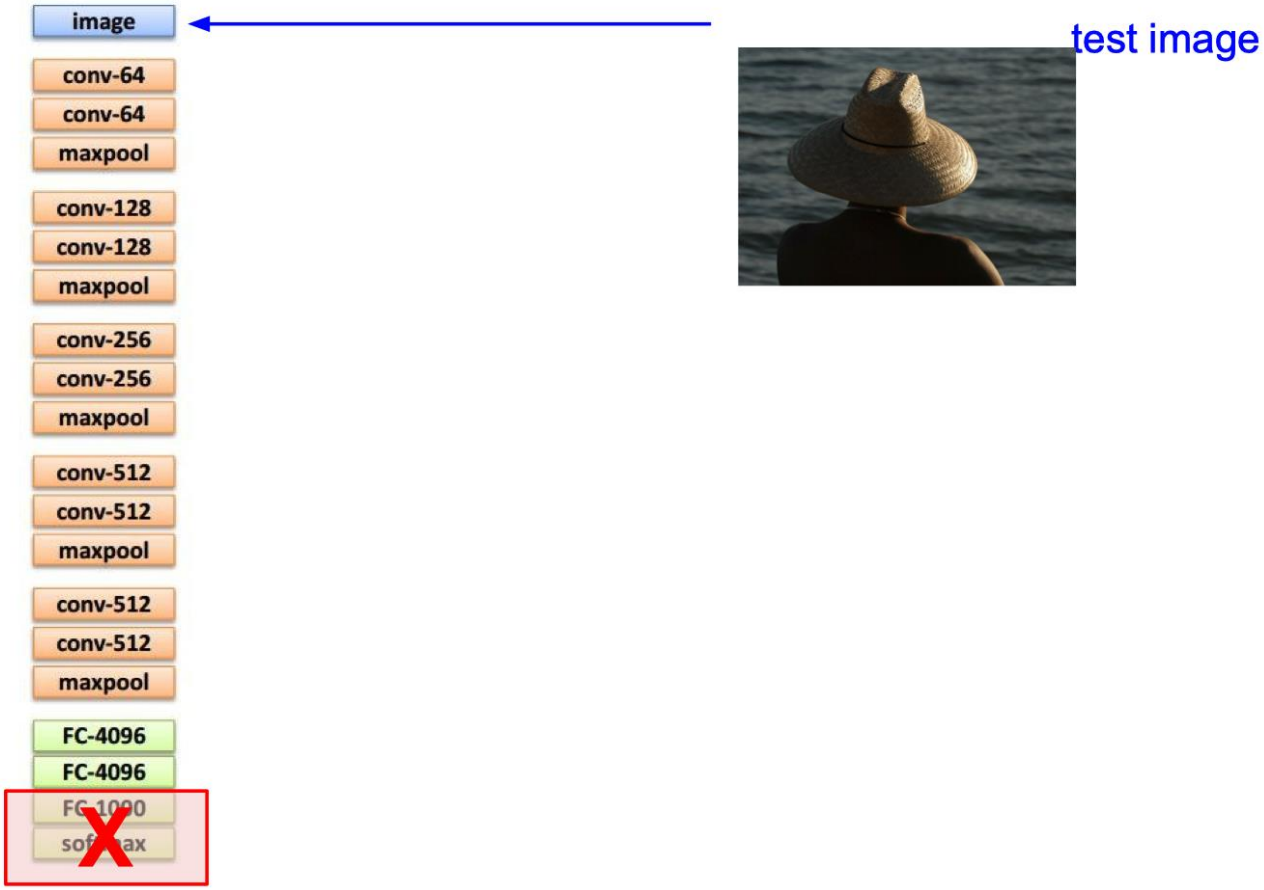

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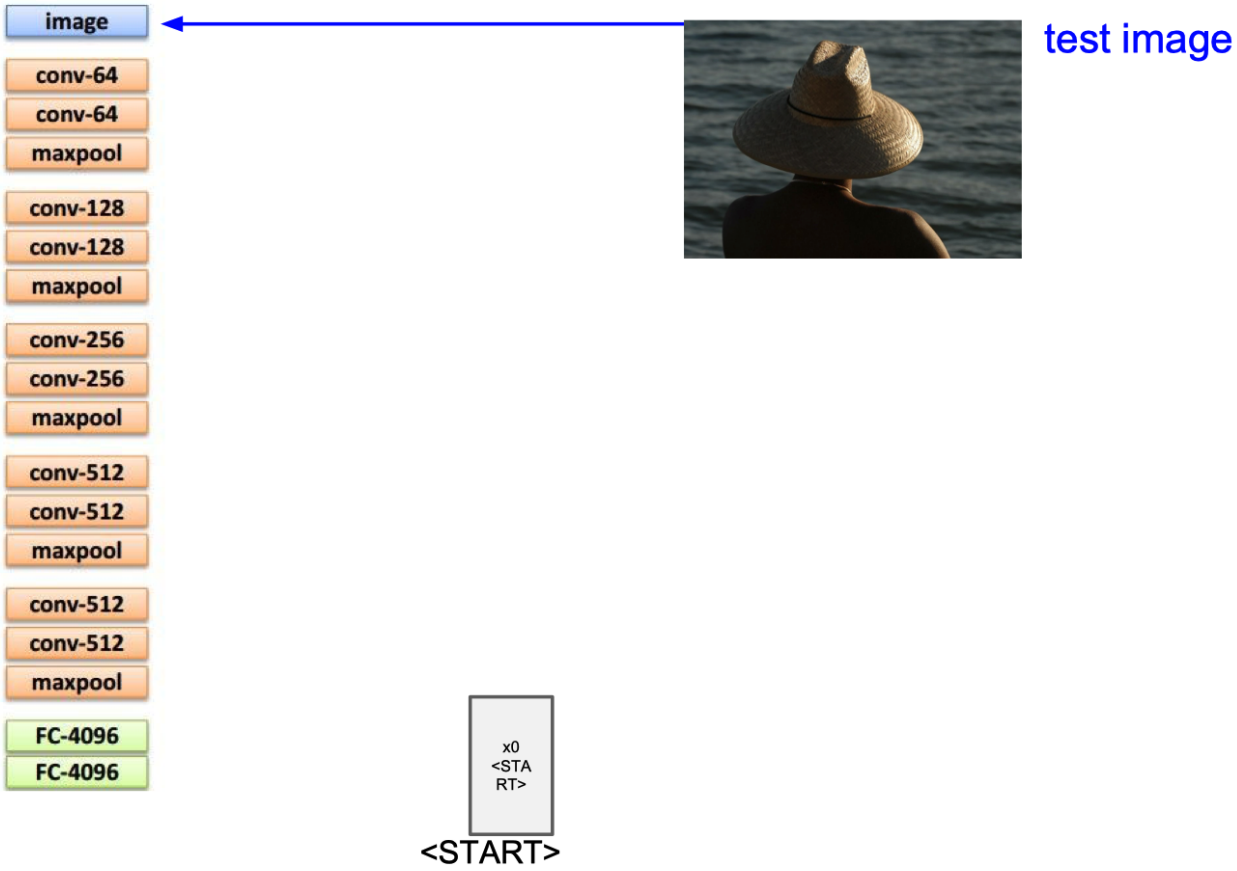
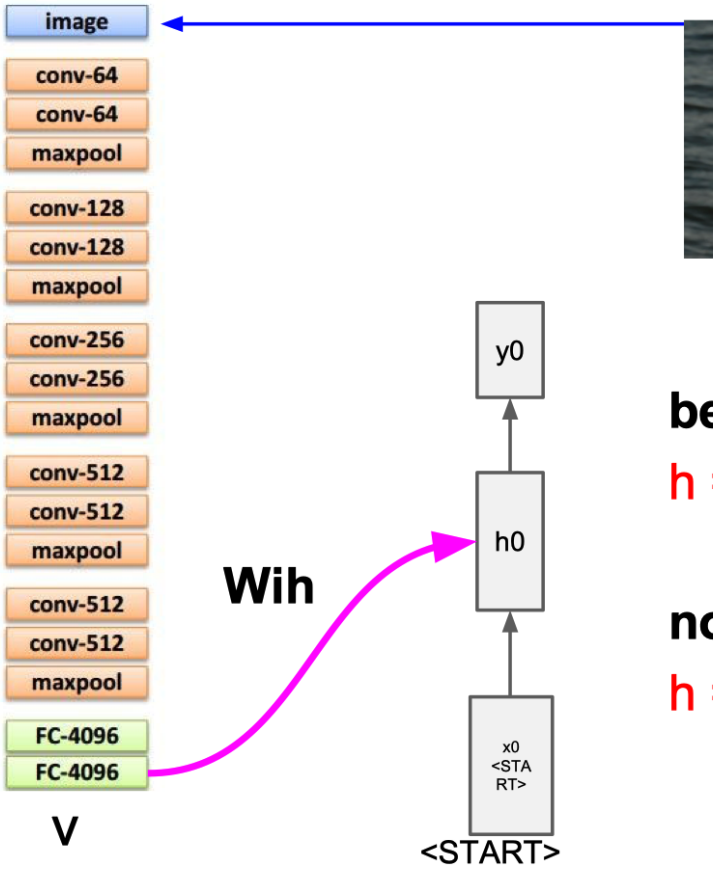


Image Captioning



test image

before:

h = tanh(Wxh * x + Whh * h)

now:

h = tanh(Wxh * x + Whh * h + Wih * v)

Image Captioning

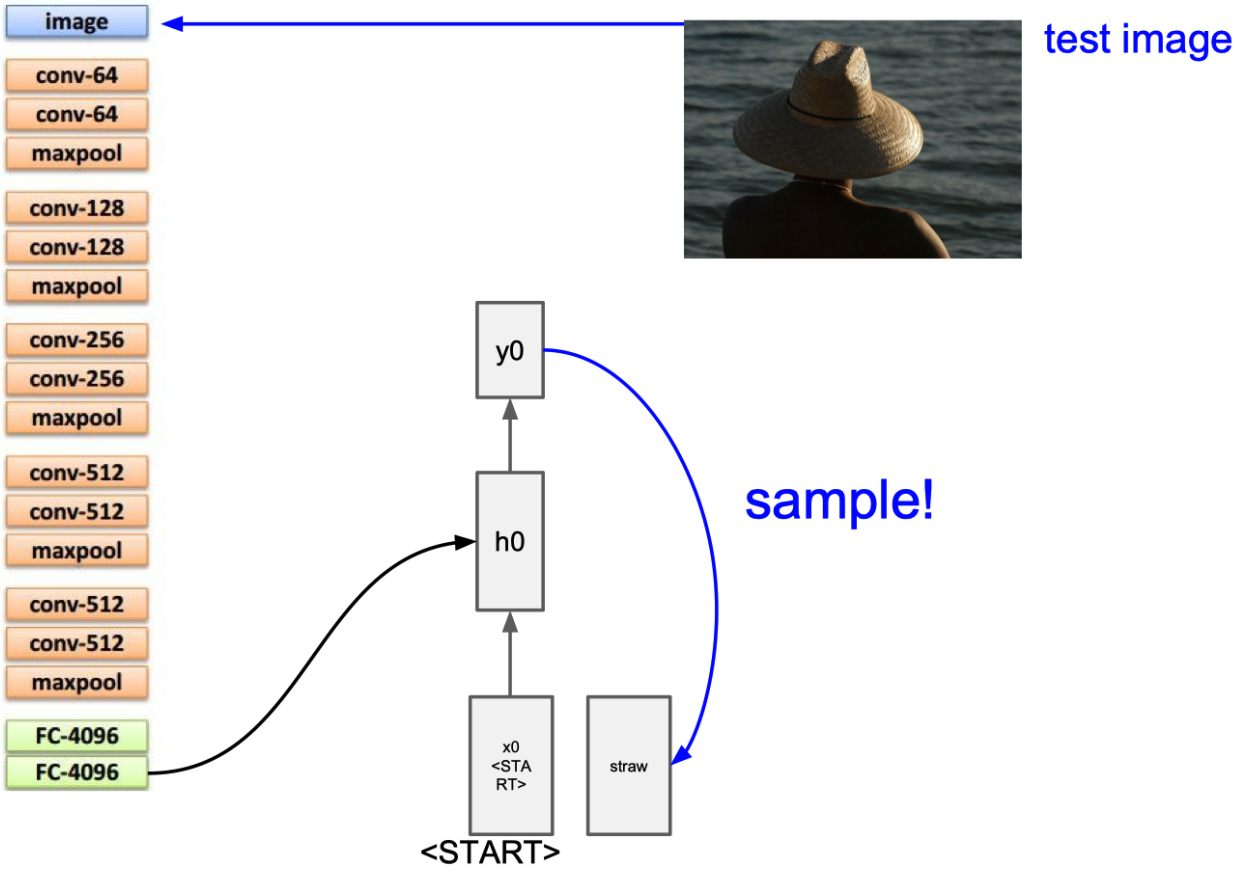
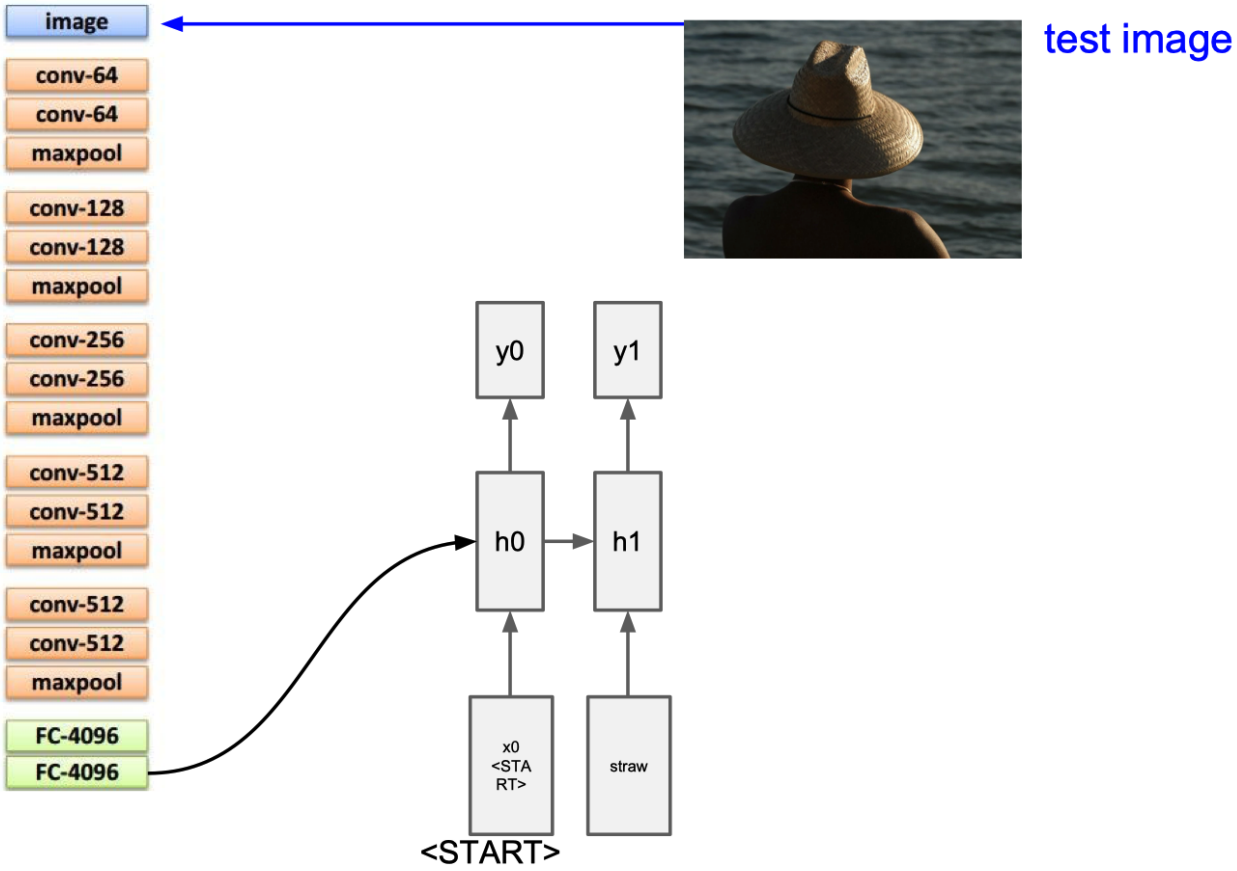


Image Captioning



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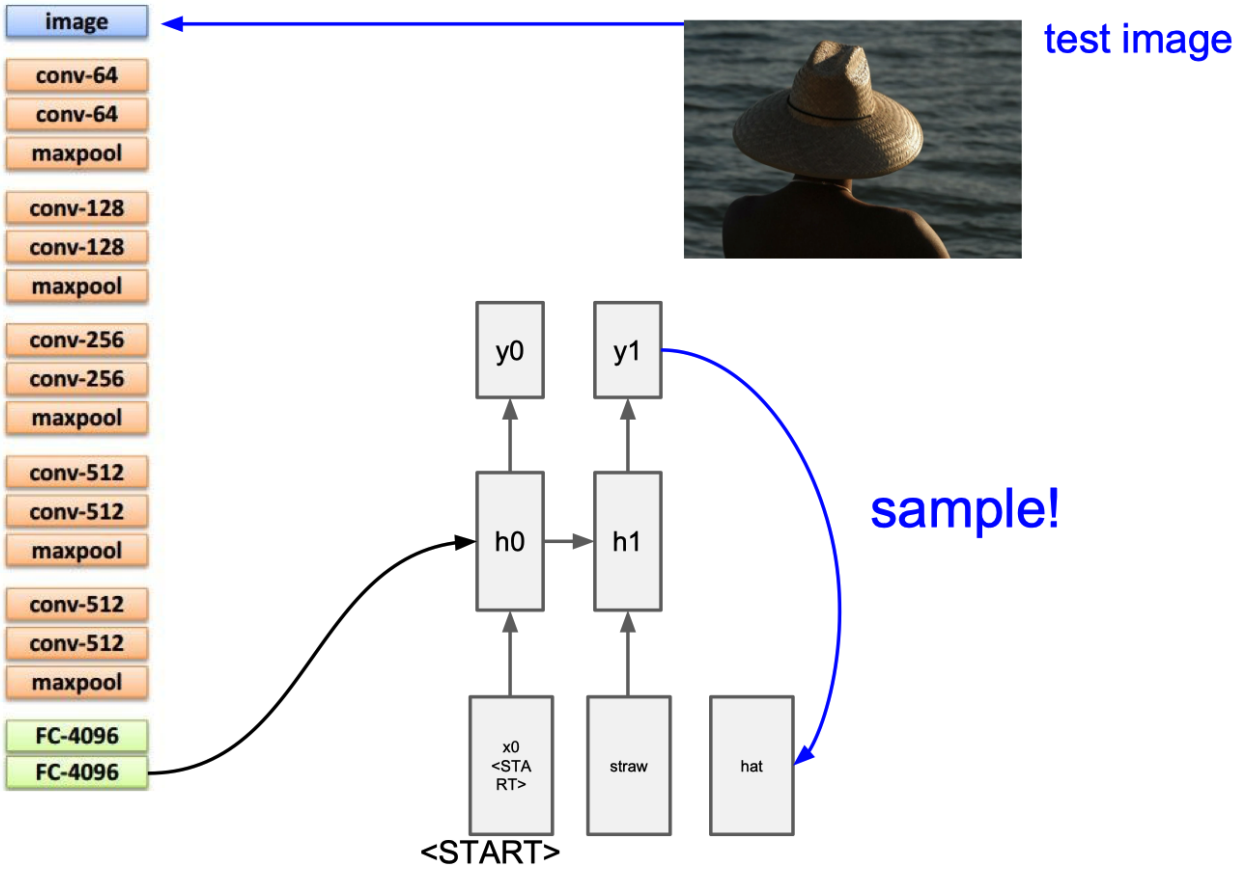

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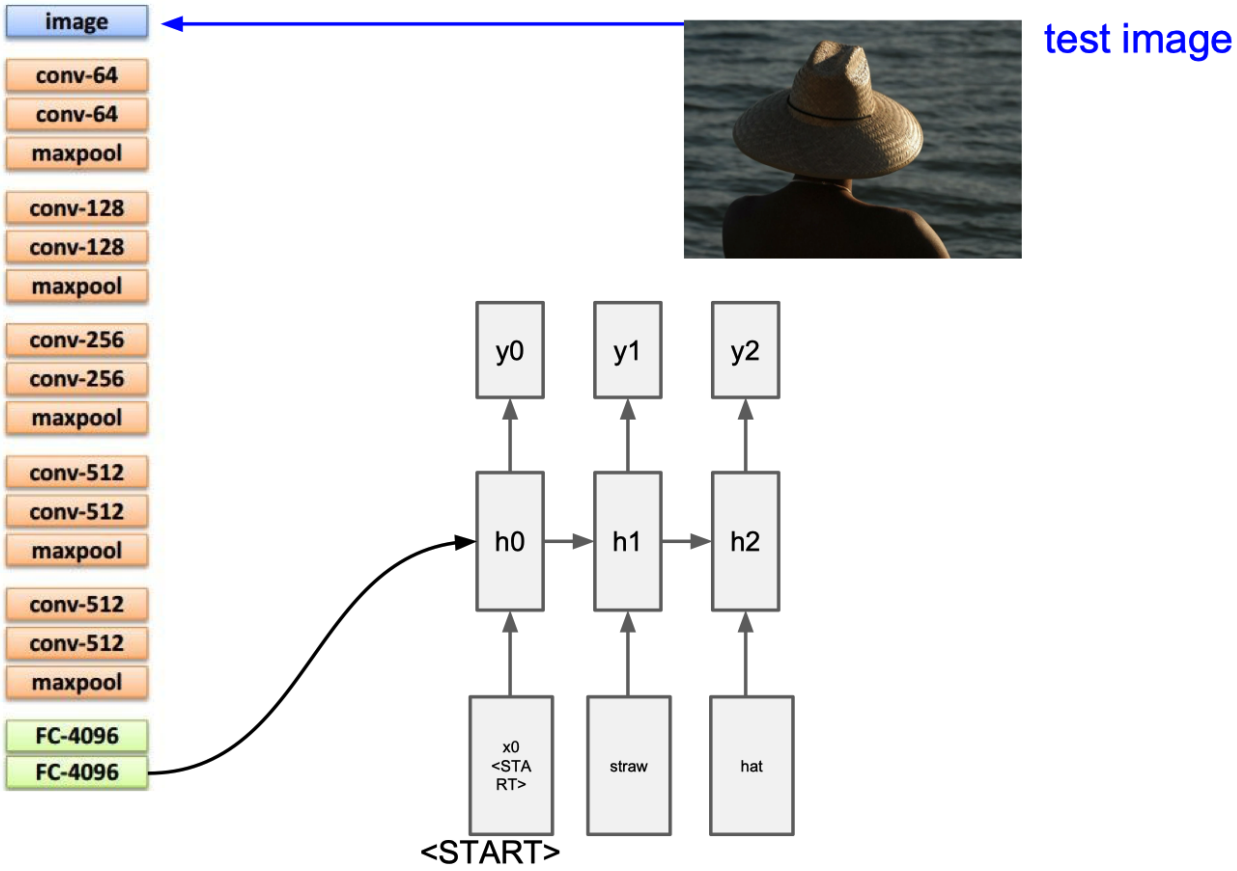


Image Captioning

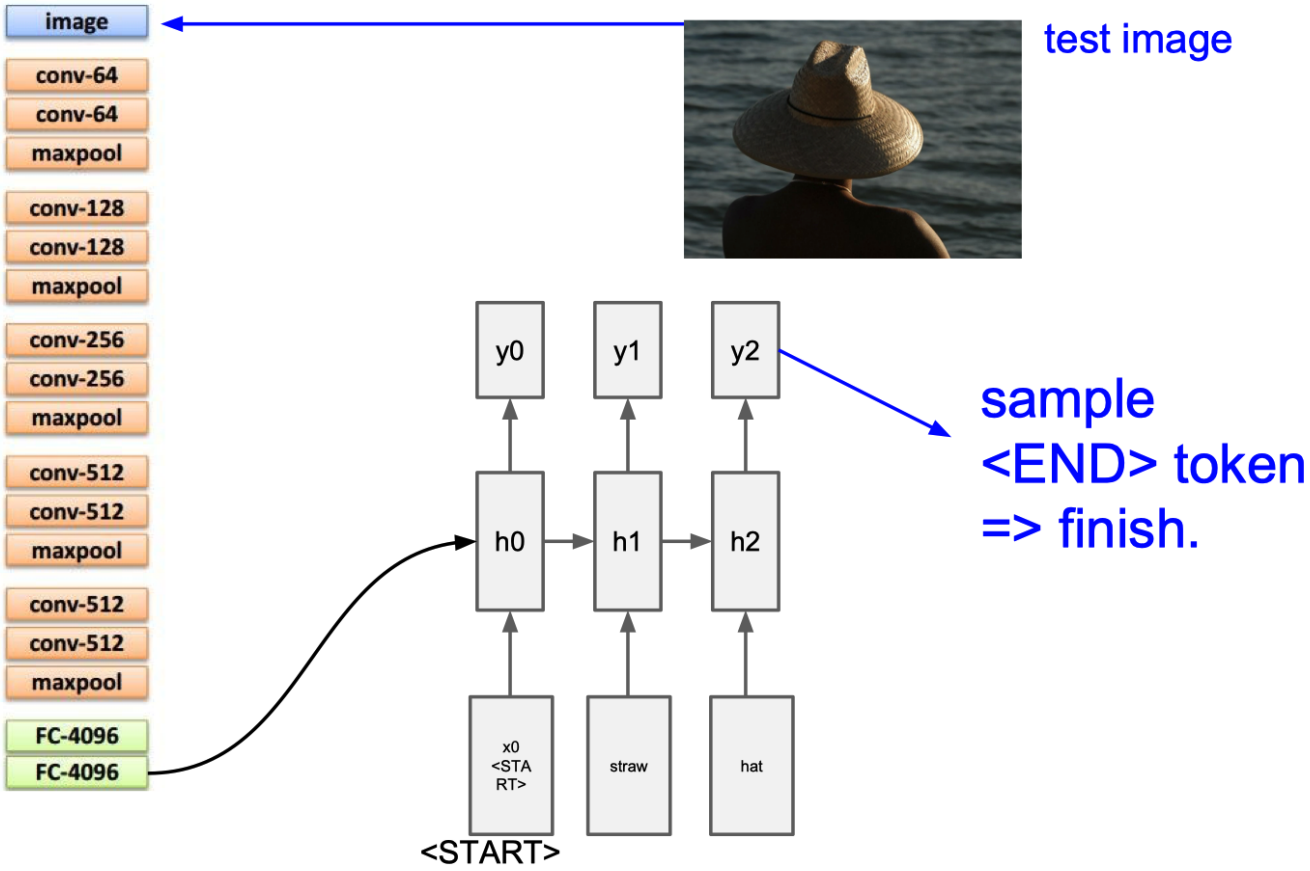


Image Captioning: Example Results

A cat sitting on a suitcase on the floor

A cat is sitting on a tree branch

A dog is running in the grass with a frisbee

A white teddy bear sitting in the grass

Two people walking on the beach with surfboards

A tennis player in action on the court

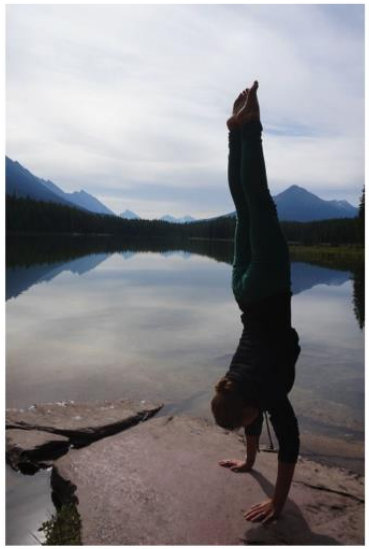
Two giraffes standing in a grassy field

A man riding a dirt bike on a dirt track

Image Captioning: Failure Cases

A woman is holding a cat in her hand

A person holding a computer mouse on a desk



A woman standing on a beach holding a surfboard

A bird is perched on a tree branch

A man in a baseball uniform throwing a ball

Image Captioning with Attention

RNN focuses its attention at a different spatial location when generating each word

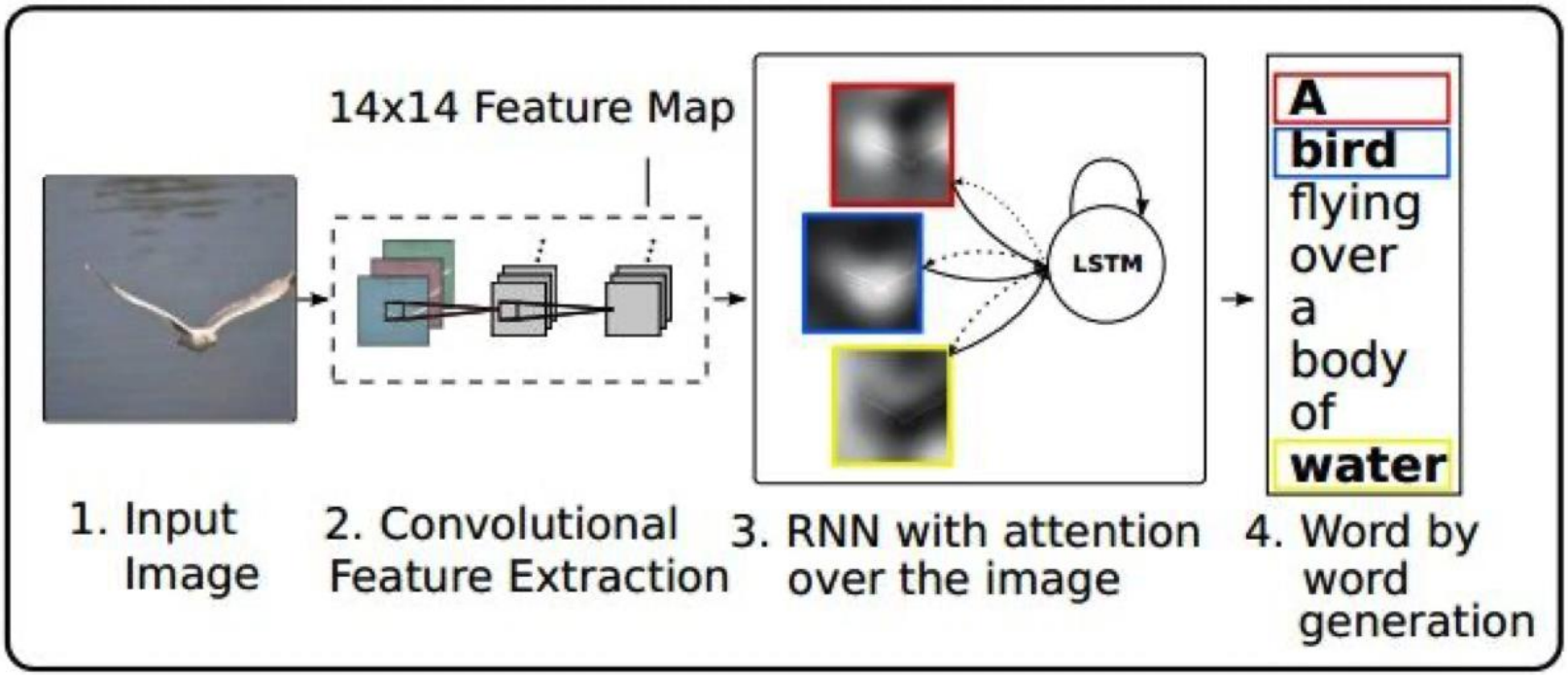
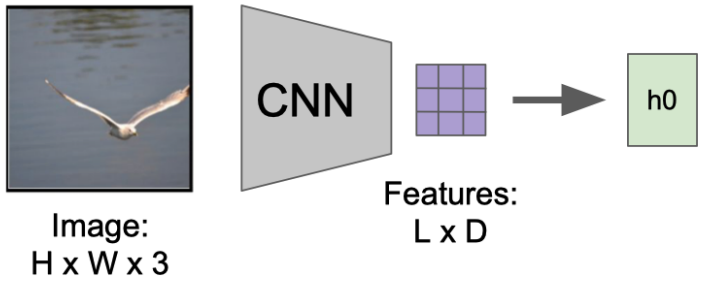
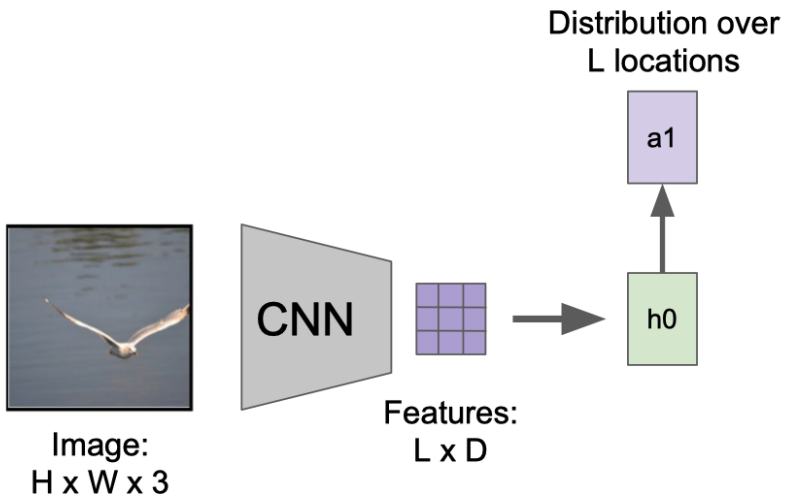


Image Captioning with Attention



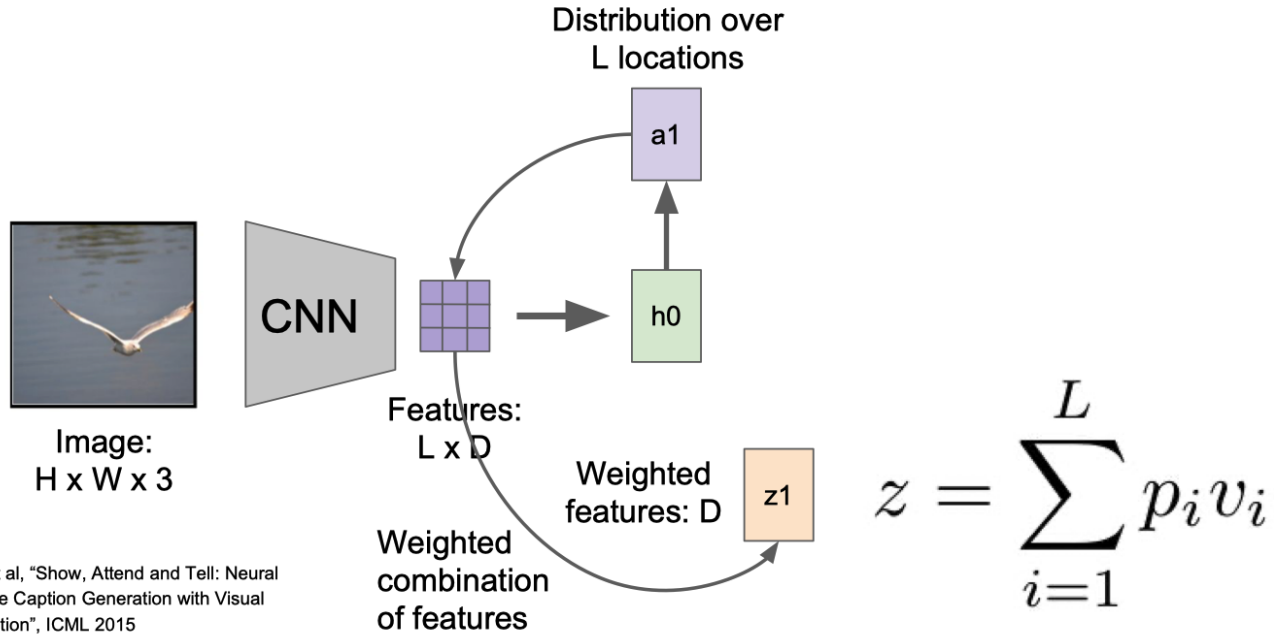
Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Image Captioning with Attention



Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

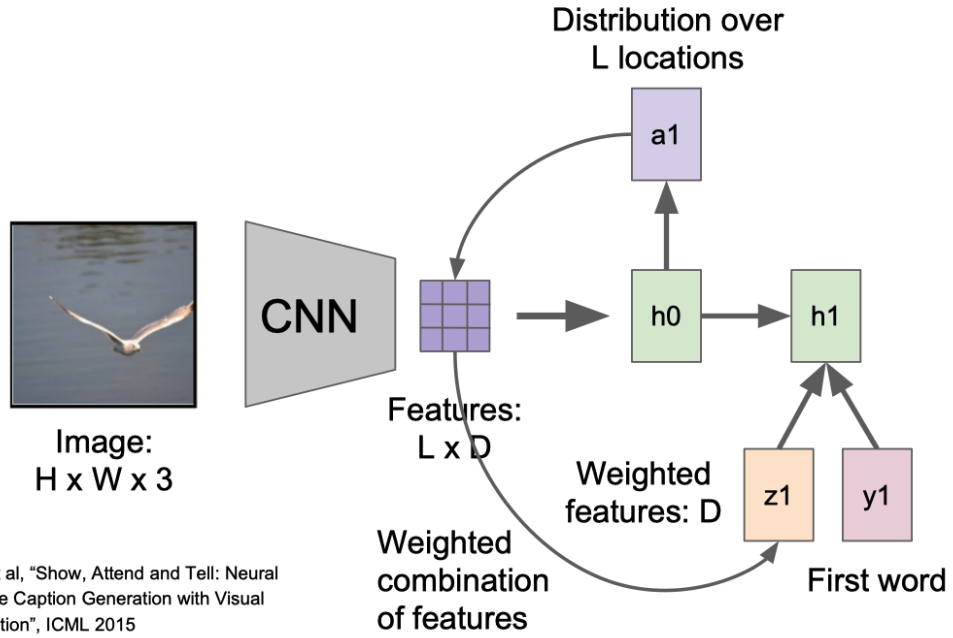
Image Captioning with Attention



Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

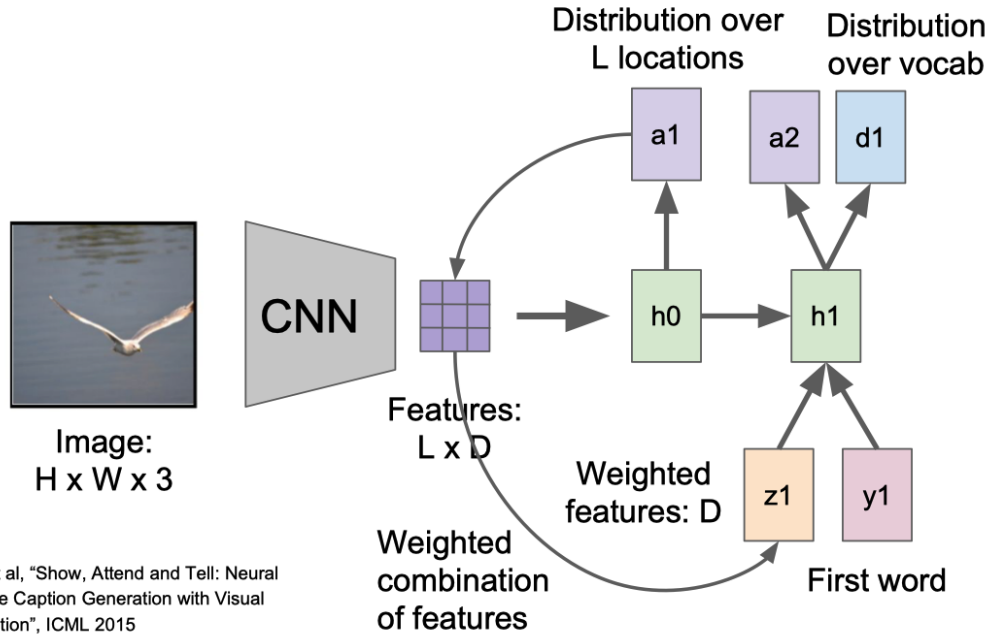
$$z = \sum_{i=1}^{L} p_i v_i$$

Image Captioning with Attention



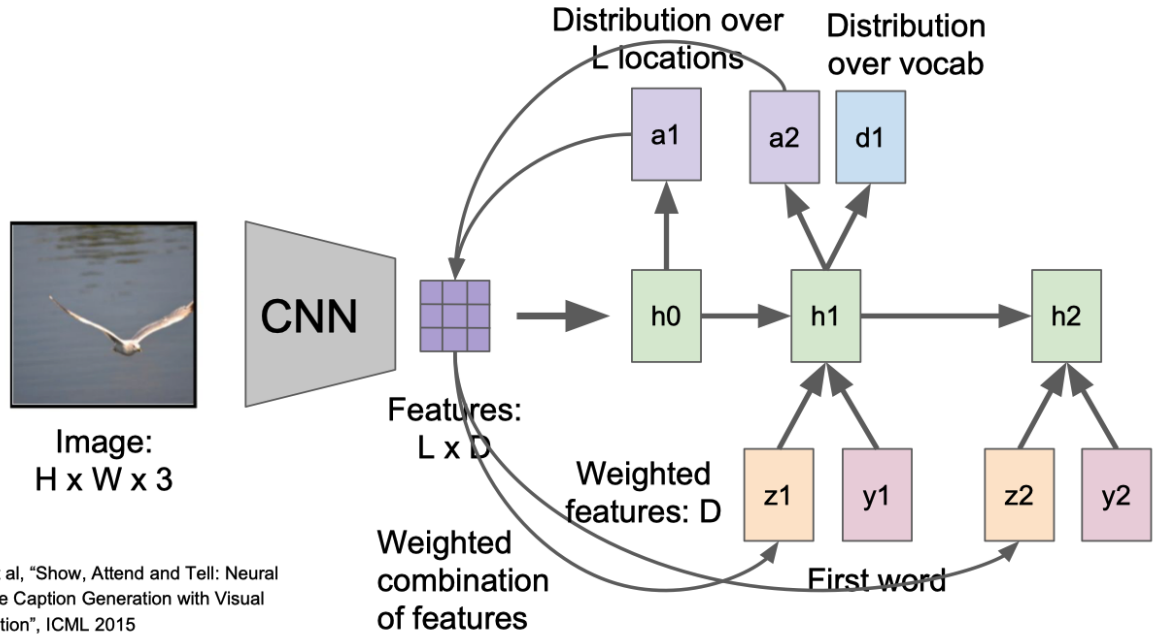
Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Image Captioning with Attention



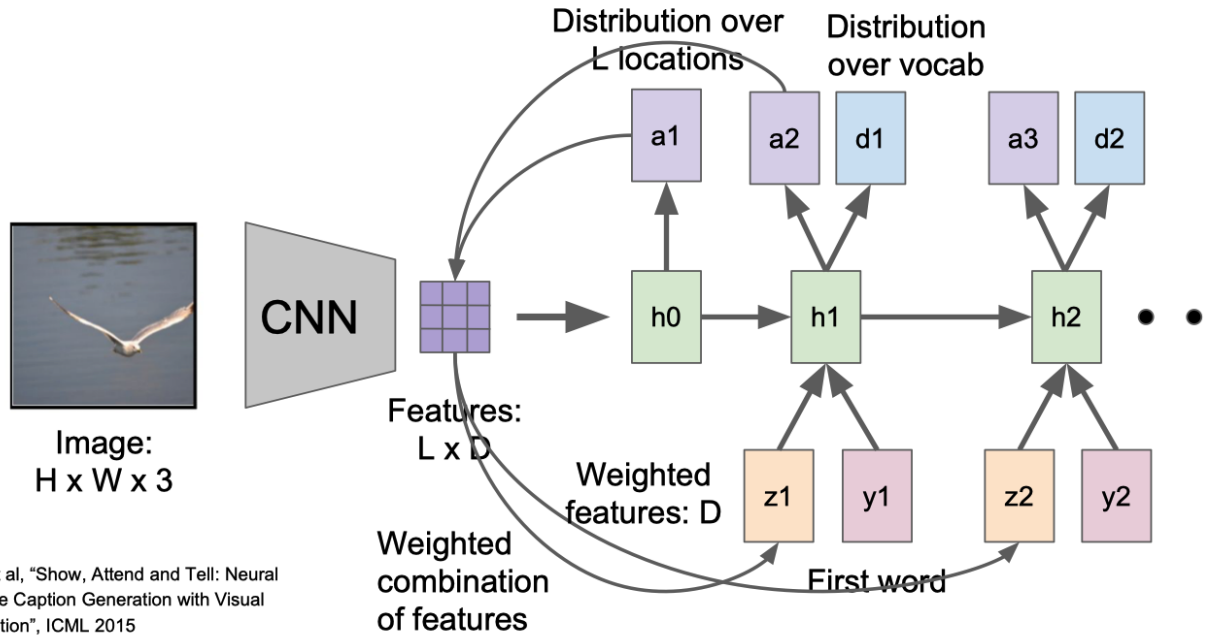
Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Image Captioning with Attention



Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Image Captioning with Attention



Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Image Captioning with Attention

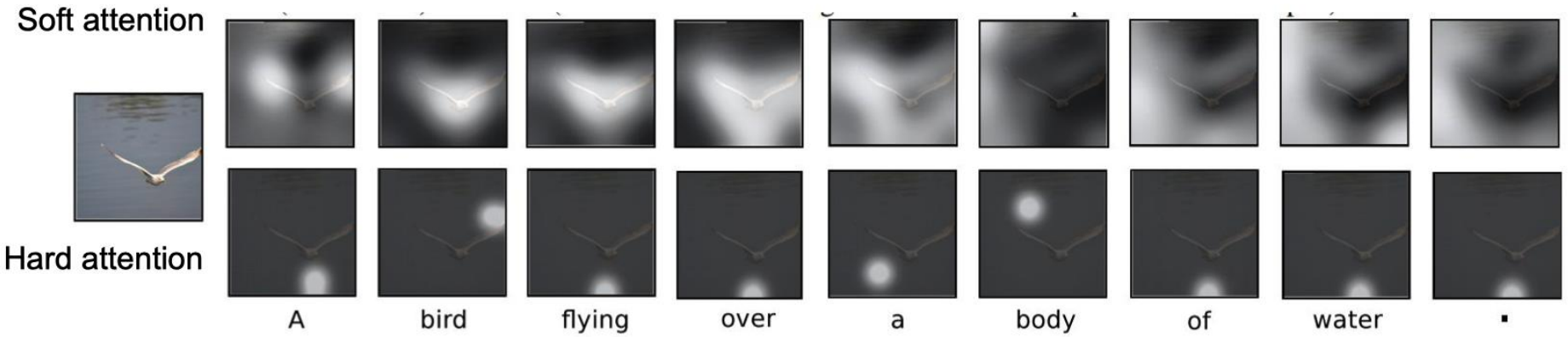


Image Captioning with Attention

A woman is throwing a frisbee in a park.

A dog is standing on a hardwood floor.

A stop sign is on a road with a mountain in the background.

A little girl sitting on a bed with a teddy bear.

A group of people sitting on a boat in the water.

A giraffe standing in a forest with trees in the background.

Visual Question Answering

Q: What endangered animal is featured on the truck?

A: **A bald eagle.**
A: A sparrow.
A: A humming bird.
A: A raven.

Q: Where will the driver go if turning right?

A: **Onto 24 ¾ Rd.**
A: Onto 25 ¾ Rd.
A: Onto 23 ¾ Rd.
A: Onto Main Street.

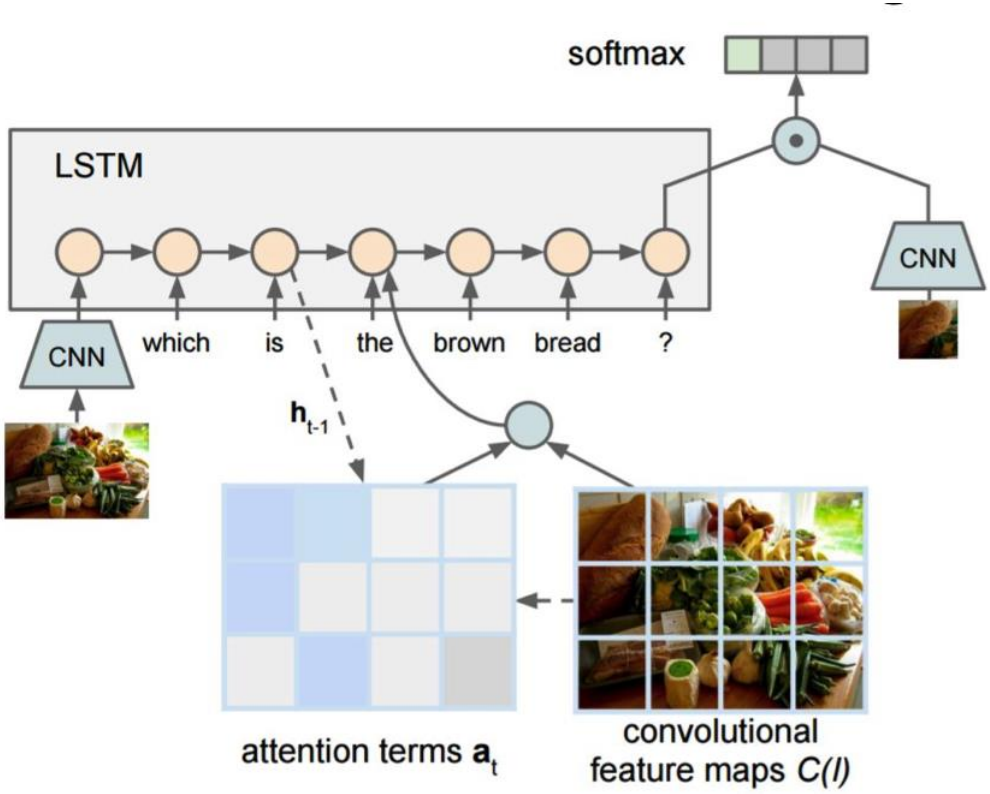
Q: When was the picture taken?

A: **During a wedding.**
A: During a bar mitzvah.
A: During a funeral.
A: During a Sunday church service

Q: Who is under the umbrella?

A: **Two women.**
A: A child.
A: An old man.
A: A husband and a wife.

Visual Question Answering



Zhu et al, "Visual 7W: Grounded Question Answering in Images", CVPR 2016

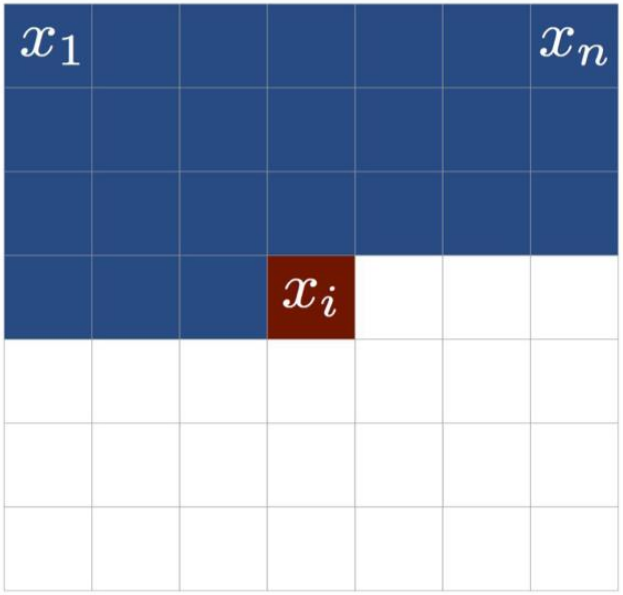
What kind of animal is in the photo?

A **cat**.

Why is the person holding a knife?

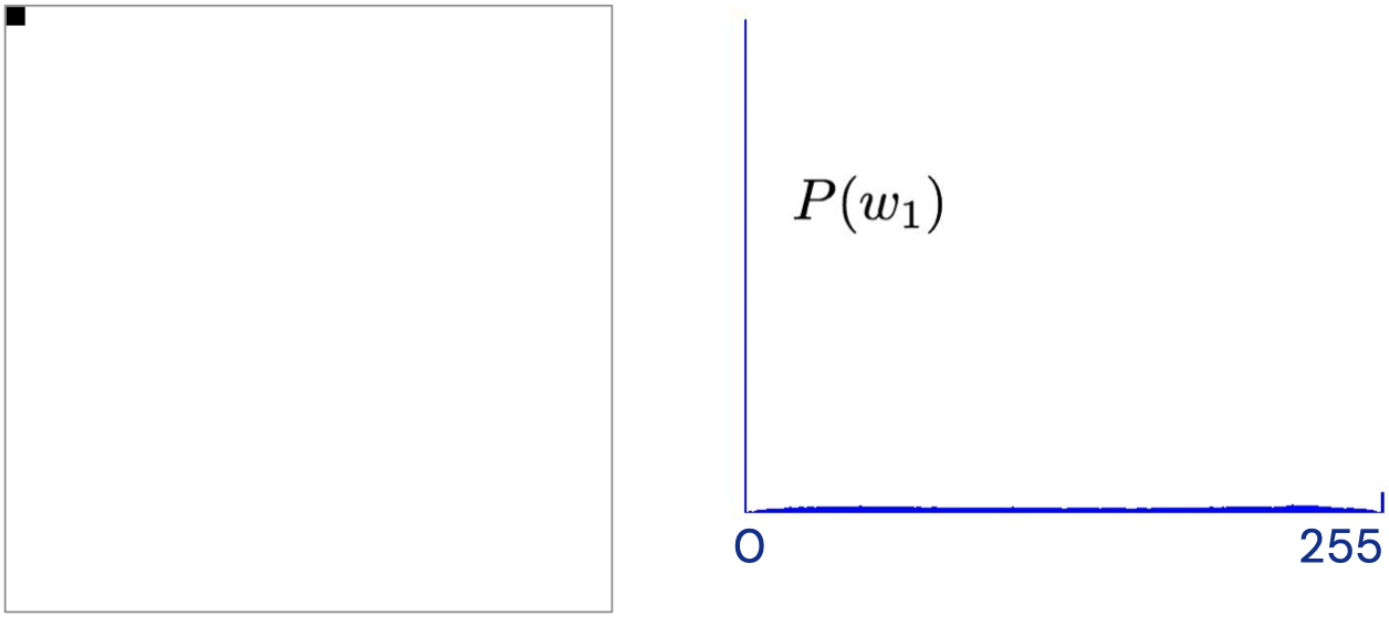
To cut the **cake** with.

Images as sequences: PixelRNN

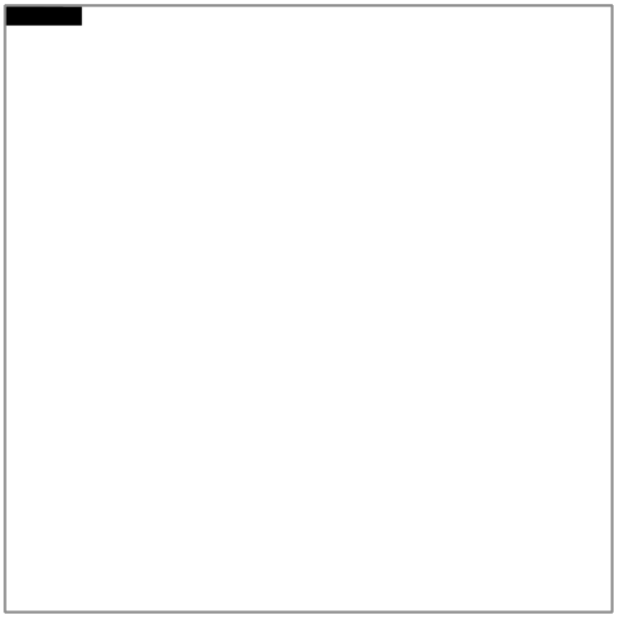


$$p(\mathbf{x}) = \prod_{i=1}^{n^2} p(x_i | x_1, ..., x_{i-1})$$

Images as sequences: PixelRNN

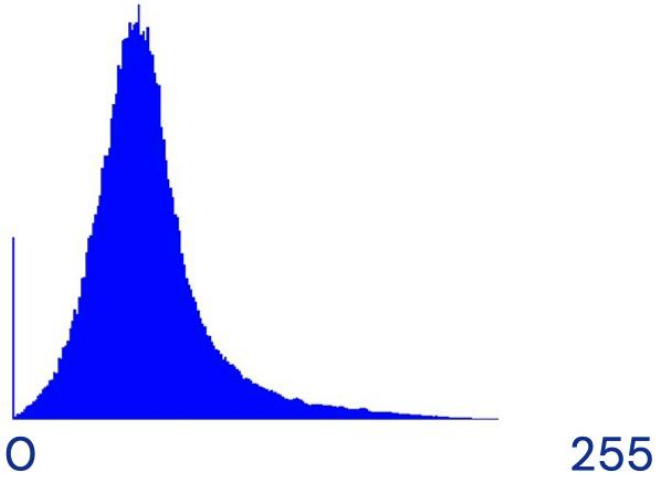


Images as sequences: PixelRNN

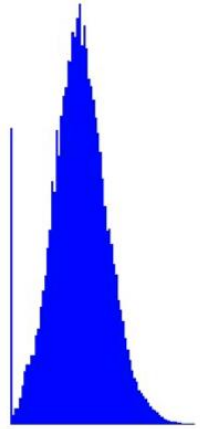


$$P(w_1)$$
$$P(w_2|w_1)$$
$$P(w_3|w_2, w_1)$$
$$P(w_4|w_3, w_2, w_1)$$

Images as sequences: PixelRNN



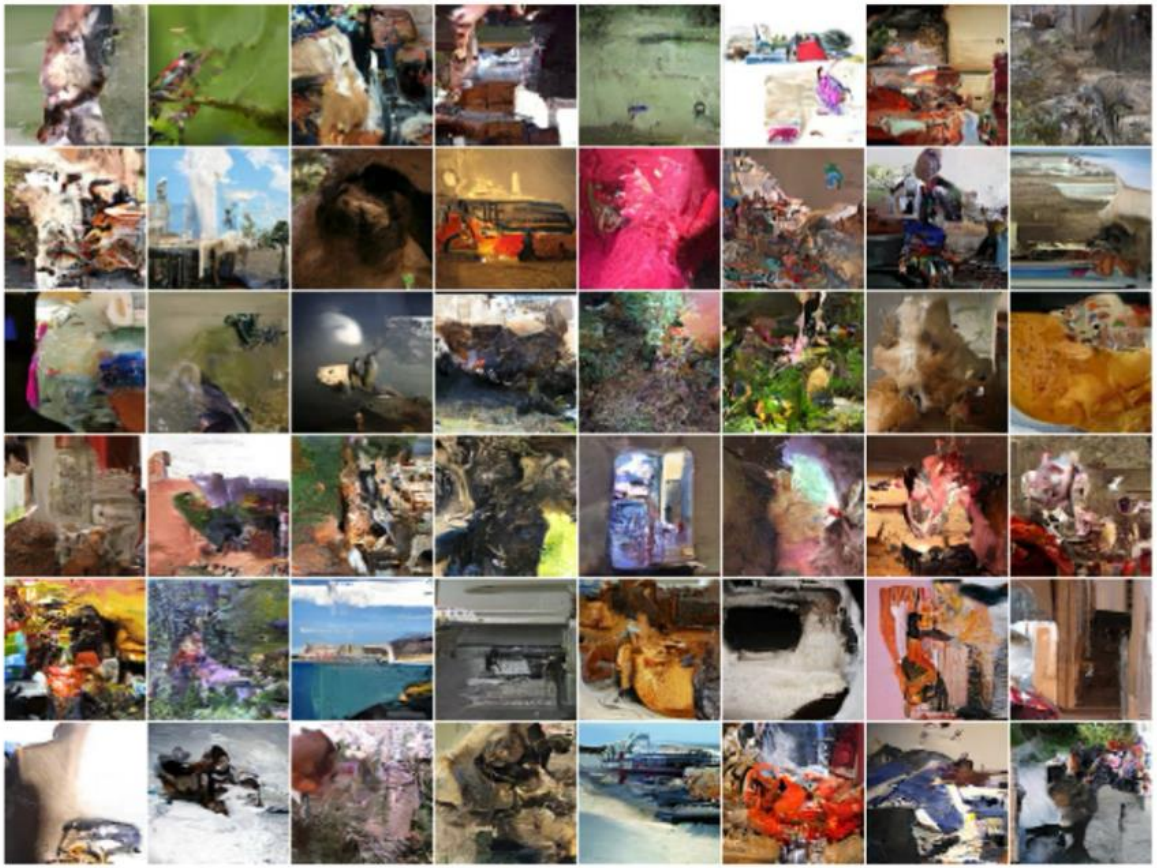
Images as sequences: PixelRNN



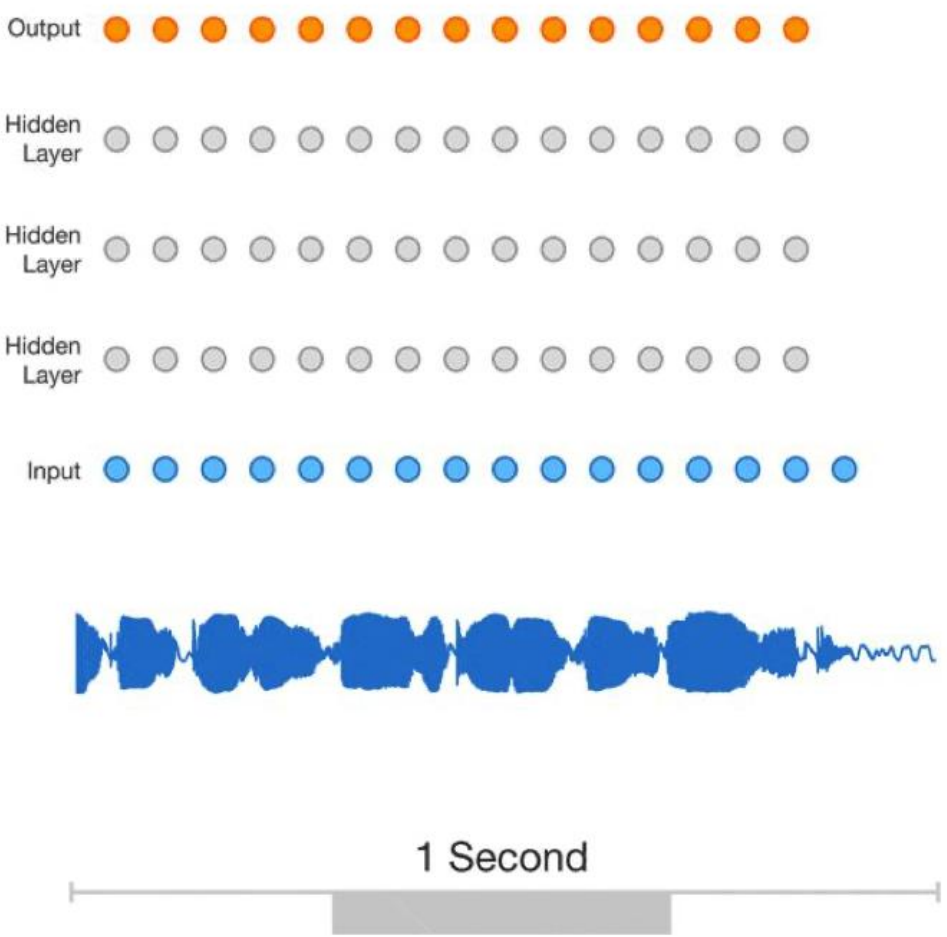
0

255

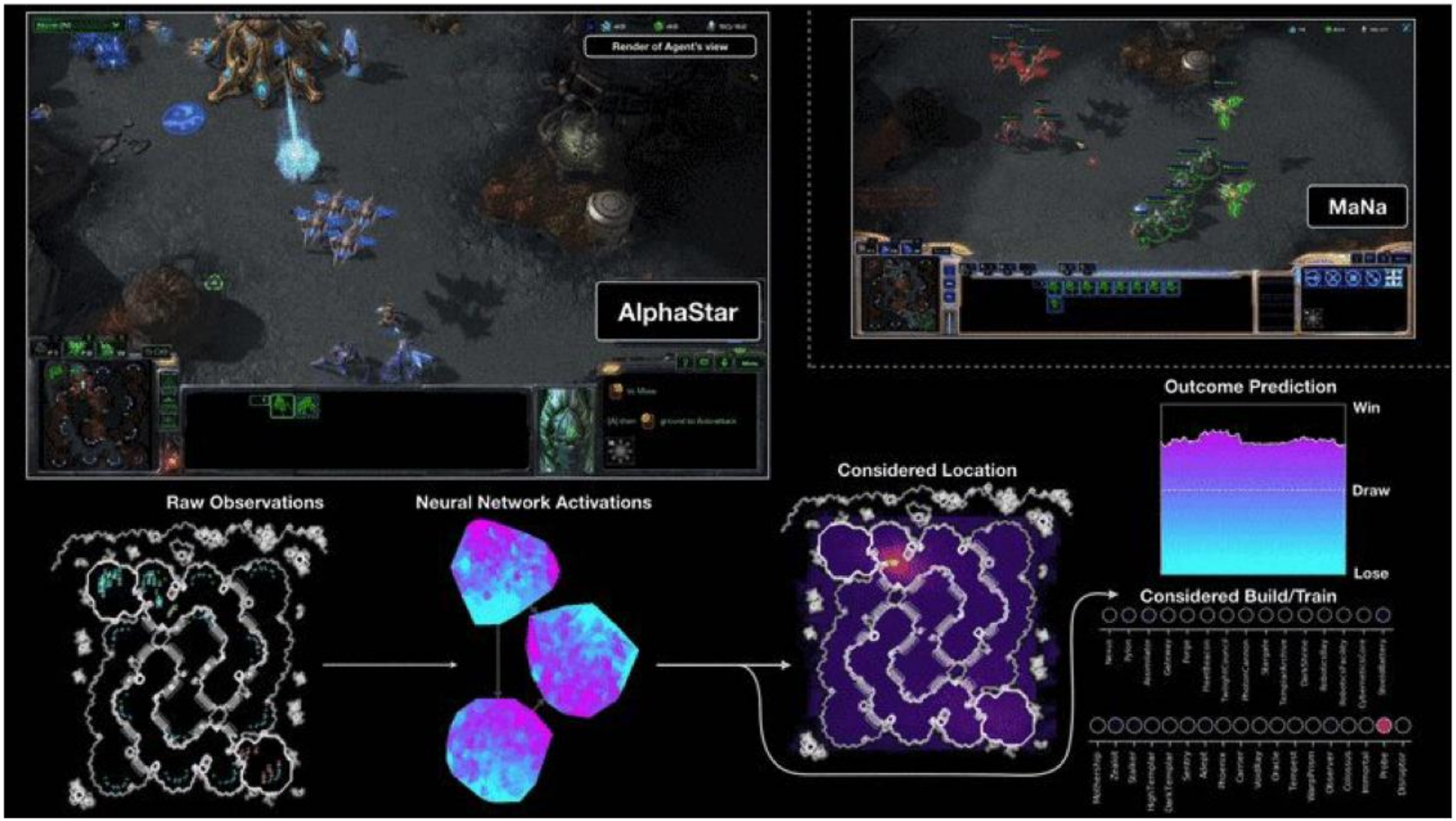
Images as sequences: PixelRNN



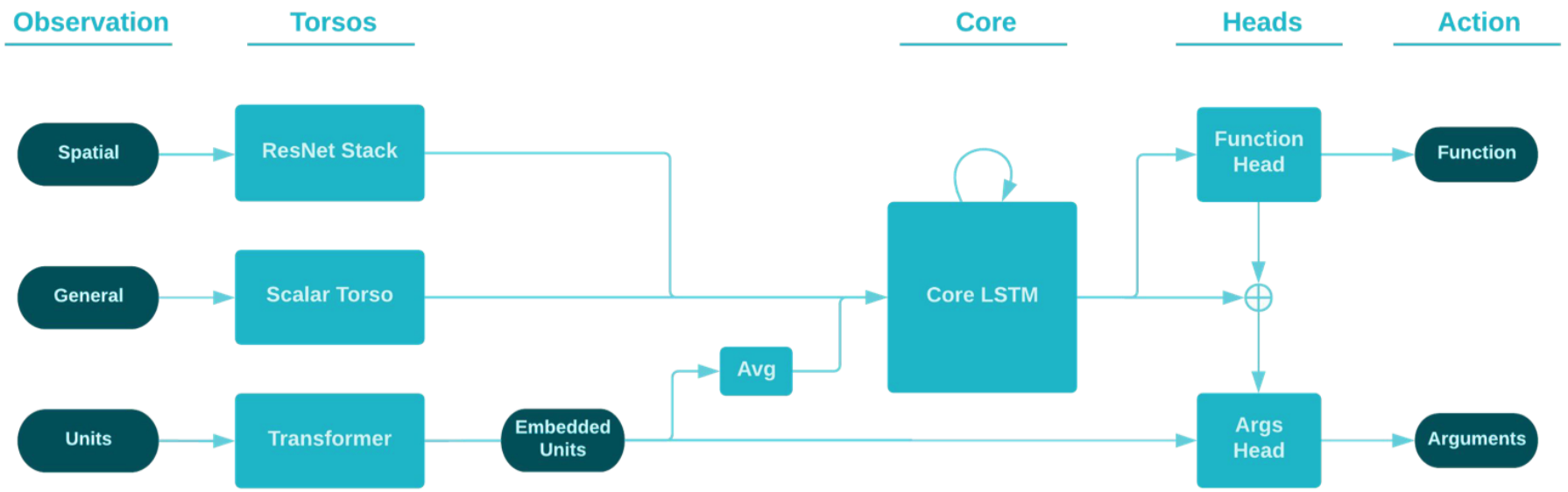
Audio waves as sequences



Policies as Sequences: Alphastar



AlphaStar Architecture



Questions?

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