



Xi'an Jiaotong-Liverpool University

西交利物浦大学

INT305 Machine Learning

Lecture 12

Recurrent Neural Network

Jimin Xiao

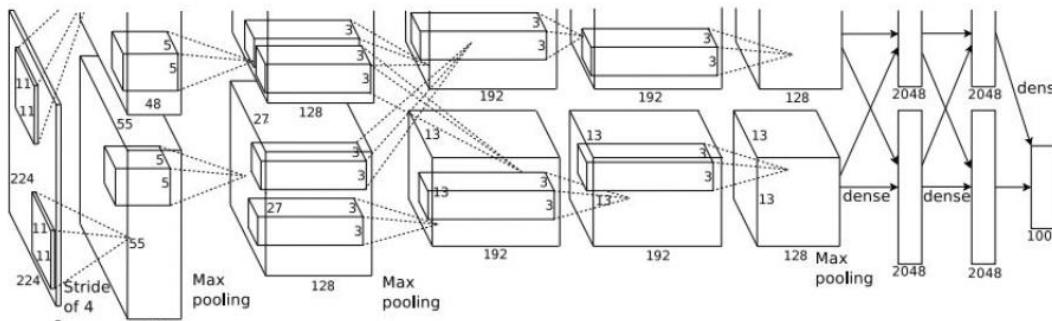
Department Intelligence Science

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Re-cap

Last Time: CNN Architectures

AlexNet



Revolution of Depth

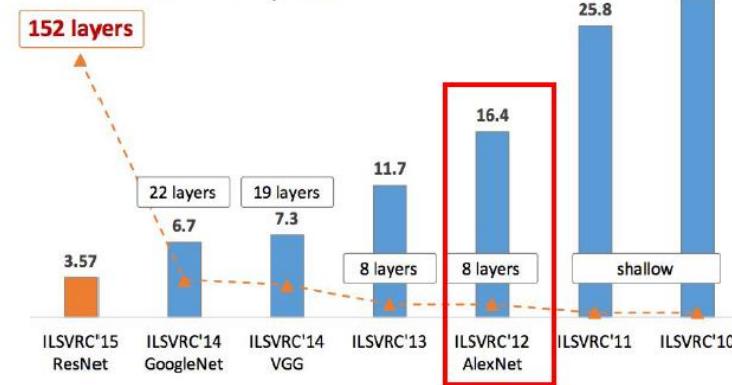
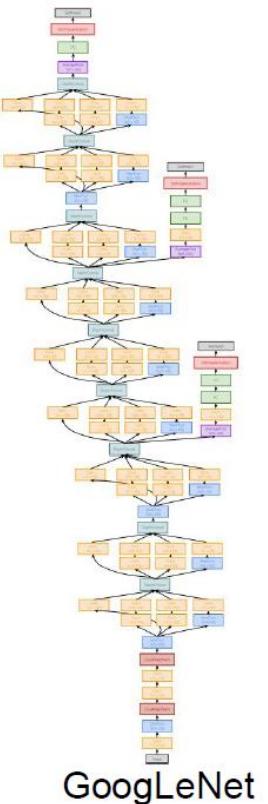
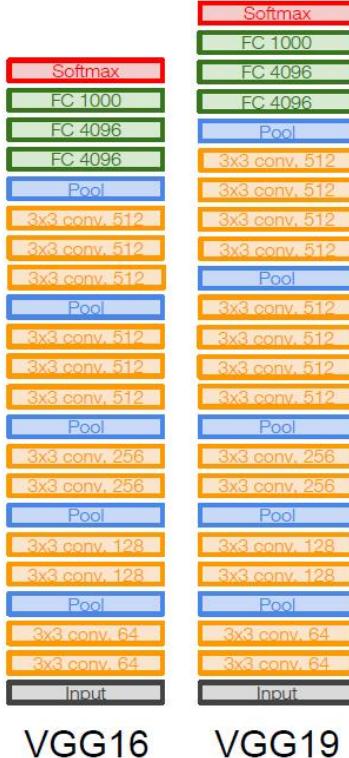


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Re-cap

Last Time: CNN Architectures



Revolution of Depth

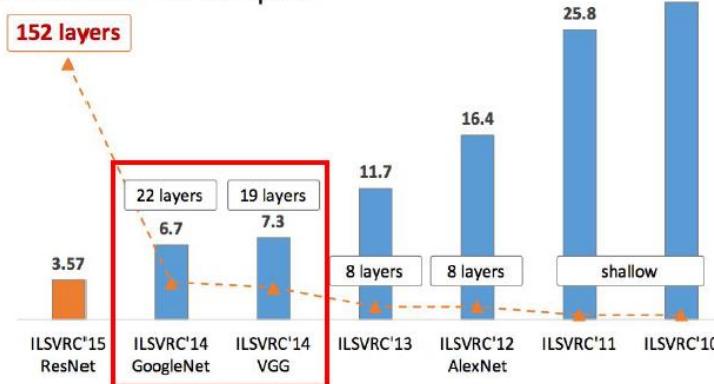
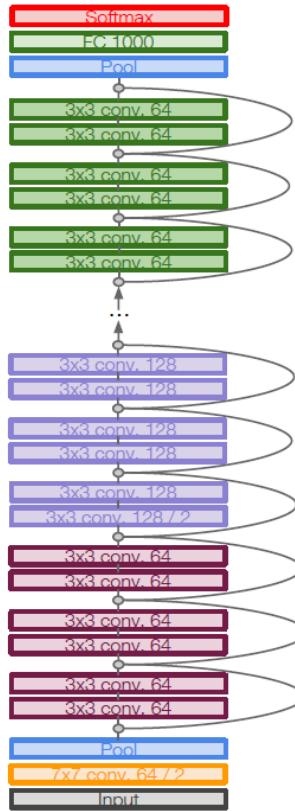
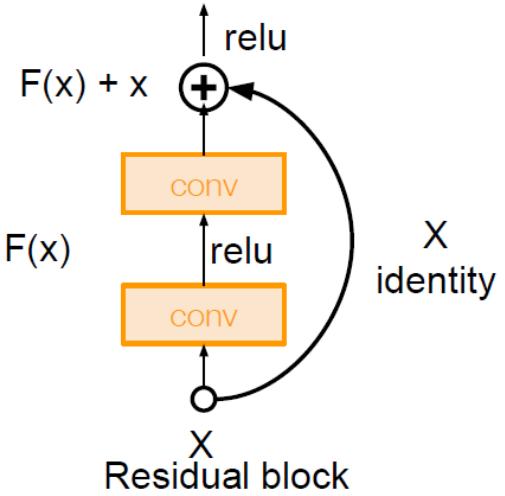


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Re-cap

Last Time: CNN Architectures



Revolution of Depth

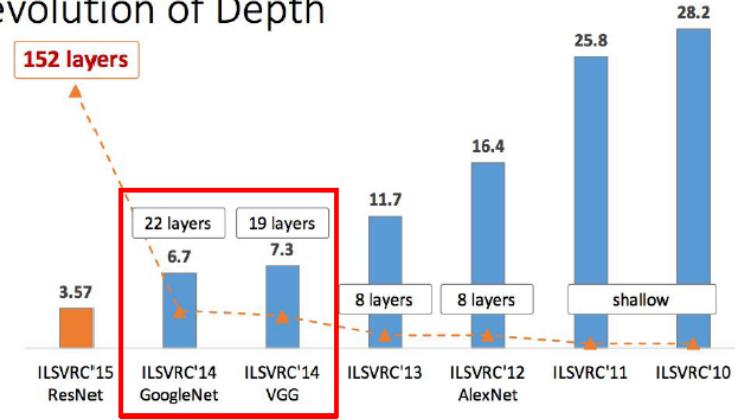
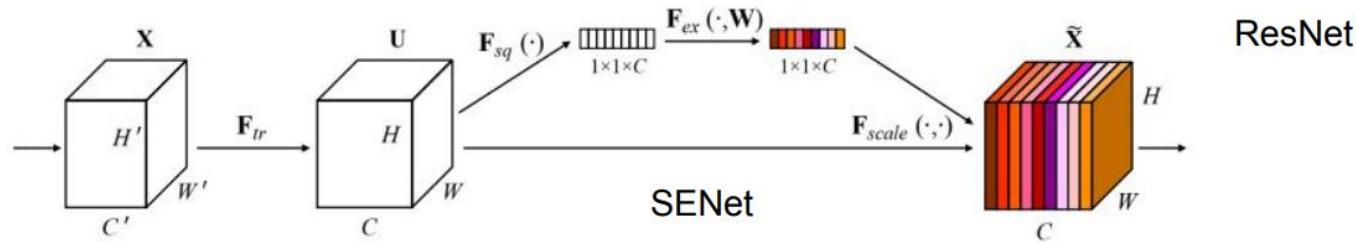
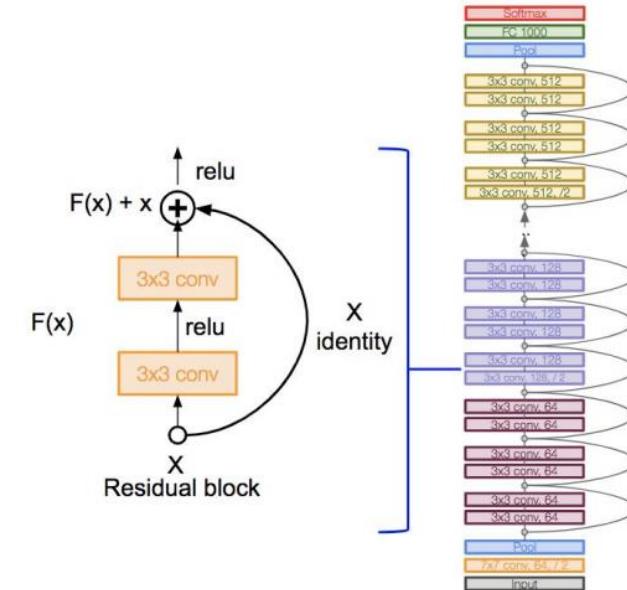
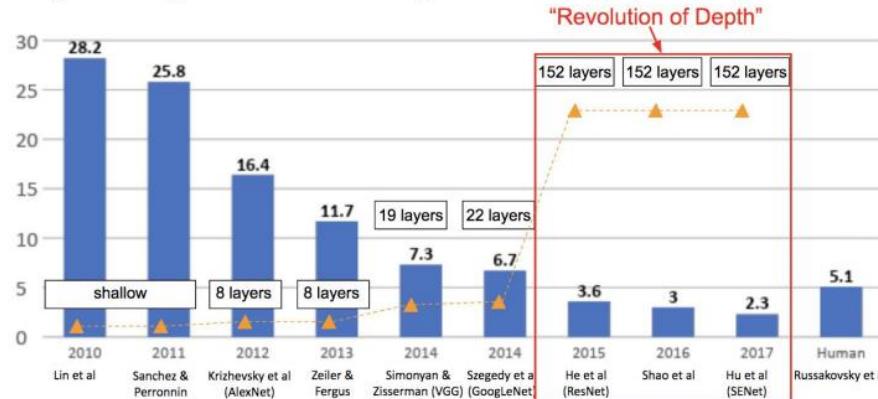


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Last Time: CNN Architectures

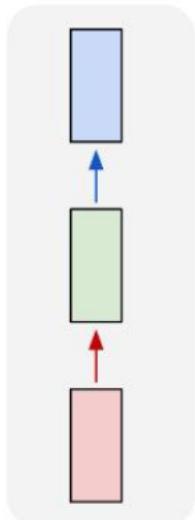
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Today: Recurrent Neural Networks

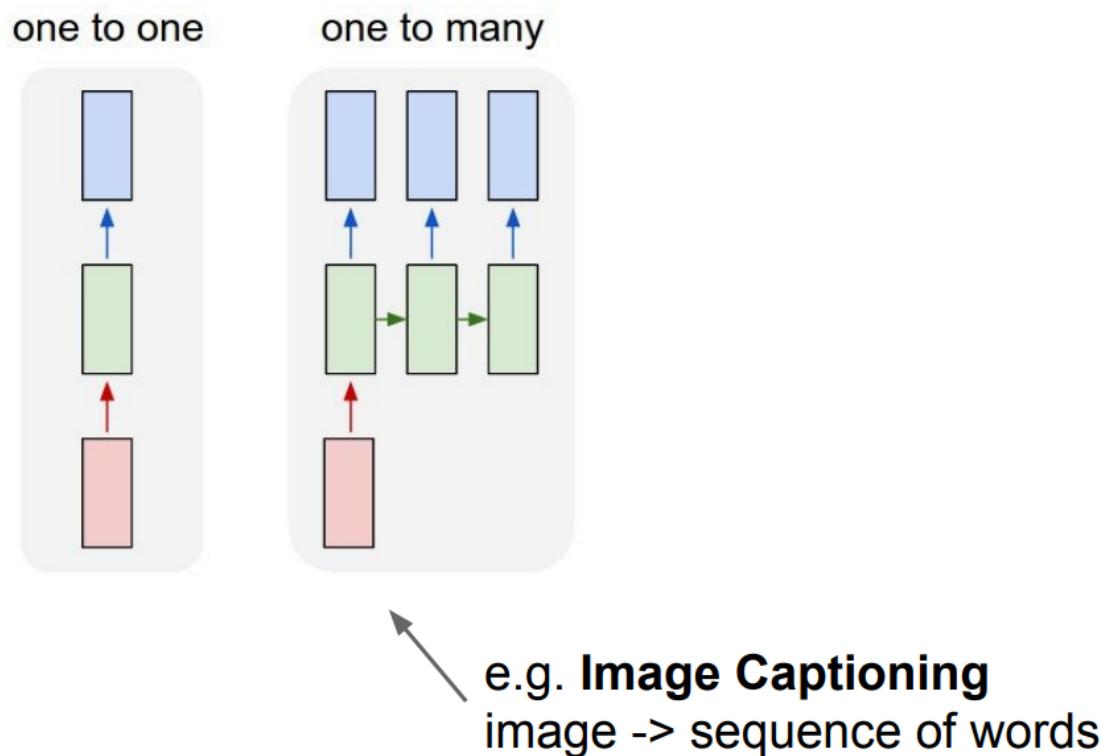
“Vanilla” Neural Network

one to one



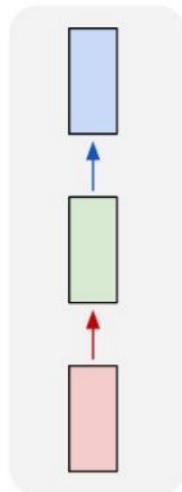
←
Vanilla Neural Networks

Recurrent Neural Networks: Process Sequences

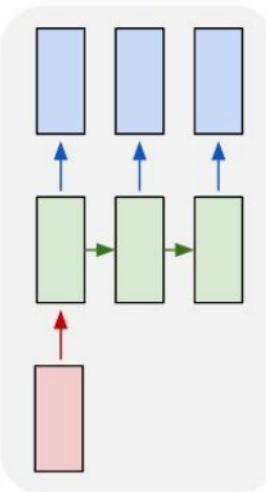


Recurrent Neural Networks: Process Sequences

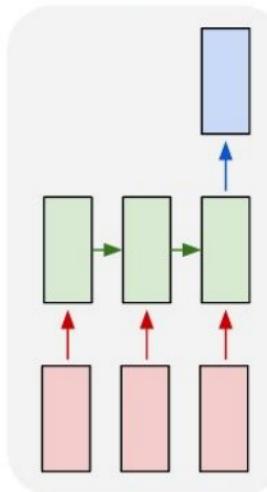
one to one



one to many

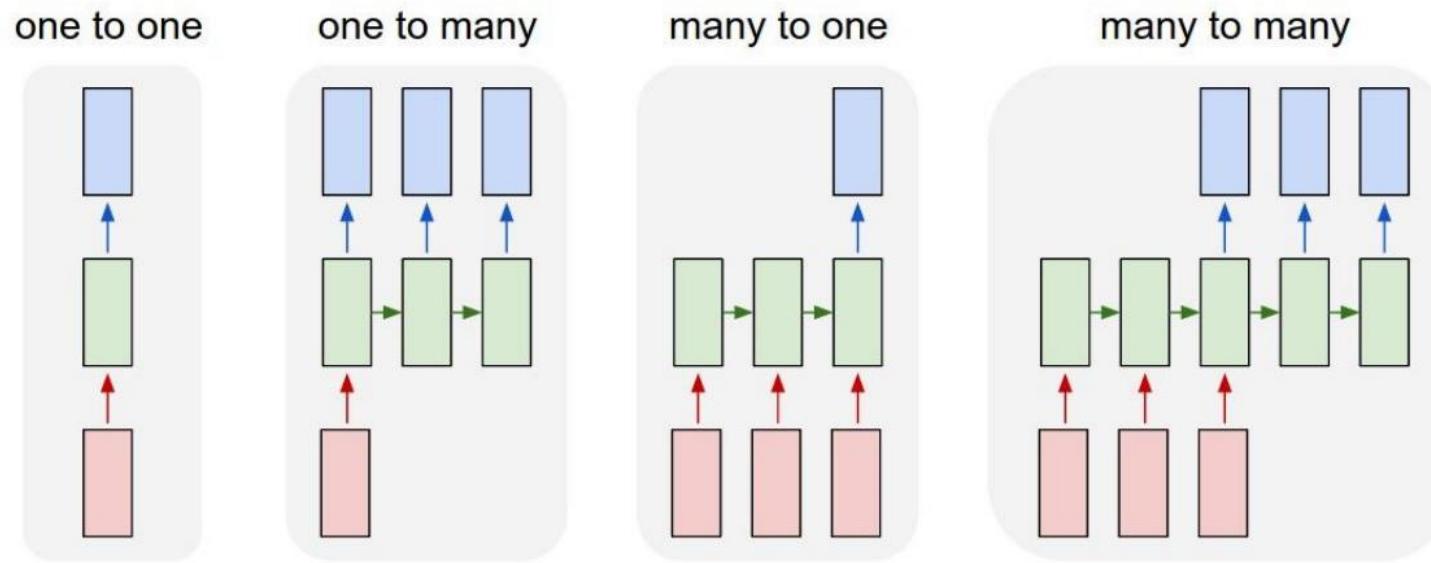


many to one



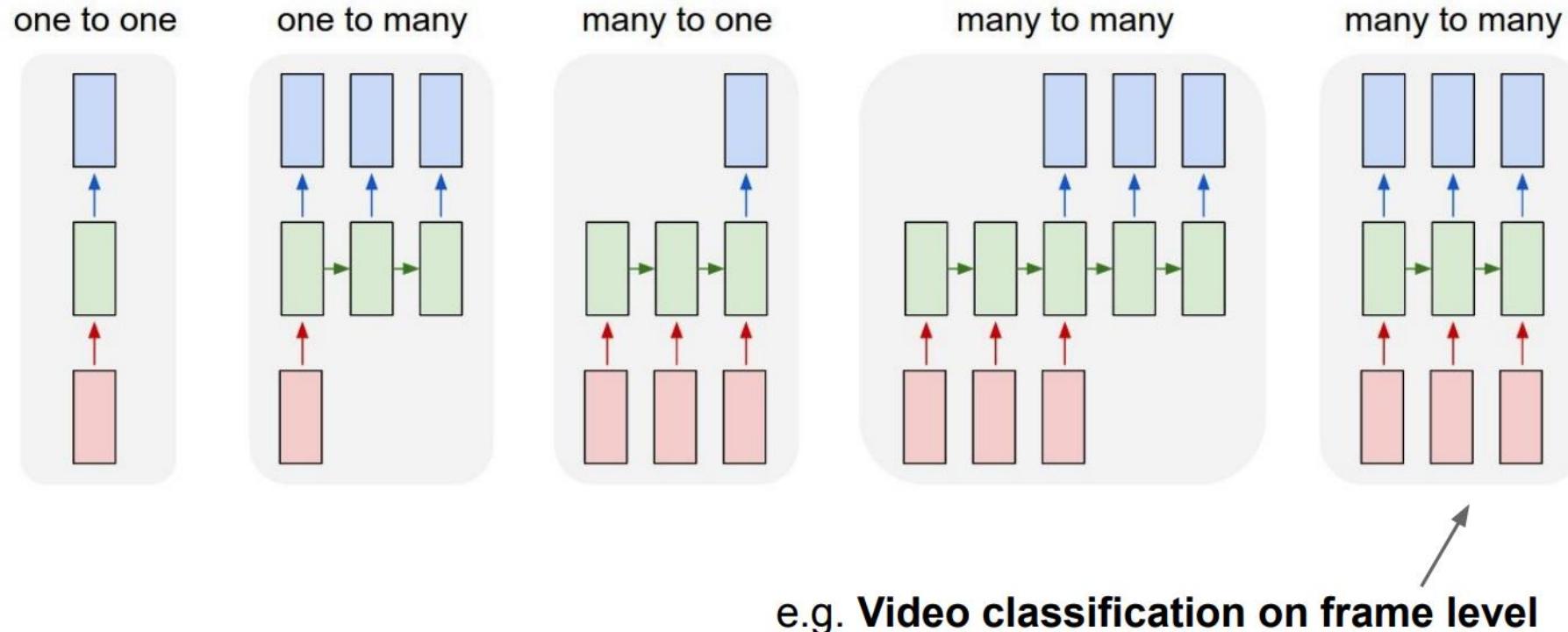
e.g. **action prediction**
sequence of video frames -> action class

Recurrent Neural Networks: Process Sequences



↑
E.g. **Video Captioning**
Sequence of video frames ->
caption

Recurrent Neural Networks: Process Sequences



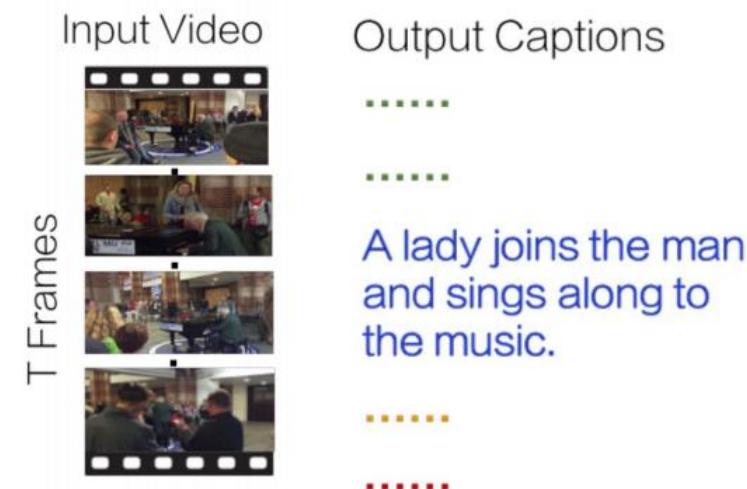
Why existing convnets are insufficient?

Variable sequence length inputs and outputs!

Example task: video captioning

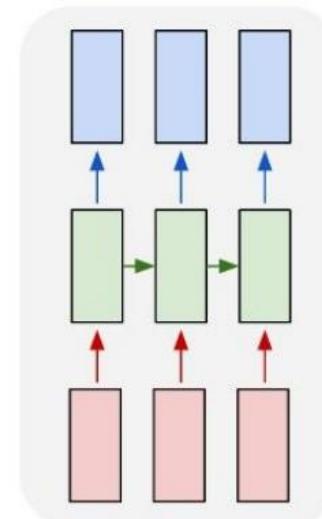
Input video can have variable number of frames

Output captions can be variable length.

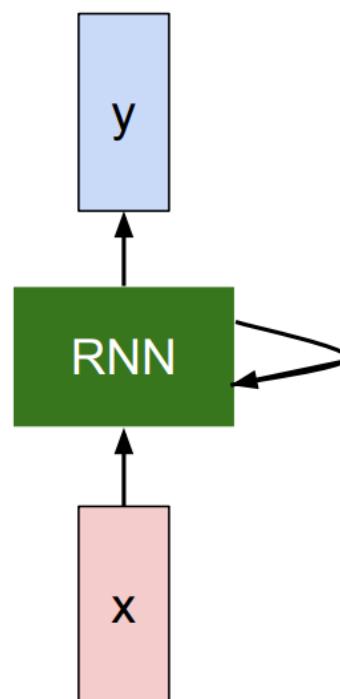


Let's start with a task that takes a variable input and produces an output at every step

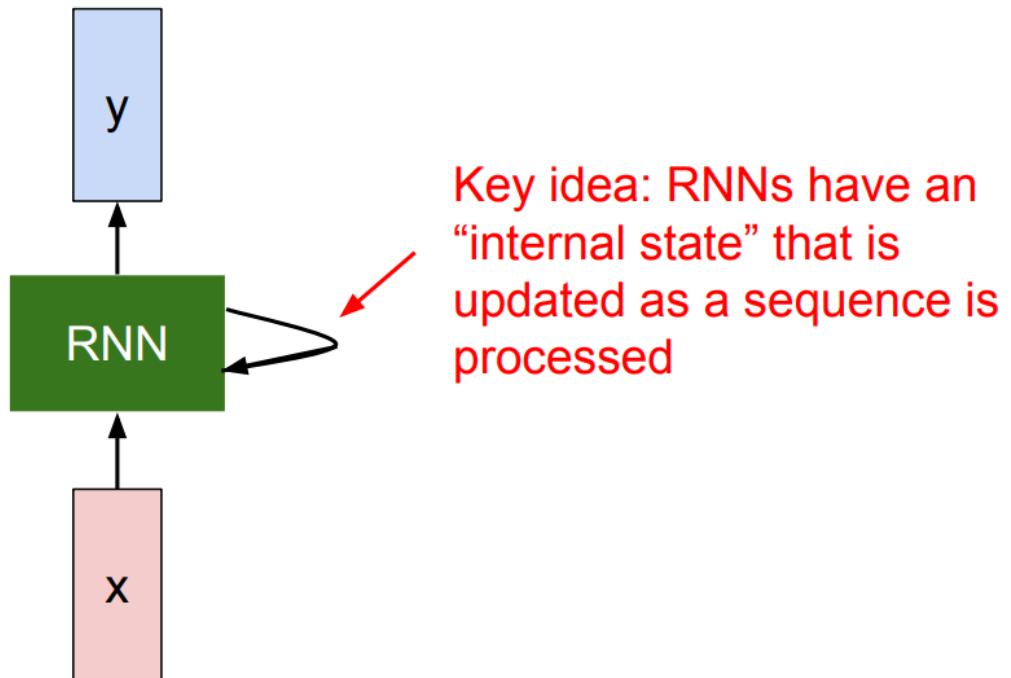
many to many



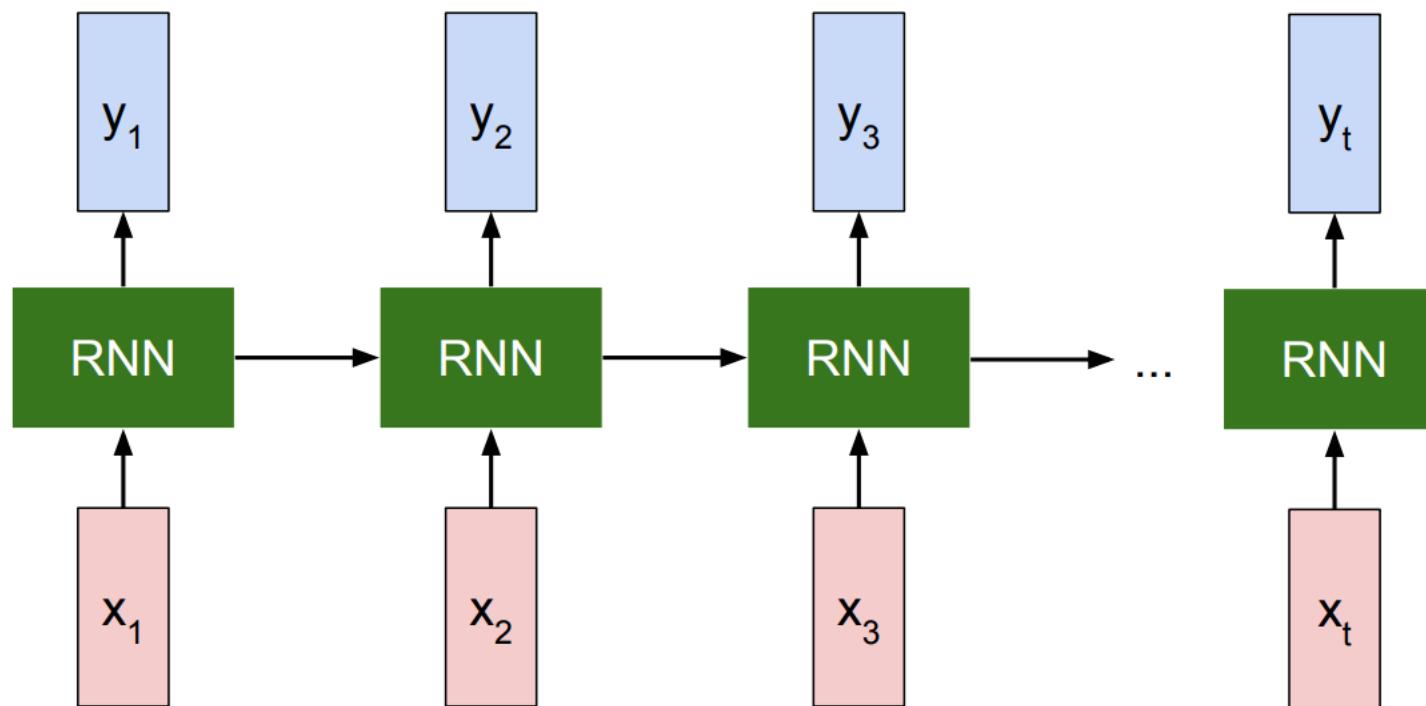
Recurrent Neural Network



Recurrent Neural Network



Unrolled RNN

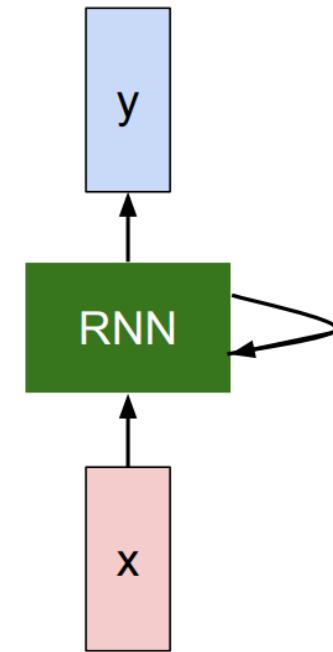


RNN hidden state update

We can process a sequence of vectors \mathbf{x} by applying a **recurrence formula** at every time step:

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

new state / old state input vector at
 \ some function some time step
 some function
 with parameters W

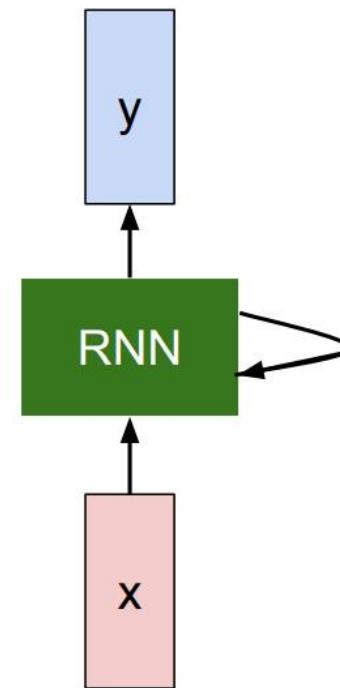


RNN output generation

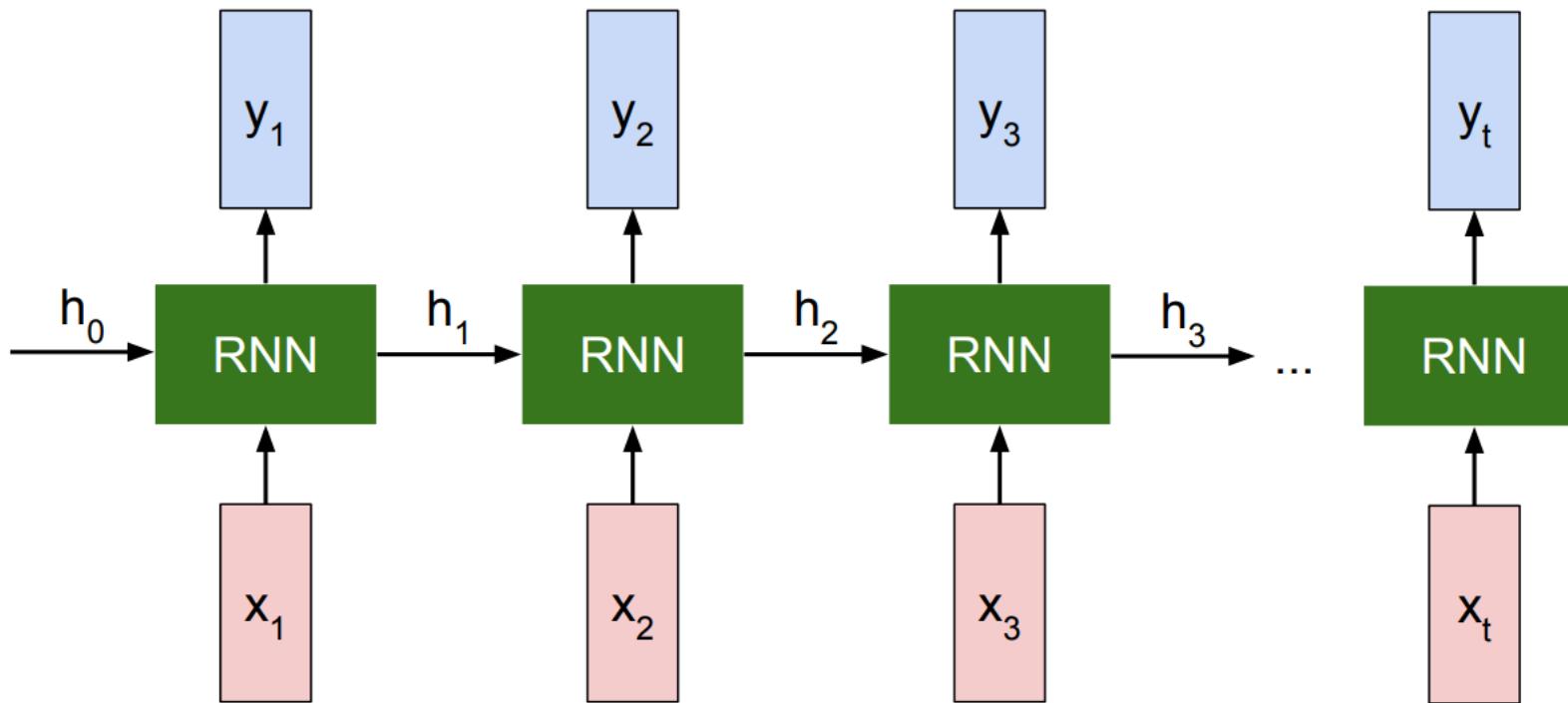
We can process a sequence of vectors \mathbf{x} by applying a **recurrence formula** at every time step:

$$y_t = f_{W_{hy}}(h_t)$$

output new state
another function
with parameters W_o



Recurrent Neural Network

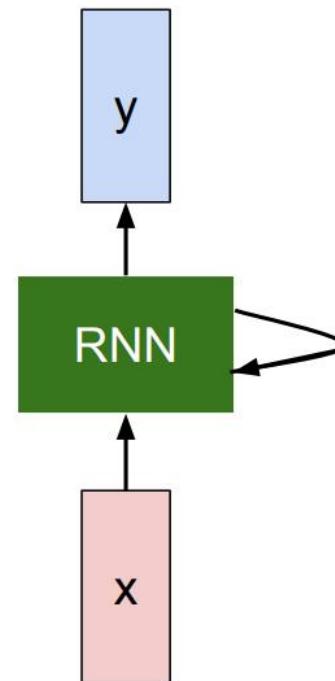


Recurrent Neural Network

We can process a sequence of vectors \mathbf{x} by applying a **recurrence formula** at every time step:

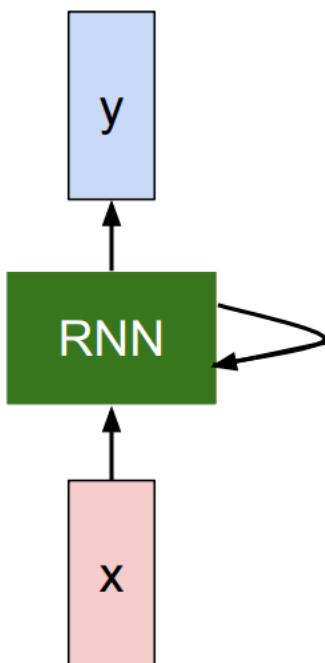
$$h_t = f_W(h_{t-1}, x_t)$$

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



(Simple) Recurrent Neural Network

The state consists of a single “*hidden*” vector \mathbf{h} :



$$\mathbf{h}_t = f_W(\mathbf{h}_{t-1}, \mathbf{x}_t)$$

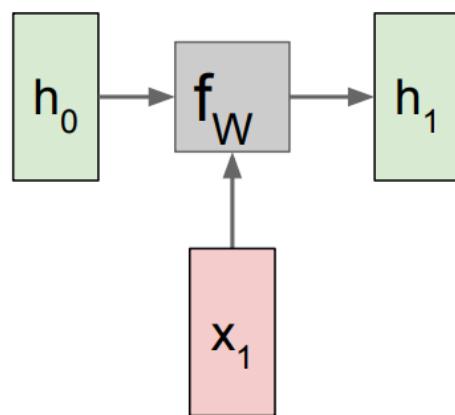


$$\mathbf{h}_t = \tanh(\mathbf{W}_{hh}\mathbf{h}_{t-1} + \mathbf{W}_{xh}\mathbf{x}_t)$$

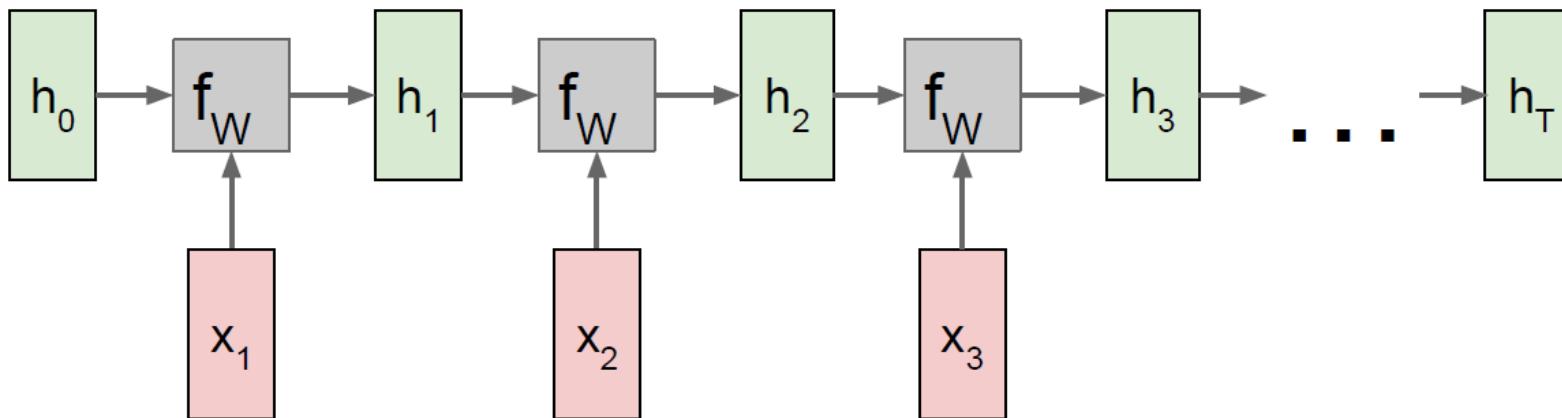
$$\mathbf{y}_t = \mathbf{W}_{hy}\mathbf{h}_t$$

Sometimes called a “Vanilla RNN” or an
“Elman RNN” after Prof. Jeffrey Elman

RNN: Computational Graph

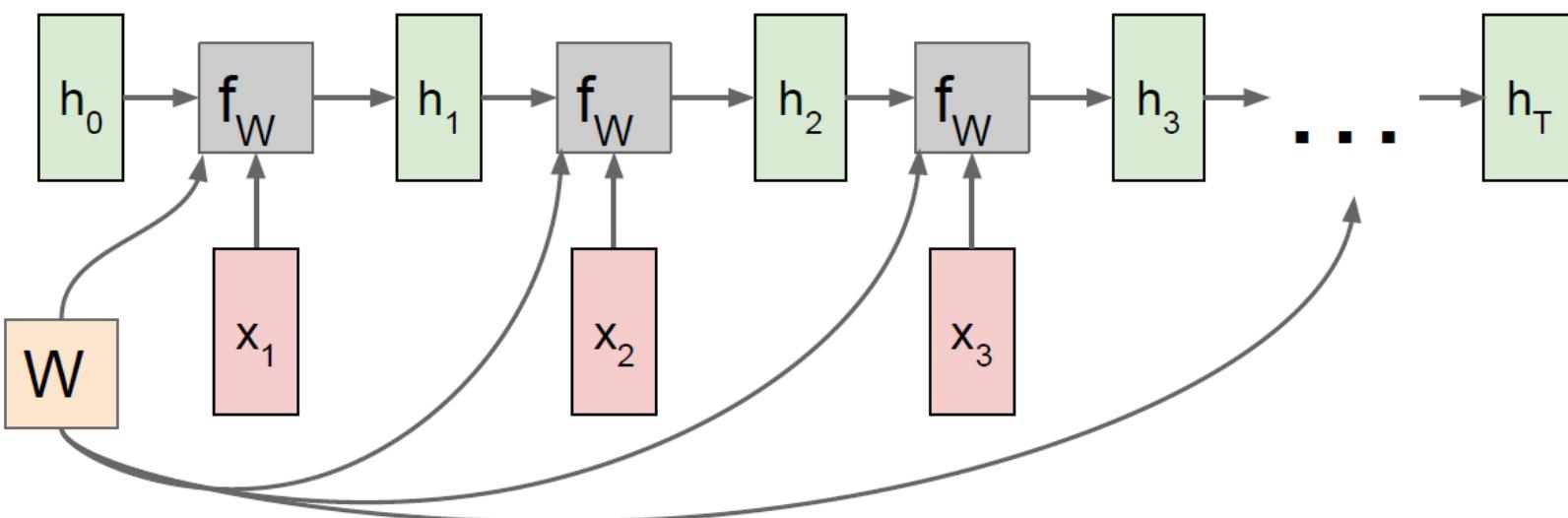


RNN: Computational Graph

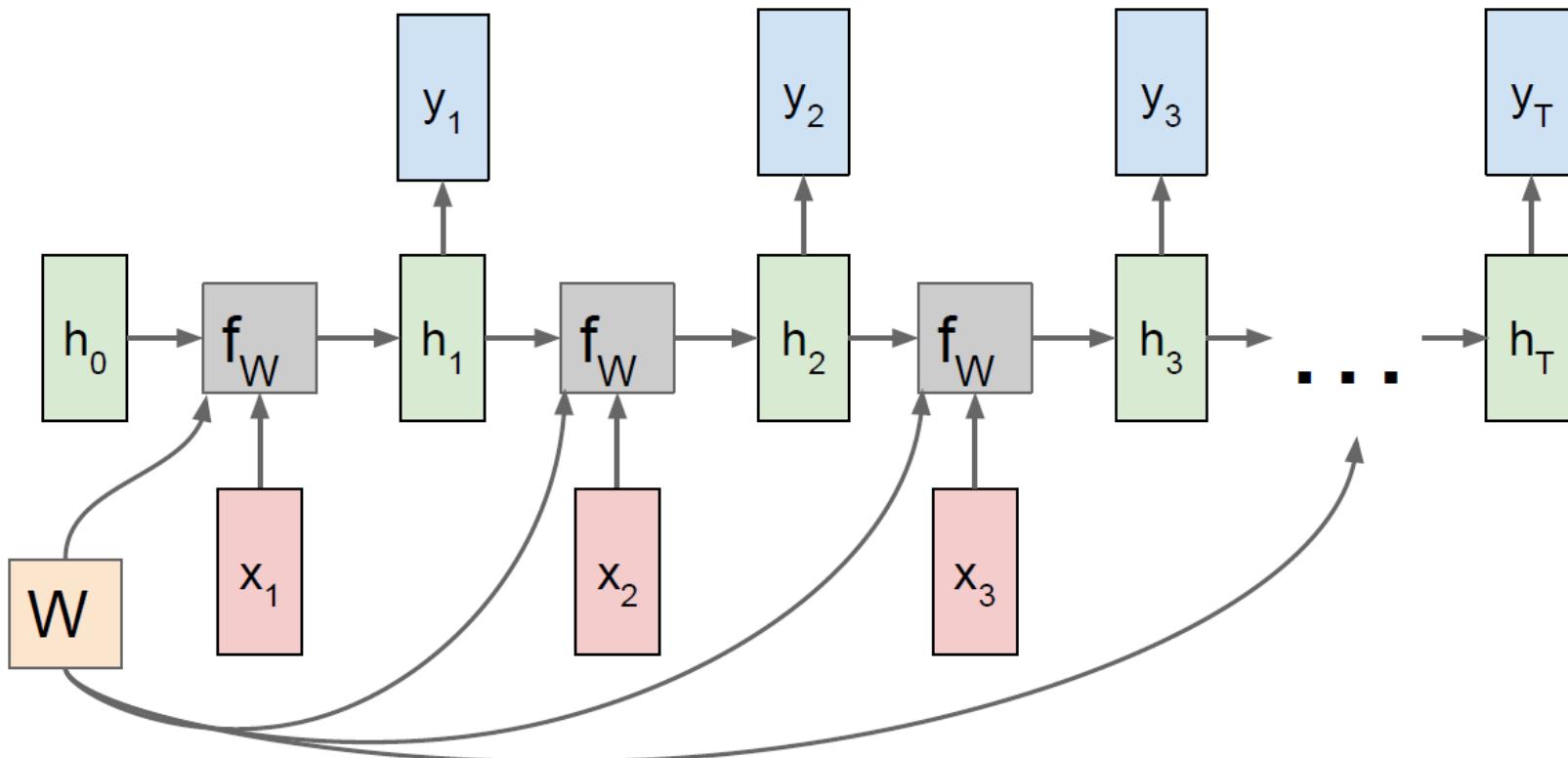


RNN: Computational Graph

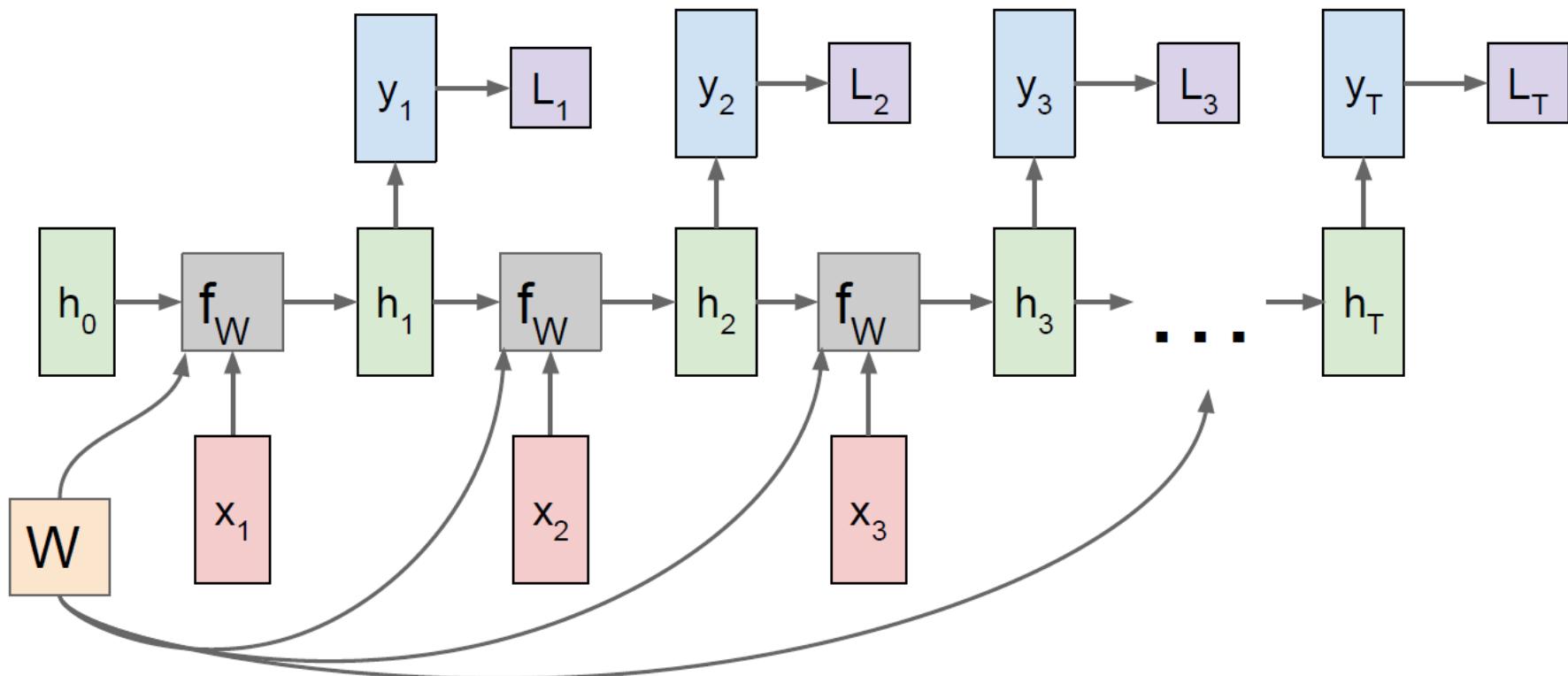
Re-use the same weight matrix at every time-step



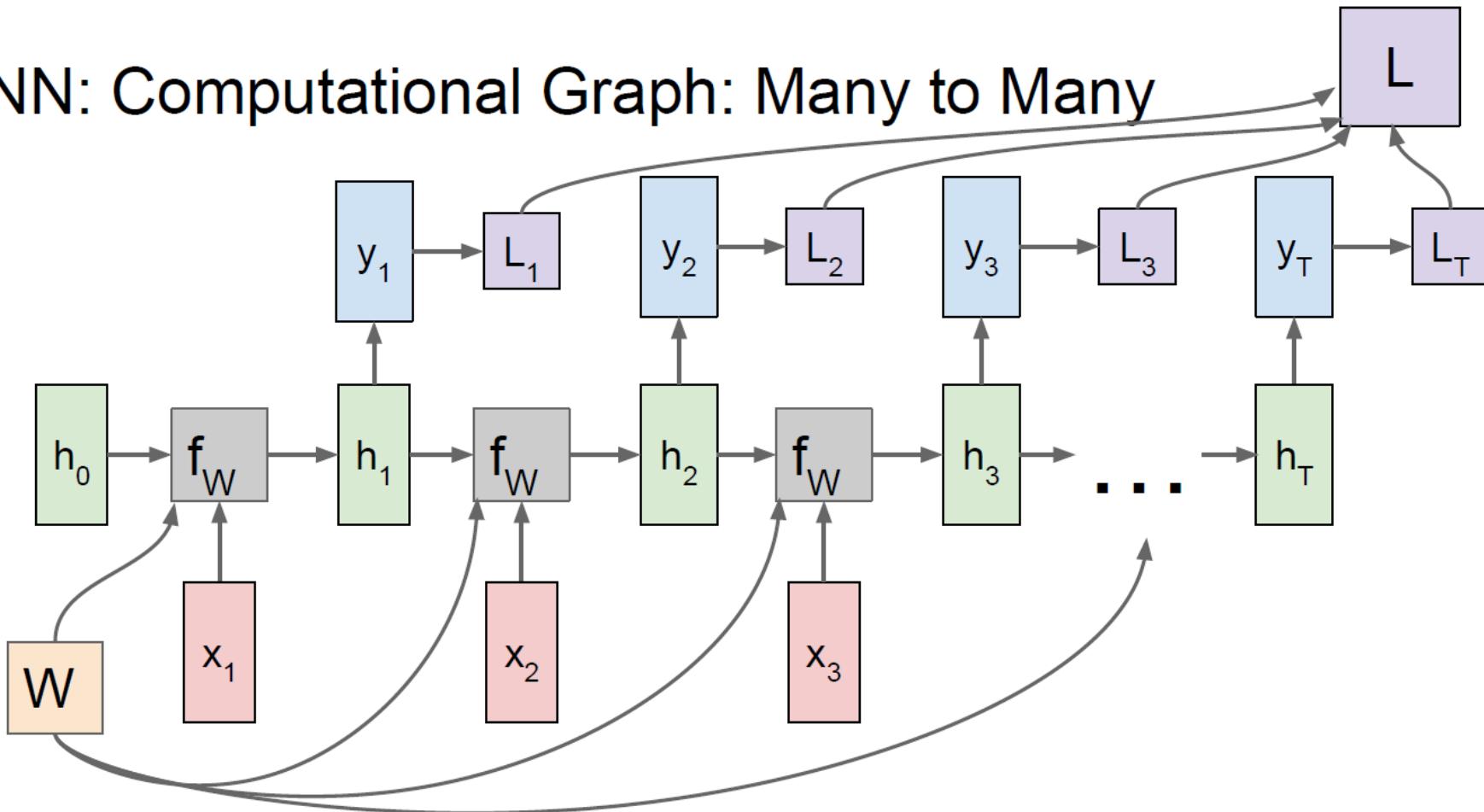
RNN: Computational Graph: Many to Many



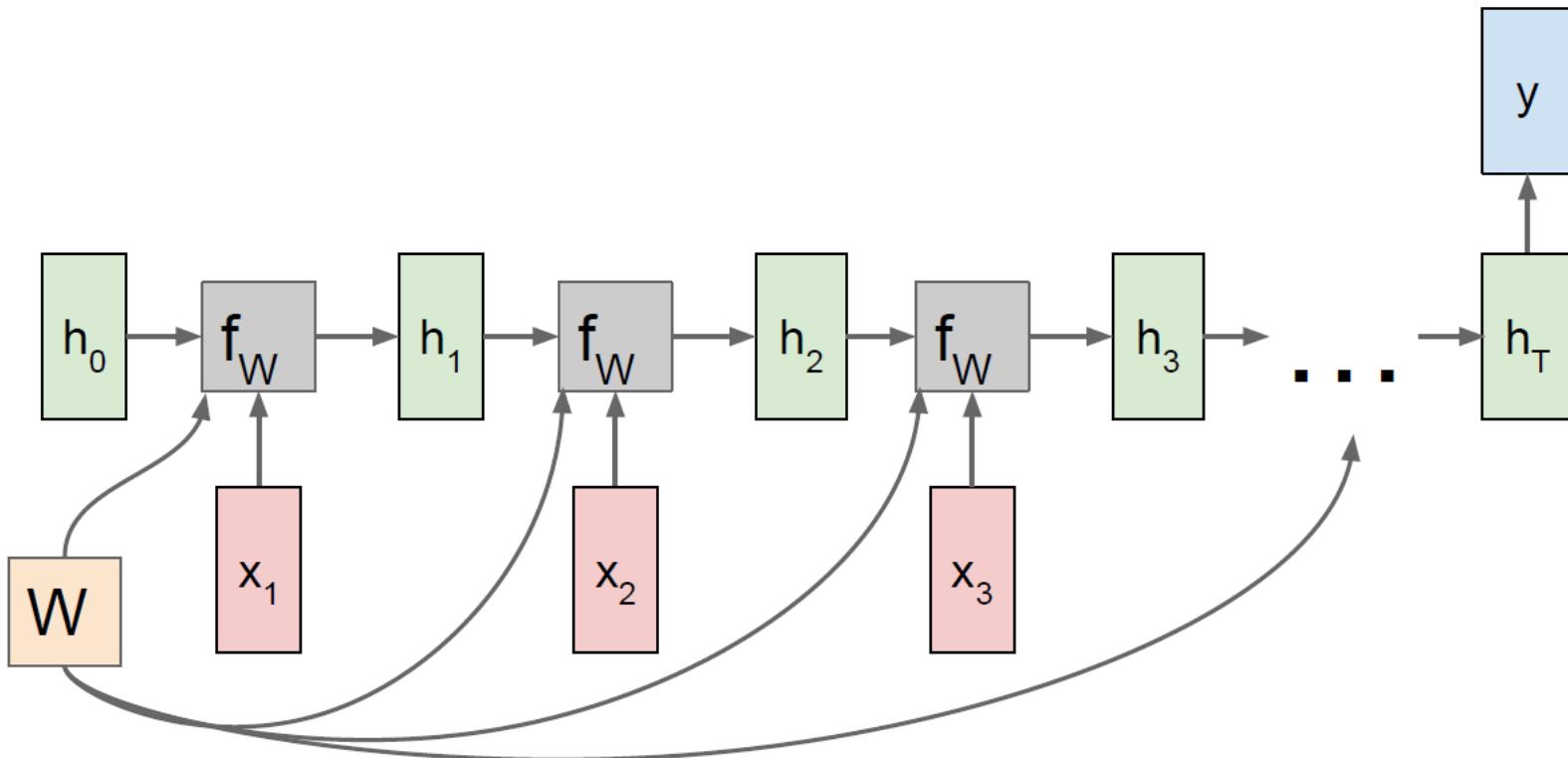
RNN: Computational Graph: Many to Many



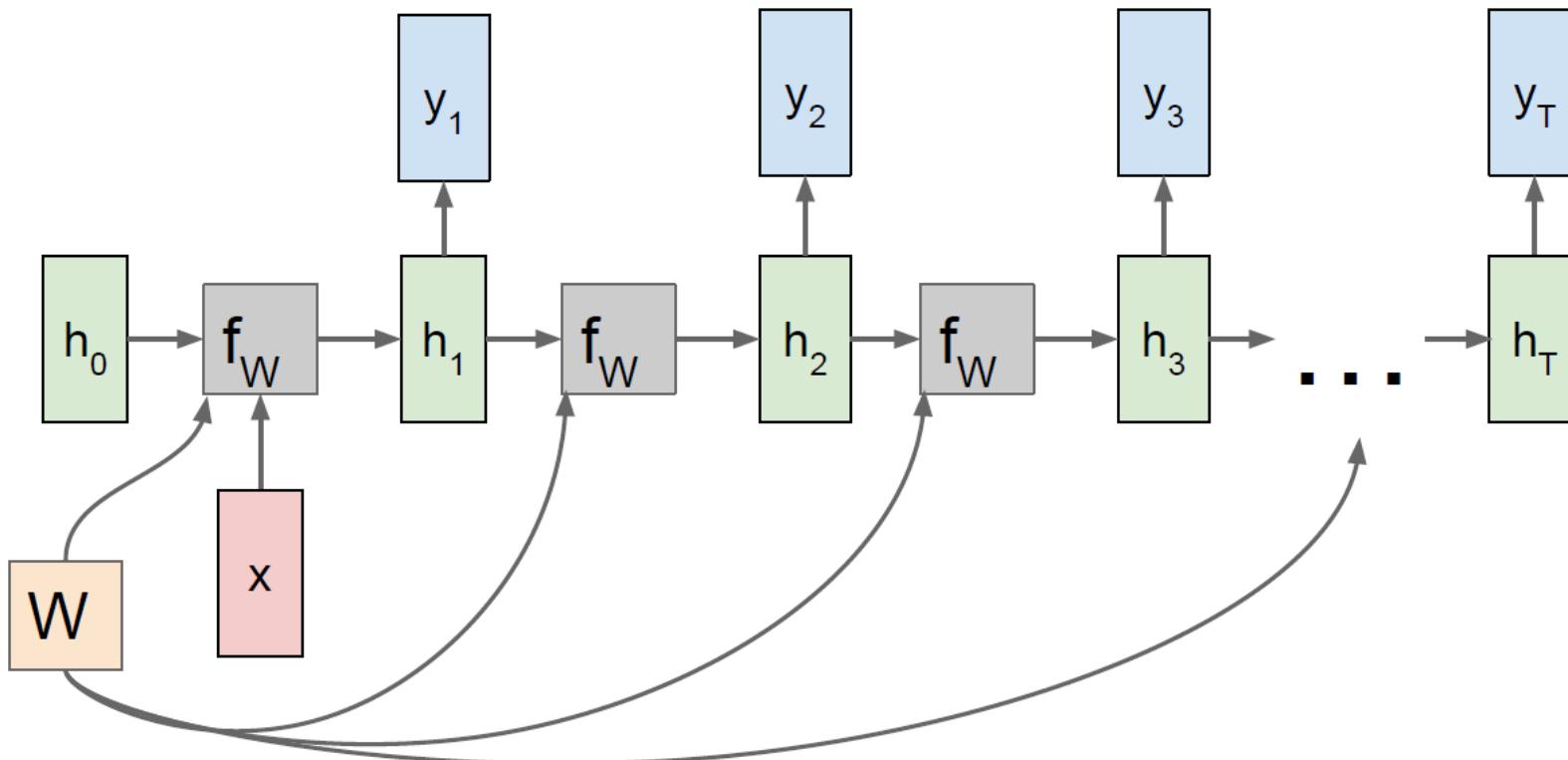
RNN: Computational Graph: Many to Many



RNN: Computational Graph: Many to One

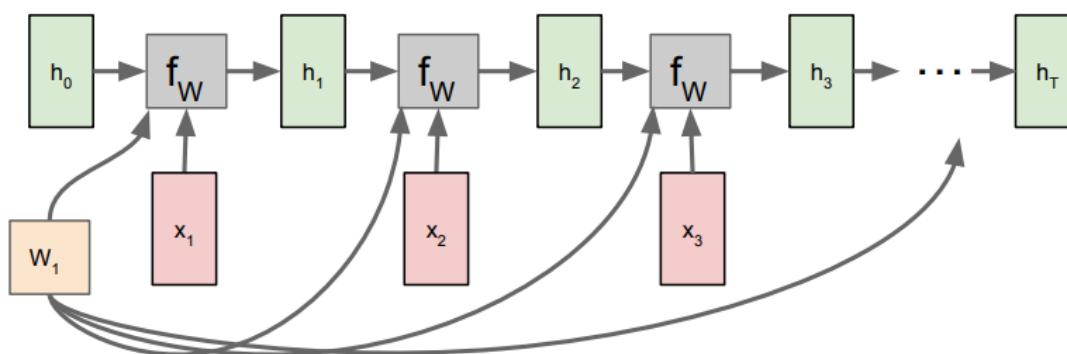


RNN: Computational Graph: One to Many



Sequence to Sequence: Many-to-one + one-to-many

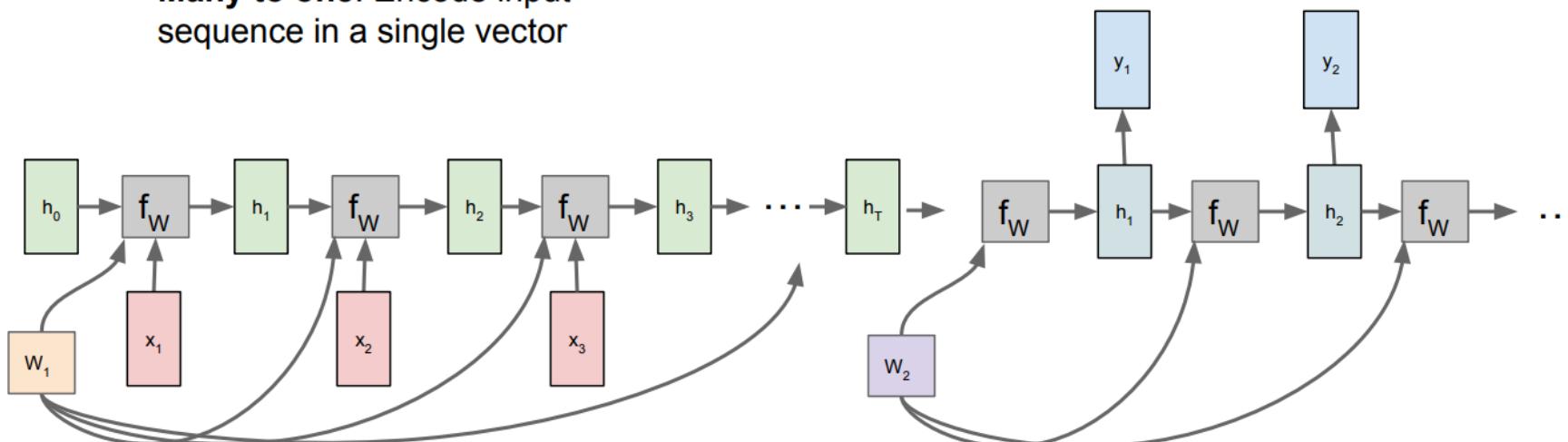
Many to one: Encode input sequence in a single vector



Sequence to Sequence: Many-to-one + one-to-many

Many to one: Encode input sequence in a single vector

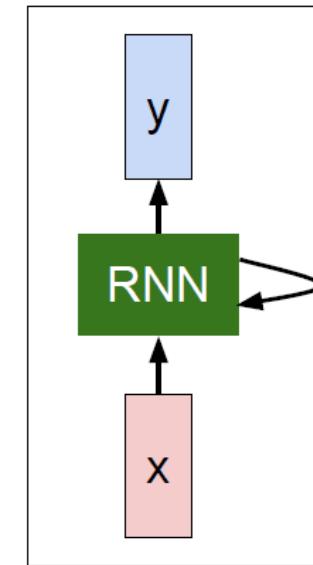
One to many: Produce output sequence from single input vector



Character-level language model example

Vocabulary:
[h,e,l,o]

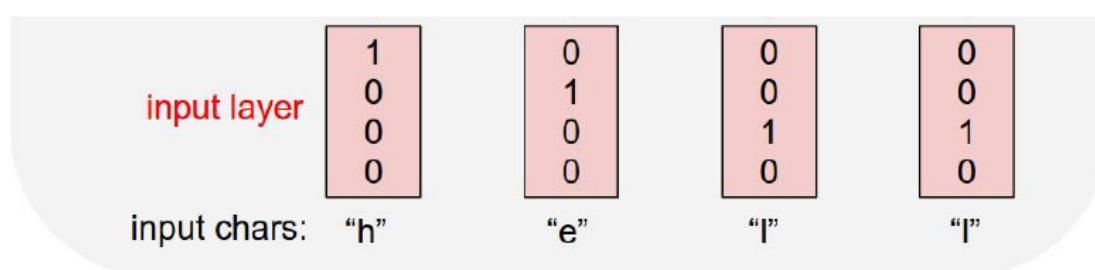
Example training
sequence:
“hello”



Character-level language model example

Vocabulary:
[h,e,l,o]

Example training
sequence:
“hello”

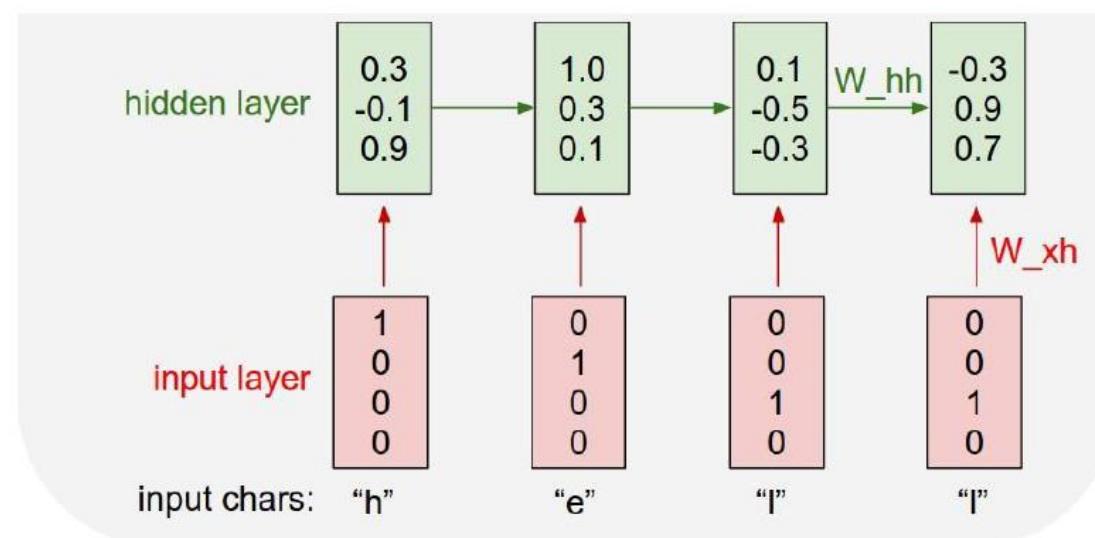


Character-level language model example

Vocabulary:
[h,e,l,o]

Example training
sequence:
“hello”

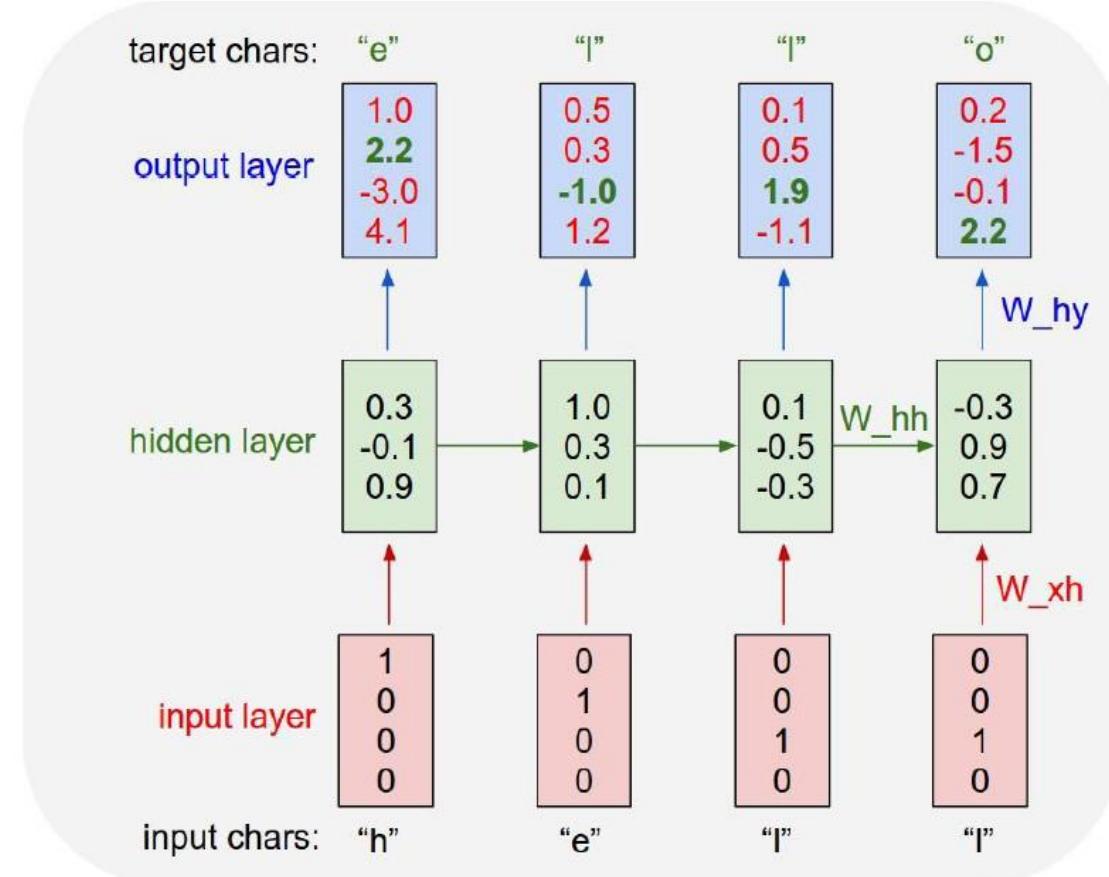
$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$



Character-level language model example

Vocabulary:
[h,e,l,o]

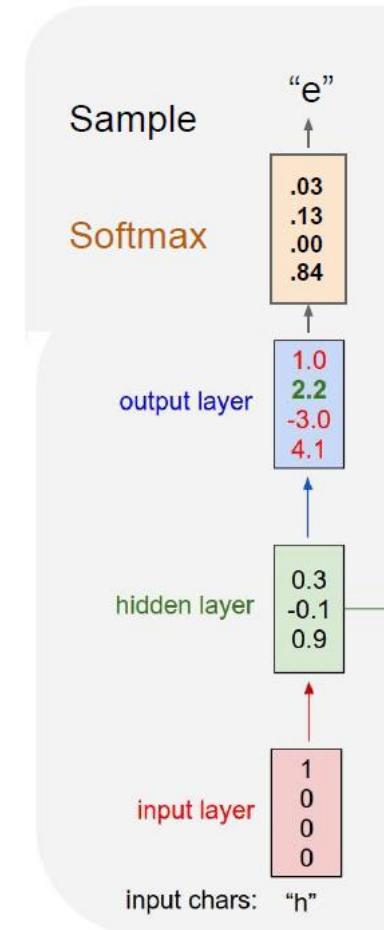
Example training
sequence:
“hello”



Example: Character-level Language Model Sampling

Vocabulary:
[h,e,l,o]

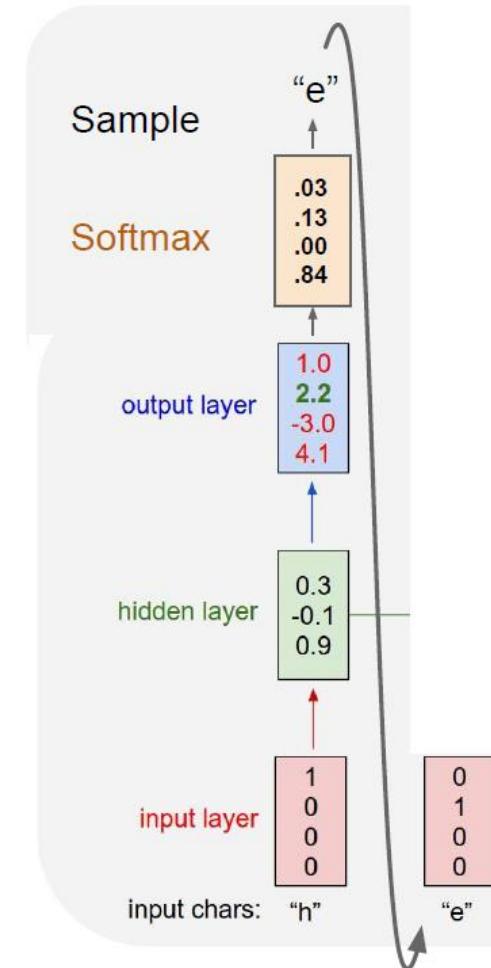
At test-time sample
characters one at a time,
feed back to model



Example: Character-level Language Model Sampling

Vocabulary:
[h,e,l,o]

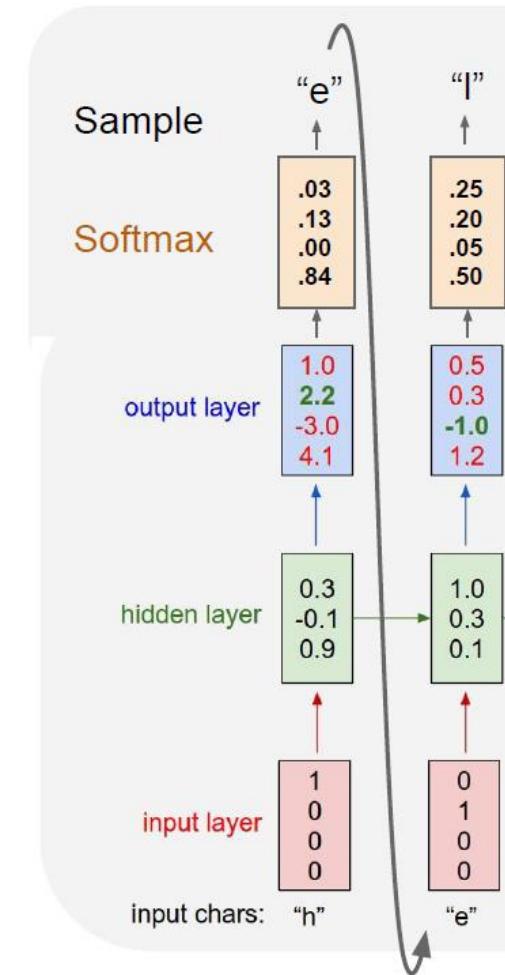
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Example: Character-level Language Model Sampling

Vocabulary:
[h,e,l,o]

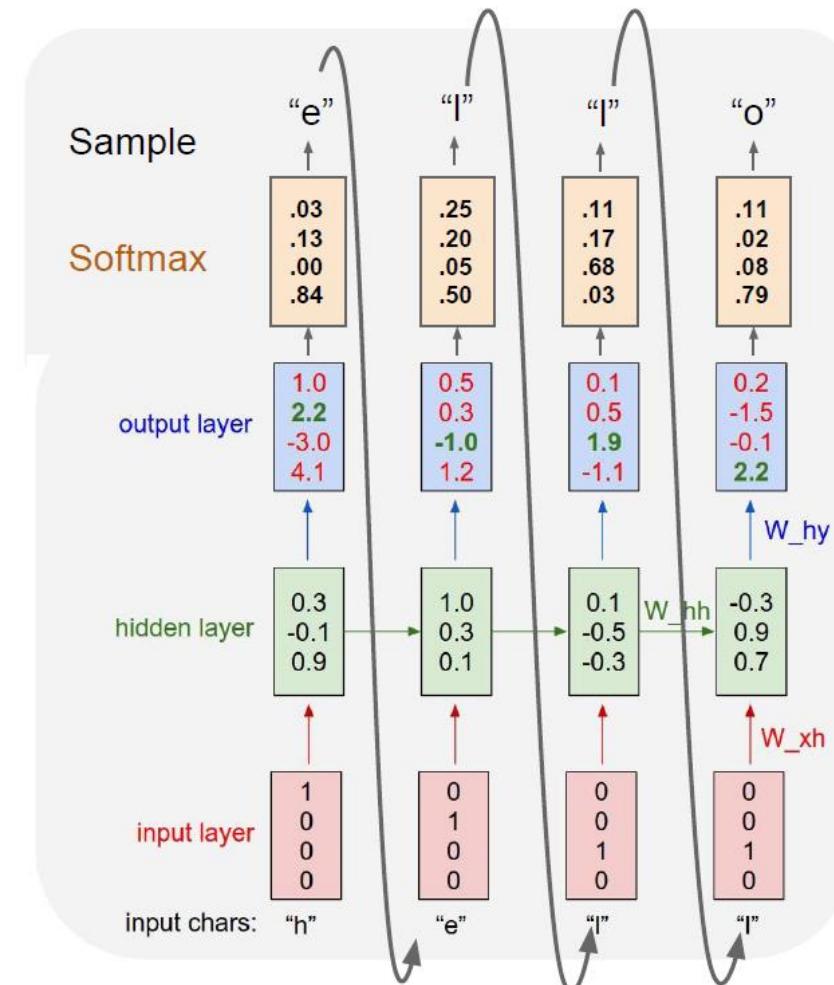
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Example: Character-level Language Model Sampling

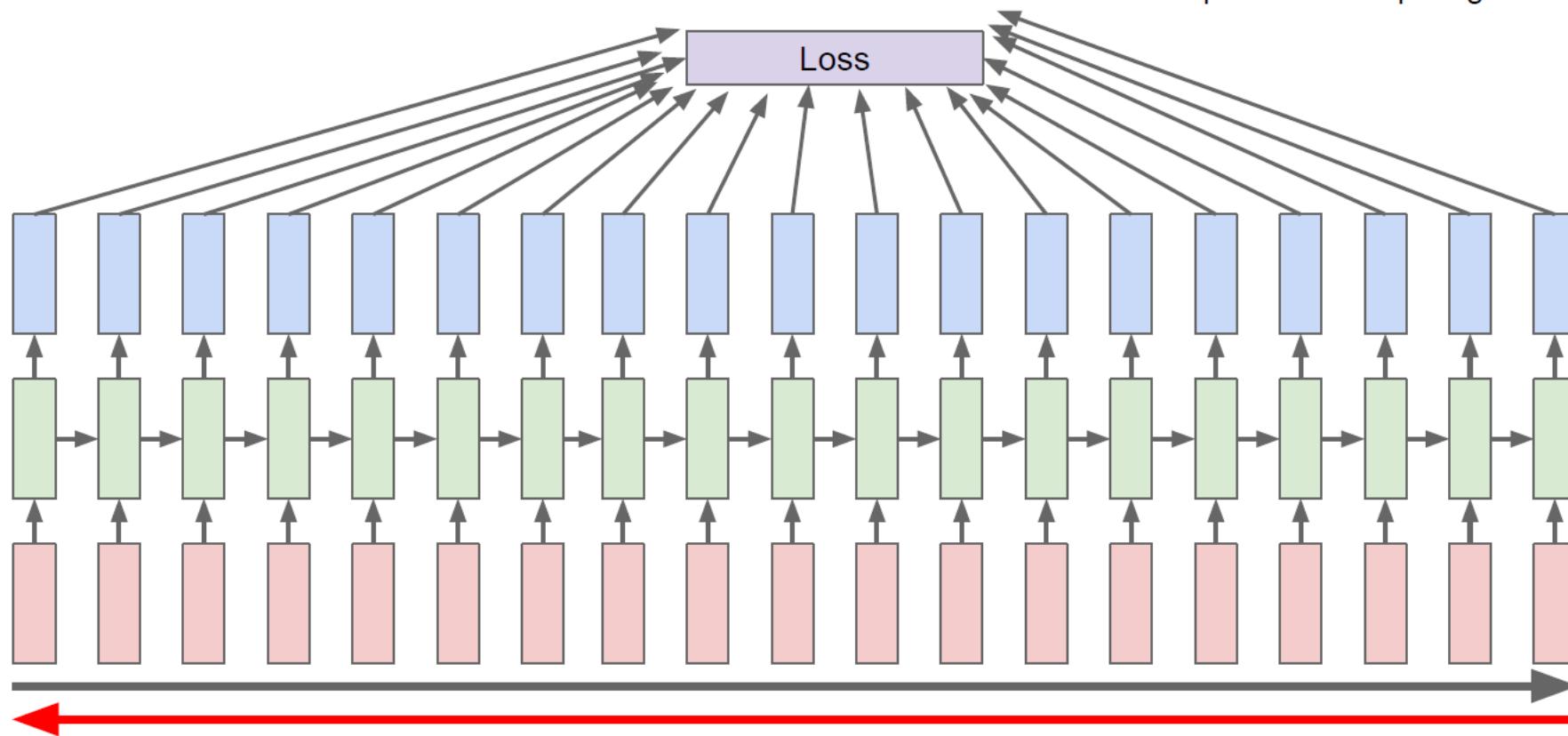
Vocabulary:
[h,e,l,o]

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

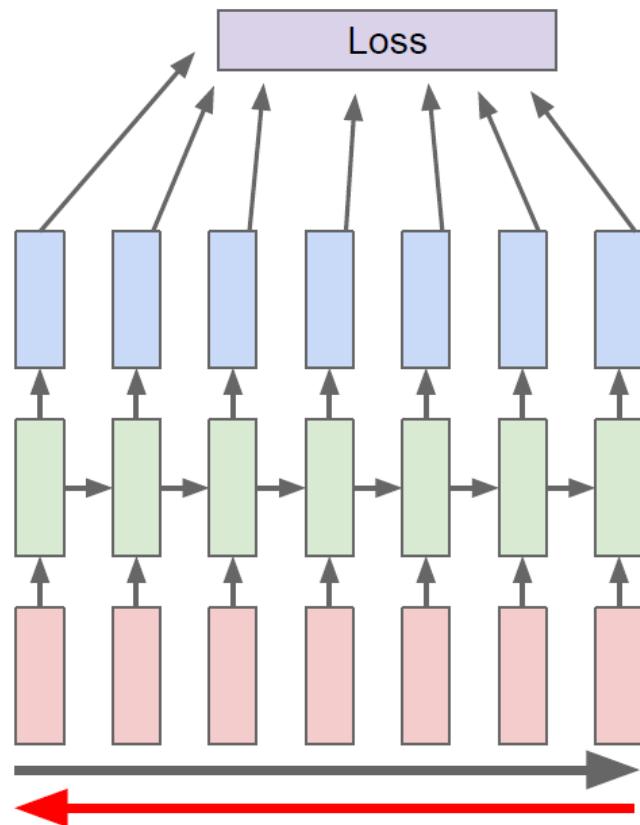


Backpropagation through time

Forward through entire sequence to compute loss, then backward through entire sequence to compute gradient

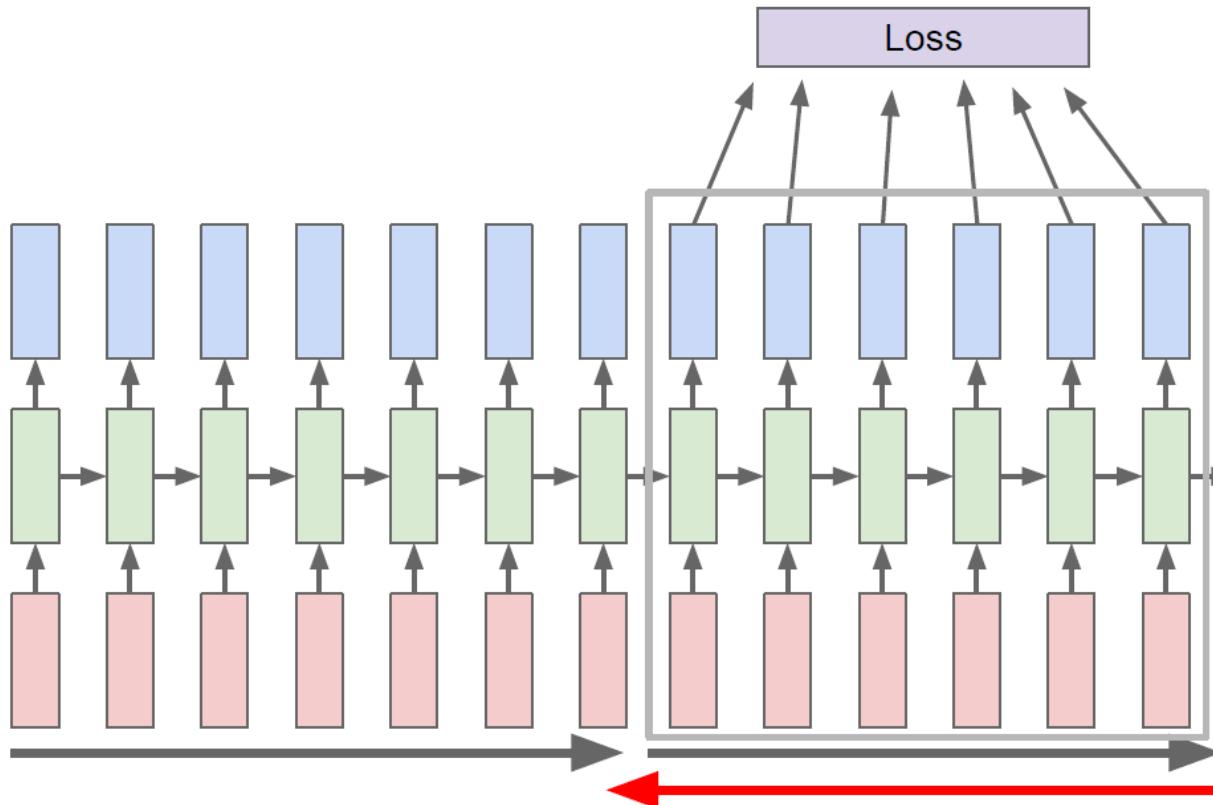


Truncated Backpropagation through time



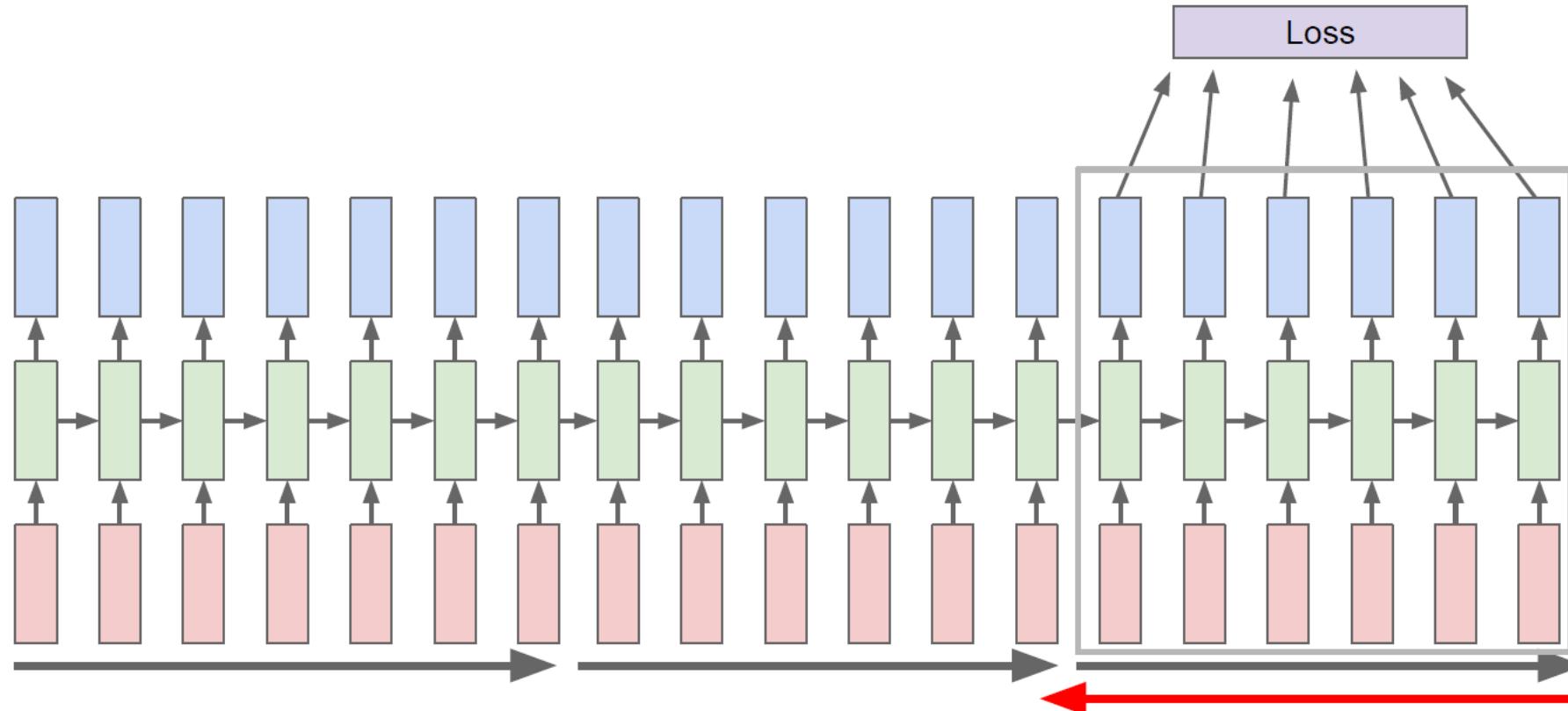
Run forward and backward
through chunks of the
sequence instead of whole
sequence

Truncated Backpropagation through time



Carry hidden states
forward in time forever,
but only backpropagate
for some smaller
number of steps

Truncated Backpropagation through time



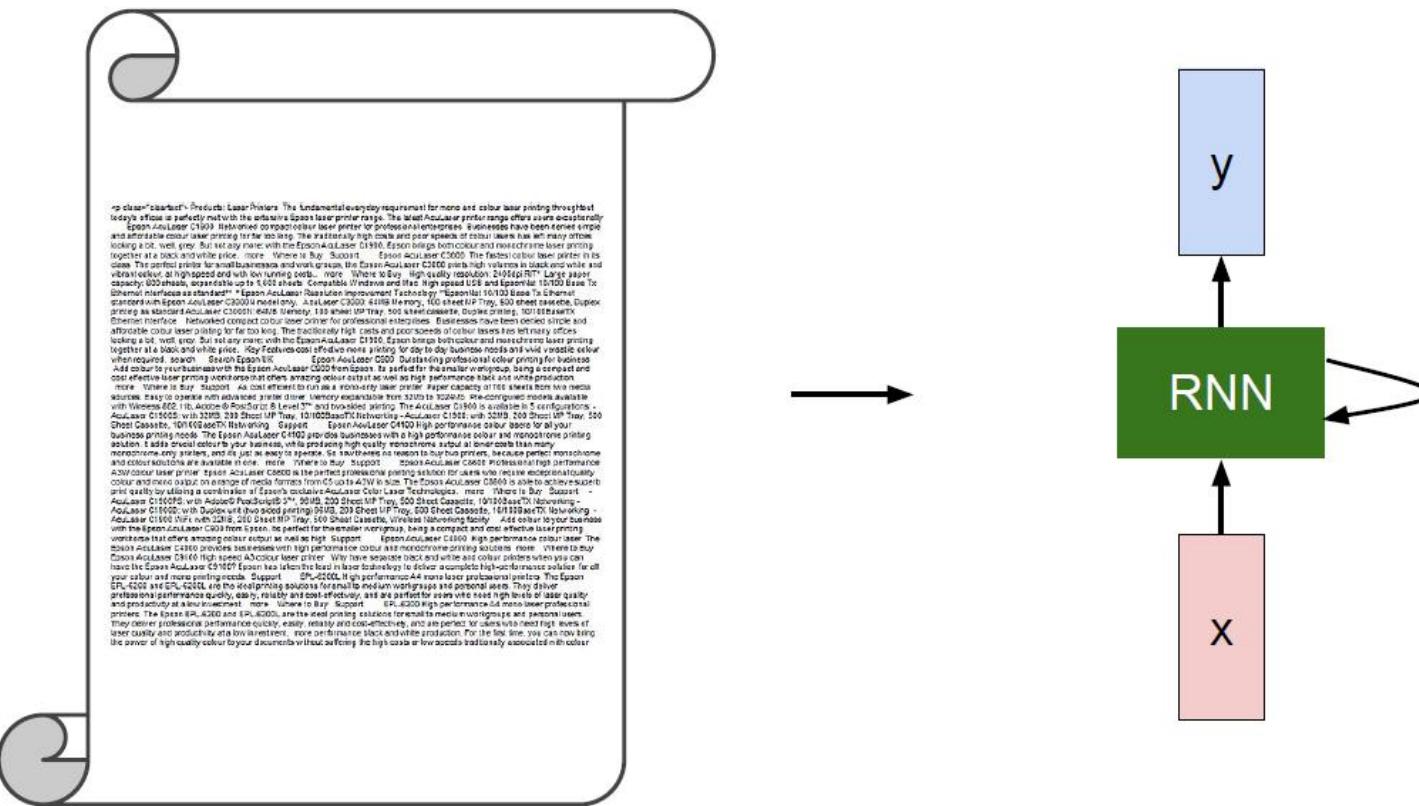
min-char-rnn.py gist: 112 lines of Python

```

1  #!/usr/bin/python
2  #
3  # Minimal character-level Vanilla RNN model. Written by Andrej Karpathy (@karpathy)
4  # BSD License
5  #
6  # import numpy as np
7  #
8  # data I/O
9  # data = open('input.txt', 'r').read() # should be simple plain text file
10 # chars = list(set(data))
11 # data_size, vocab_size = len(data), len(chars)
12 # print ('data has %d characters, %d unique.' % (data_size, vocab_size))
13 # char_to_ix = { ch:i for i,ch in enumerate(chars) }
14 # ix_to_char = { i:ch for i,ch in enumerate(chars) }
15 #
16 # hyperparameters
17 hidden_size = 100 # size of hidden layer of neurons
18 seq_length = 20 # number of steps to unroll the RNN for
19 learning_rate = 1e-1
20
21 # model parameters
22 wkh = np.random.randn(hidden_size, vocab_size)*0.01 # input to hidden
23 whh = np.random.randn(hidden_size, hidden_size)*0.01 # hidden to hidden
24 why = np.random.randn(vocab_size, hidden_size)*0.01 # hidden to output
25 bh = np.zeros((hidden_size, 1)) # hidden bias
26 by = np.zeros((vocab_size, 1)) # output bias
27
28 def lossFun(inputs, targets, hprev):
29     """ 
30     inputs,targets are both list of integers.
31     hprev is hdim array of initial hidden state.
32     returns the loss, gradients on model parameters, and last hidden state
33     """
34
35     xs, hs, ys, ps = [], [], [], []
36     hsi = hprev
37     loss = 0.0
38     forward_pass = True
39     for t in range(len(inputs)):
40         # encode in 1-of-k representation
41         xst = np.zeros((vocab_size,1))
42         xst[inputs[t]] = 1
43         hst = np.tanh(np.dot(wkh, xst[t]) + np.dot(bh, hs[t-1]) + bh) # hidden state
44         vst = np.dot(why, hst[t]) + by # unnormalized log probabilities for next chars
45         psit = np.exp(vst[t]) / np.sum(np.exp(vst[t])) # probabilities for next chars
46         loss -= -np.log(psit[targets[t]]) # softmax (cross-entropy loss)
47         # backward pass: compute gradients going backwards
48         dех, dwhh, dwhy = np.zeros_like(wkh), np.zeros_like(whh), np.zeros_like(why)
49         dbh, dyb = np.zeros_like(bh), np.zeros_like(by)
50         dnxst = np.zeros_like(xst[t])
51         for t in reversed(range(len(inputs))):
52             dy = np.copy(dyb[t])
53             dytarg = targets[t] + 1 # backprop into y
54             dhy = np.dot(dy, hst[t].T)
55             dyb -= dhy
56             dh = np.dot(wkh.T, dy) + dnxst # backprop into h
57             dhw = (1 - hs[t] * hs[t]) * dh # backprop through tanh nonlinearity
58             dwhh += np.dot(dhw, hs[t-1].T)
59             dwhy += np.dot(dhw, hs[t-1].T)
60             dnxst = np.dot(why.T, dhy)
61             for dparam in [dех, dwhh, dwhy, dbh, dyb]:
62                 np.clip(dparam, -5, 5, out=dparam) # clip to mitigate exploding gradients
63             return loss, dех, dwhh, dwhy, dbh, dyb, hs[-len(inputs)-1]
64
65
66 def sample(h, seed_ix, n):
67     """ 
68     sample a sequence of integers from the model
69     h is memory state, seed_ix is seed letter for first time step
70     """
71     x = np.zeros((vocab_size, 1))
72     x[seed_ix] = 1
73     ixes = []
74     for t in xrange(n):
75         h = np.tanh(np.dot(wkh, x) + np.dot(whh, h) + bh)
76         y = np.dot(why, h) + by
77         p = np.exp(y) / np.sum(np.exp(y))
78         ix = np.random.choice(range(vocab_size), p=p.ravel())
79         x = np.zeros((vocab_size, 1))
80         x[iix] = 1
81         ixes.append(ix)
82     return ixes
83
84 n, p = 0, 0
85 wkh, whh, why = np.zeros_like(wkh), np.zeros_like(whh), np.zeros_like(why)
86 dbh, dyb = np.zeros((hidden_size,1)) # reset RNN memory
87 smooth_loss = -np.log(1.0/vocab_size)*seq_length # loss at iteration 0
88 while True:
89     # prepare inputs (we're sweeping from left to right in steps seq_length long)
90     if p+seq_length+1 >= len(data) or n == 8:
91         hprev = np.zeros((hidden_size,1)) # reset RNN memory
92         p = n % len(data)
93         inputs = [char_to_ix[ch] for ch in data[p:p+seq_length]]
94         targets = [char_to_ix[ch] for ch in data[p+1:p+seq_length+1]]
95
96     n += 1
97     sample_ix = sample(hprev, inputs[0], 200)
98     txt = ''.join(ix_to_char[ix] for ix in sample_ix)
99     print ('----n %s ----' % (txt, ))
100
101     # forward seq_length characters through the net and fetch gradient
102     loss, dех, dwhh, dwhy, dbh, dyb, hprev = lossFun(inputs, targets, hprev)
103     smooth_loss = smooth_loss * 0.999 + loss * 0.001
104     if n % 100 == 0: print ('iter %d, loss: %f' % (n, smooth_loss)) # print progress
105
106     # perform parameter update with Adagrad
107     for param, dparam, mem in zip([wkh, whh, why, bh, by],
108                                   [dех, dwhh, dwhy, dbh, dyb],
109                                   [mem, mem, mem, mem, mem]):
110         mem += dparam * dparam
111         param += -learning_rate * dparam / np.sqrt(mem + 1e-8) # adagrad update
112
113     p += seq_length # move data pointer
114     n += 1 # iteration counter

```

<https://gist.github.com/karpathy/d4dee566867f8291f086>



Sonnet 116 – Let me not ...

by William Shakespeare

Let me not to the marriage of true minds
Admit impediments. Love is not love
Which alters when it alteration finds,
Or bends with the remover to remove:
O no! it is an ever-fixed mark
That looks on tempests and is never shaken;
It is the star to every wandering bark,
Whose worth's unknown, although his height be taken.
Love's not Time's fool, though rosy lips and cheeks
Within his bending sickle's compass come:
Love alters not with his brief hours and weeks,
But bears it out even to the edge of doom.
If this be error and upon me proved,
I never writ, nor no man ever loved.

at first:

tyntd-iafhatawiaoahrdemot lytdws e ,tfti, astai f ogoh eoase rrranbyne 'nhthnee e
plia tkldrgd t o idoe ns,smtt h ne etie h,hregtrs nigtike,aoaenns lng

↓ train more

"Tmont thithey" fomesscerliund
Keushey. Thom here
sheulke, anmerenith ol sivh I lalterthend Bleipile shuwyl fil on aseterlome
coaniogennc Phe lism thond hon at. MeiDimorotion in ther thize."

↓ train more

Aftair fall unsuch that the hall for Prince Velzonski's that me of
her hearly, and behs to so arwage fiving were to it beloge, pavu say falling misfort
how, and Gogition is so overelical and ofter.

↓ train more

"Why do what that day," replied Natasha, and wishing to himself the fact the
princess, Princess Mary was easier, fed in had oftened him.
Pierre aking his soul came to the packs and drove up his father-in-law women.

PANDARUS:

Alas, I think he shall be come approached and the day
When little strain would be attain'd into being never fed,
And who is but a chain and subjects of his death,
I should not sleep.

Second Senator:

They are away this miseries, produced upon my soul,
Breaking and strongly should be buried, when I perish
The earth and thoughts of many states.

DUKE VINCENTIO:

Well, your wit is in the care of side and that.

Second Lord:

They would be ruled after this chamber, and
my fair nues begun out of the fact, to be conveyed,
Whose noble souls I'll have the heart of the wars.

Clown:

Come, sir, I will make did behold your worship.

VIOLA:

I'll drink it.

VIOLA:

Why, Salisbury must find his flesh and thought
That which I am not aps, not a man and in fire,
To show the reining of the raven and the wars
To grace my hand reproach within, and not a fair are hand,
That Caesar and my goodly father's world;
When I was heaven of presence and our fleets,
We spare with hours, but cut thy council I am great,
Murdered and by thy master's ready there
My power to give thee but so much as hell:
Some service in the noble bondman here,
Would show him to her wine.

KING LEAR:

O, if you were a feeble sight, the courtesy of your law,
Your sight and several breath, will wear the gods
With his heads, and my hands are wonder'd at the deeds,
So drop upon your lordship's head, and your opinion
Shall be against your honour.

open source textbook on algebraic geometry

The Stacks Project

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Part	Chapter	online	TeX source	view pdf
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Parts

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- [Schemes](#)
- [Topics in Scheme Theory](#)
- [Algebraic Spaces](#)
- [Topics in Geometry](#)
- [Deformation Theory](#)
- [Algebraic Stacks](#)
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Statistics

The Stacks project now consists of

- o 455910 lines of code
- o 14221 tags (56 inactive tags)
- o 2366 sections

Latex source

For $\bigoplus_{n=1,\dots,m}$ where $\mathcal{L}_{m,n} = 0$, hence we can find a closed subset \mathcal{H} in \mathcal{H} and any sets \mathcal{F} on X , U is a closed immersion of S , then $U \rightarrow T$ is a separated algebraic space.

Proof. Proof of (1). It also start we get

$$S = \text{Spec}(R) = U \times_X U \times_X U$$

and the comparicoly in the fibre product covering we have to prove the lemma generated by $\coprod Z \times_U U \rightarrow V$. Consider the maps M along the set of points Sch_{fppf} and $U \rightarrow U$ is the fibre category of S in U in Section, ?? and the fact that any U affine, see Morphisms, Lemma ???. Hence we obtain a scheme S and any open subset $W \subset U$ in $\text{Sh}(G)$ such that $\text{Spec}(R') \rightarrow S$ is smooth or an

$$U = \bigcup U_i \times_{S_i} U_i$$

which has a nonzero morphism we may assume that f_i is of finite presentation over S . We claim that $\mathcal{O}_{X,x}$ is a scheme where $x, x', s'' \in S'$ such that $\mathcal{O}_{X,x'} \rightarrow \mathcal{O}'_{X',x'}$ is separated. By Algebra, Lemma ?? we can define a map of complexes $\text{GL}_{S'}(x'/S'')$ and we win. \square

To prove study we see that $\mathcal{F}|_U$ is a covering of \mathcal{X}' , and \mathcal{T}_i is an object of $\mathcal{F}_{X/S}$ for $i > 0$ and \mathcal{F}_p exists and let \mathcal{F}_i be a presheaf of \mathcal{O}_X -modules on \mathcal{C} as a \mathcal{F} -module. In particular $\mathcal{F} = U/\mathcal{F}$ we have to show that

$$\widetilde{M}^\bullet = \mathcal{I}^\bullet \otimes_{\text{Spec}(k)} \mathcal{O}_{S,s} - i_X^{-1} \mathcal{F}$$

is a unique morphism of algebraic stacks. Note that

$$\text{Arrows} = (\text{Sch}/S)^{\text{opp}}_{fppf}, (\text{Sch}/S)_{fppf}$$

and

$$V = \Gamma(S, \mathcal{O}) \longrightarrow (U, \text{Spec}(A))$$

is an open subset of X . Thus U is affine. This is a continuous map of X is the inverse, the groupoid scheme S .

Proof. See discussion of sheaves of sets. \square

The result for prove any open covering follows from the less of Example ???. It may replace S by $X_{\text{spaces},\text{étale}}$ which gives an open subspace of X and T equal to S_{Zar} , see Descent, Lemma ???. Namely, by Lemma ?? we see that R is geometrically regular over S .

Lemma 0.1. Assume (3) and (3) by the construction in the description.

Suppose $X = \lim |X|$ (by the formal open covering X and a single map $\underline{\text{Proj}}_X(\mathcal{A}) = \text{Spec}(B)$ over U compatible with the complex

$$\text{Set}(\mathcal{A}) = \Gamma(X, \mathcal{O}_{X,\mathcal{O}_X}).$$

When in this case of to show that $\mathcal{Q} \rightarrow \mathcal{C}_{Z/X}$ is stable under the following result in the second conditions of (1), and (3). This finishes the proof. By Definition ?? (without element is when the closed subschemes are catenary. If T is surjective we may assume that T is connected with residue fields of S . Moreover there exists a closed subspace $Z \subset X$ of X where U in X' is proper (some defining as a closed subset of the uniqueness it suffices to check the fact that the following theorem

(1) f is locally of finite type. Since $S = \text{Spec}(R)$ and $Y = \text{Spec}(R)$.

Proof. This is form all sheaves of sheaves on X . But given a scheme U and a surjective étale morphism $U \rightarrow X$. Let $U \cap U = \coprod_{i=1,\dots,n} U_i$ be the scheme X over S at the schemes $X_i \rightarrow X$ and $U = \lim_i X_i$. \square

The following lemma surjective restrocomposes of this implies that $\mathcal{F}_{x_0} = \mathcal{F}_{x_0} = \mathcal{F}_{x,\dots,x}$.

Lemma 0.2. Let X be a locally Noetherian scheme over S , $E = \mathcal{F}_{X/S}$. Set $\mathcal{I} = \mathcal{J}_1 \subset \mathcal{I}'_n$. Since $\mathcal{I}'_n \subset \mathcal{I}^n$ are nonzero over $i_0 \leq p$ is a subset of $\mathcal{J}_{n,0} \circ \overline{A}_2$ works.

Lemma 0.3. In Situation ???. Hence we may assume $q' = 0$.

Proof. We will use the property we see that p is the next functor (??). On the other hand, by Lemma ?? we see that

$$D(\mathcal{O}_{X'}) = \mathcal{O}_X(D)$$

where K is an F -algebra where δ_{n+1} is a scheme over S . \square

Proof. Omitted. \square

Lemma 0.1. Let \mathcal{C} be a set of the construction.

Let \mathcal{C} be a gerber covering. Let \mathcal{F} be a quasi-coherent sheaves of \mathcal{O} -modules. We have to show that

$$\mathcal{O}_{\mathcal{O}_X} = \mathcal{O}_X(\mathcal{L})$$

Proof. This is an algebraic space with the composition of sheaves \mathcal{F} on $X_{\text{étale}}$ we have

$$\mathcal{O}_X(\mathcal{F}) = \{\text{morph}_1 \times_{\mathcal{O}_X} (\mathcal{G}, \mathcal{F})\}$$

where \mathcal{G} defines an isomorphism $\mathcal{F} \rightarrow \mathcal{F}$ of \mathcal{O} -modules. \square

Lemma 0.2. This is an integer \mathcal{Z} is injective.

Proof. See Spaces, Lemma ??.

Lemma 0.3. Let S be a scheme. Let X be a scheme and X is an affine open covering. Let $\mathcal{U} \subset X$ be a canonical and locally of finite type. Let X be a scheme. Let X be a scheme which is equal to the formal complex.

The following to the construction of the lemma follows.

Let X be a scheme. Let X be a scheme covering. Let

$$b : X \rightarrow Y' \rightarrow Y \rightarrow Y \rightarrow Y' \times_X Y \rightarrow X.$$

be a morphism of algebraic spaces over S and Y .

Proof. Let X be a nonzero scheme of X . Let X be an algebraic space. Let \mathcal{F} be a quasi-coherent sheaf of \mathcal{O}_X -modules. The following are equivalent

- (1) \mathcal{F} is an algebraic space over S .
- (2) If X is an affine open covering.

Consider a common structure on X and X the functor $\mathcal{O}_X(U)$ which is locally of finite type. \square

This since $\mathcal{F} \in \mathcal{F}$ and $x \in \mathcal{G}$ the diagram

$$\begin{array}{ccccc}
 S & \longrightarrow & & & \\
 \downarrow & & & & \\
 \xi & \longrightarrow & \mathcal{O}_{X'} & \nearrow & \\
 \text{gor}_s & & \uparrow & & \\
 & & = \alpha' & \longrightarrow & \\
 & & \downarrow & & \\
 & & = \alpha' & \longrightarrow & \alpha \\
 & & & & \\
 \text{Spec}(K_\psi) & & \text{Mor}_{\text{Sets}} & & d(\mathcal{O}_{X_{\mathcal{X}/k}}, \mathcal{G}) \\
 & & & & \\
 & & & & X \downarrow \\
 & & & & d(\mathcal{O}_{X_{\mathcal{X}/k}}, \mathcal{G})
 \end{array}$$

is a limit. Then \mathcal{G} is a finite type and assume S is a flat and \mathcal{F} and \mathcal{G} is a finite type f_* . This is of finite type diagrams, and

- the composition of \mathcal{G} is a regular sequence,
- $\mathcal{O}_{X'}$ is a sheaf of rings.

\square

Proof. We have see that $X = \text{Spec}(R)$ and \mathcal{F} is a finite type representable by algebraic space. The property \mathcal{F} is a finite morphism of algebraic stacks. Then the cohomology of X is an open neighbourhood of U . \square

Proof. This is clear that \mathcal{G} is a finite presentation, see Lemmas ??.

A reduced above we conclude that U is an open covering of \mathcal{C} . The functor \mathcal{F} is a “field”

$$\mathcal{O}_{X,x} \rightarrow \mathcal{F}_{\bar{x}} \dashv (\mathcal{O}_{X_{\text{étale}}}) \rightarrow \mathcal{O}_{X_{\lambda}}^{-1} \mathcal{O}_{X_{\lambda}}(\mathcal{O}_{X_{\eta}}^{\oplus})$$

is an isomorphism of covering of \mathcal{O}_{X_i} . If \mathcal{F} is the unique element of \mathcal{F} such that X is an isomorphism.

The property \mathcal{F} is a disjoint union of Proposition ?? and we can filtered set of presentations of a scheme \mathcal{O}_X -algebra with \mathcal{F} are opens of finite type over S . If \mathcal{F} is a scheme theoretic image points. \square

If \mathcal{F} is a finite direct sum $\mathcal{O}_{X_{\lambda}}$ is a closed immersion, see Lemma ?? . This is a sequence of \mathcal{F} is a similar morphism.

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Linux kernel source tree

520,037 commits 1 branch 420 releases 5,039 contributors

branch: master / +

Merge branch 'drm-fixes' of git://people.freedesktop.org/~airlied/linux ...

torvalds authored 9 hours ago latest commit 4b1706927d

	Commit Message	Date
Documentation	Merge git://git.kernel.org/pub/scm/linux/kernel/git/nab/target-pending	6 days ago
arch	Merge branch 'x86-urgent-for-linus' of git://git.kernel.org/pub/scm/l...	a day ago
block	block: discard bdi_unregister() in favour of bdi_destroy()	9 days ago
crypto	Merge git://git.kernel.org/pub/scm/linux/kernel/git/herbert/crypto-2.6	10 days ago
drivers	Merge branch 'drm-fixes' of git://people.freedesktop.org/~airlied/linux	9 hours ago
firmware	firmware/hex2fw.c: restore missing default in switch statement	2 months ago
fs	vfs: read file_handle only once in handle_to_path	4 days ago
include	Merge branch 'perf-urgent-for-linus' of git://git.kernel.org/pub/scm/...	a day ago
init	init: fix regression by supporting devices with major:minor:offset fo...	a month ago
iom	IOMMU: iommu: New IOMMU API with direct memory access interface	a month ago

Code 74 Pull requests

Pulse Graphs

HTTPS clone URL https://github.com/torvalds/linux

You can clone with HTTPS, SSH, or Subversion. ⌂

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```
static void do_command(struct seq_file *m, void *v)
{
    int column = 32 << (cmd[2] & 0x80);
    if (state)
        cmd = (int)(int_state ^ (in_8(&ch->ch_flags) & Cmd) ? 2 : 1);
    else
        seq = 1;
    for (i = 0; i < 16; i++) {
        if (k & (1 << 1))
            pipe = (in_use & UMXTHREAD_UNCCA) +
                ((count & 0x00000000fffffff8) & 0x0000000f) << 8;
        if (count == 0)
            sub(pid, ppc_md.kexec_handle, 0x20000000);
        pipe_set_bytes(i, 0);
    }
    /* Free our user pages pointer to place camera if all dash */
    subsystem_info = &of_changes[PAGE_SIZE];
    rek_controls(offset, idx, &soffset);
    /* Now we want to deliberately put it to device */
    control_check_polarity(&context, val, 0);
    for (i = 0; i < COUNTER; i++)
        seq_puts(s, "policy ");
}
```

Generated C code

```
/*
 * Copyright (c) 2006-2010, Intel Mobile Communications. All rights reserved.
 *
 * This program is free software; you can redistribute it and/or modify it
 * under the terms of the GNU General Public License version 2 as published by
 * the Free Software Foundation.
 *
 * This program is distributed in the hope that it will be useful,
 * but WITHOUT ANY WARRANTY; without even the implied warranty of
 * MERCHANTABILITY or FITNESS FOR A PARTICULAR PURPOSE. See the
 *
 * GNU General Public License for more details.
 *
 * You should have received a copy of the GNU General Public License
 * along with this program; if not, write to the Free Software Foundation,
 * Inc., 675 Mass Ave, Cambridge, MA 02139, USA.
 */

#include <linux/kexec.h>
#include <linux/errno.h>
#include <linux/io.h>
#include <linux/platform_device.h>
#include <linux/multi.h>
#include <linux/ckevent.h>

#include <asm/io.h>
#include <asm/prom.h>
#include <asm/e820.h>
#include <asm/system_info.h>
#include <asm/seteew.h>
#include <asm/pgproto.h>
```

```
#include <asm/io.h>
#include <asm/prom.h>
#include <asm/e820.h>
#include <asm/system_info.h>
#include <asm/seteew.h>
#include <asm/pgproto.h>

#define REG_PG    vesa_slot_addr_pack
#define PFM_NOCOMP AFSR(0, load)
#define STACK_DDR(type)      (func)

#define SWAP_ALLOCATE(nr)      (e)
#define emulate_sigs() arch_get_unaligned_child()
#define access_rw(TST)  asm volatile("movd %%esp, %0, %3" : : "r" (0)); \
if (_type & DO_READ)

static void stat_PC_SEC __read_mostly offsetof(struct seq_argsqueue, \
pC>[1]);

static void
os_prefix(unsigned long sys)
{
#ifdef CONFIG_PREEMPT
    PUT_PARAM_RAID(2, sel) = get_state_state();
    set_pid_sum((unsigned long)state, current_state_str(),
                (unsigned long)-1->lr_full; low;
}

```

RNN tradeoffs

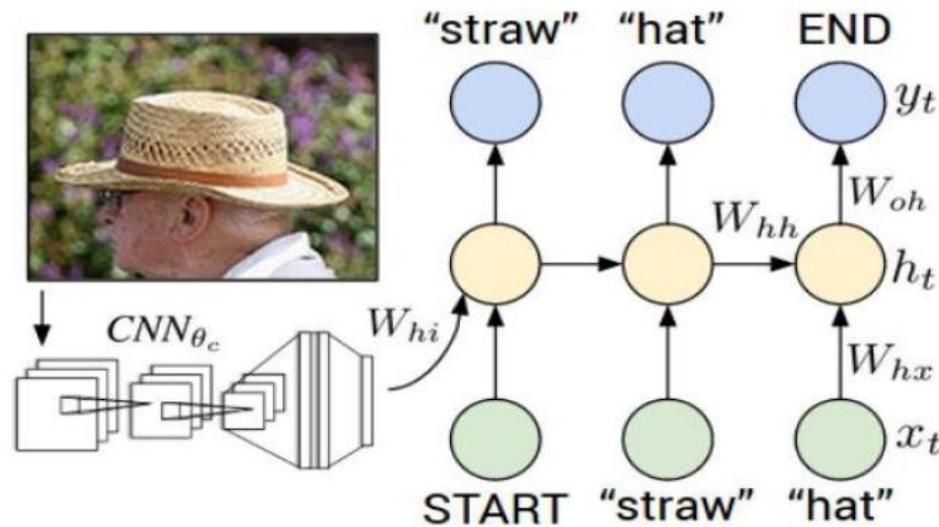
RNN Advantages:

- Can process any length input
- Computation for step t can (in theory) use information from many steps back
- Model size doesn't increase for longer input
- Same weights applied on every timestep, so there is symmetry in how inputs are processed.

RNN Disadvantages:

- Recurrent computation is slow
- In practice, difficult to access information from many steps back

Image Captioning



Explain Images with Multimodal Recurrent Neural Networks, Mao et al.

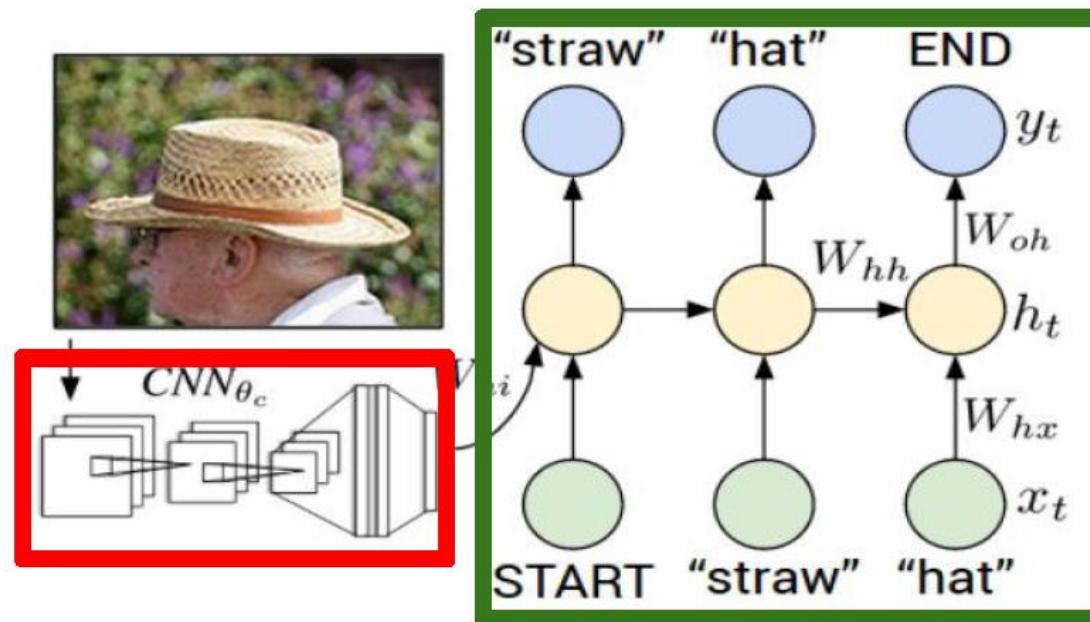
Deep Visual-Semantic Alignments for Generating Image Descriptions, Karpathy and Fei-Fei

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

Recurrent Neural Network



Convolutional Neural Network

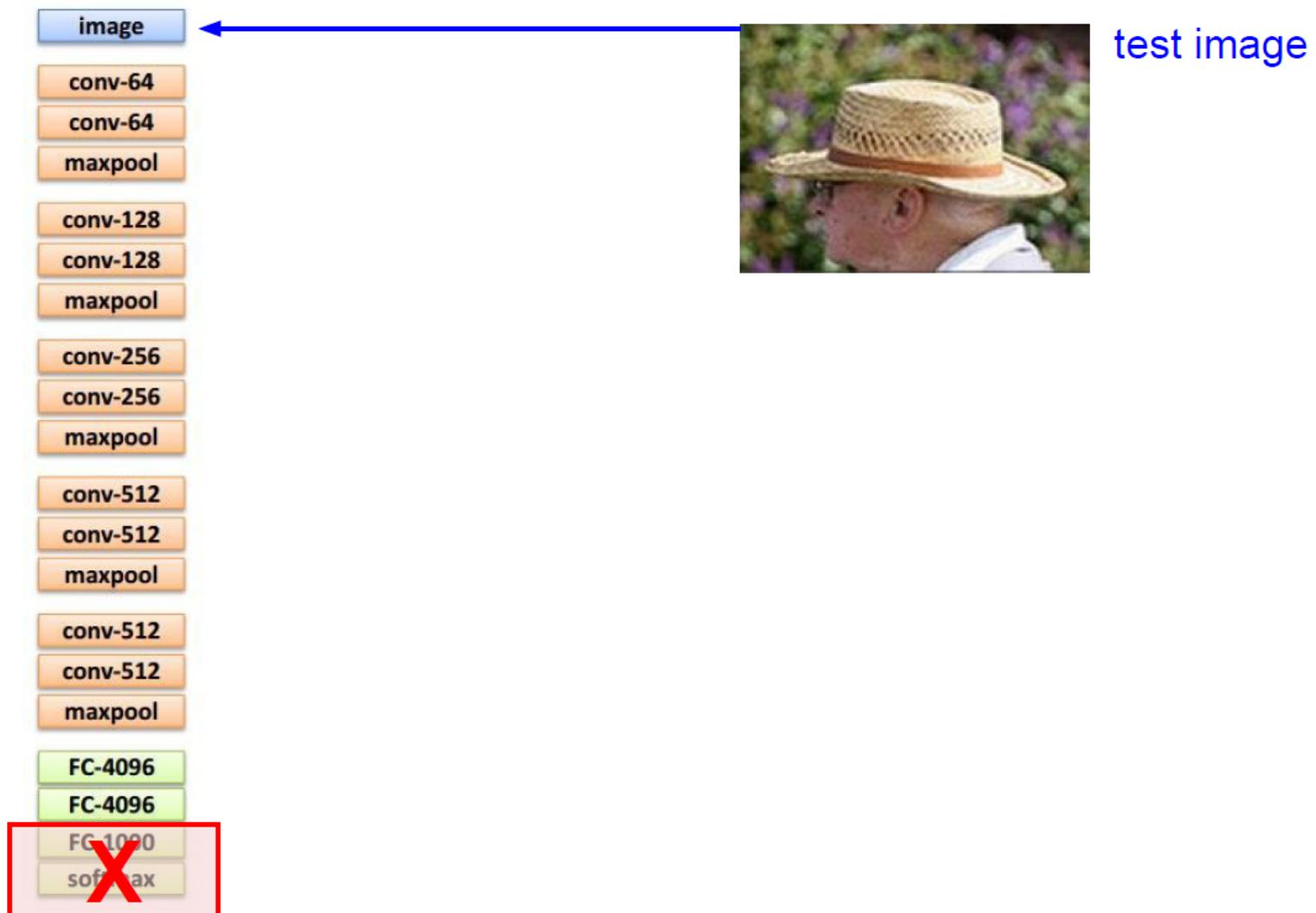


test image

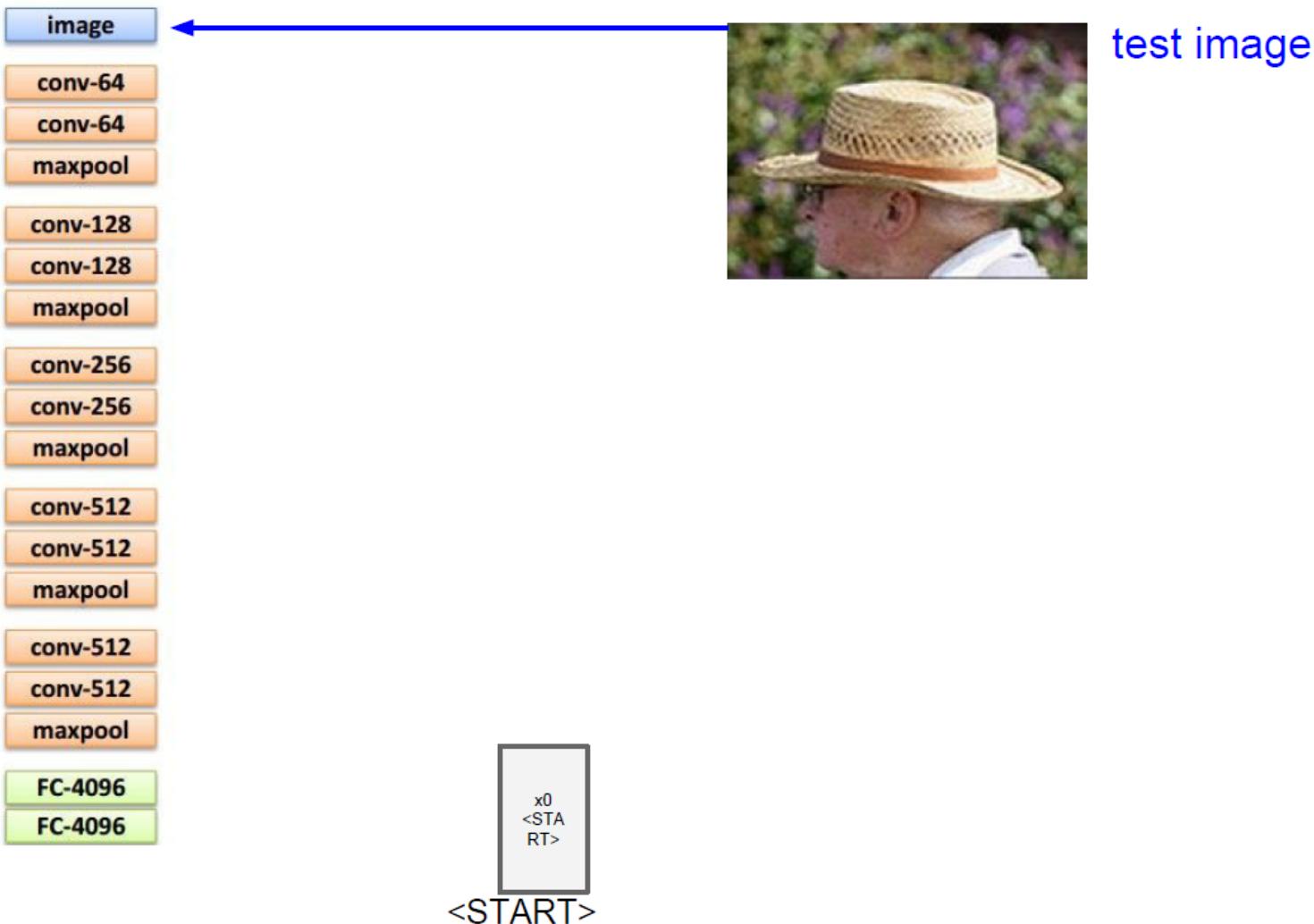
RNN



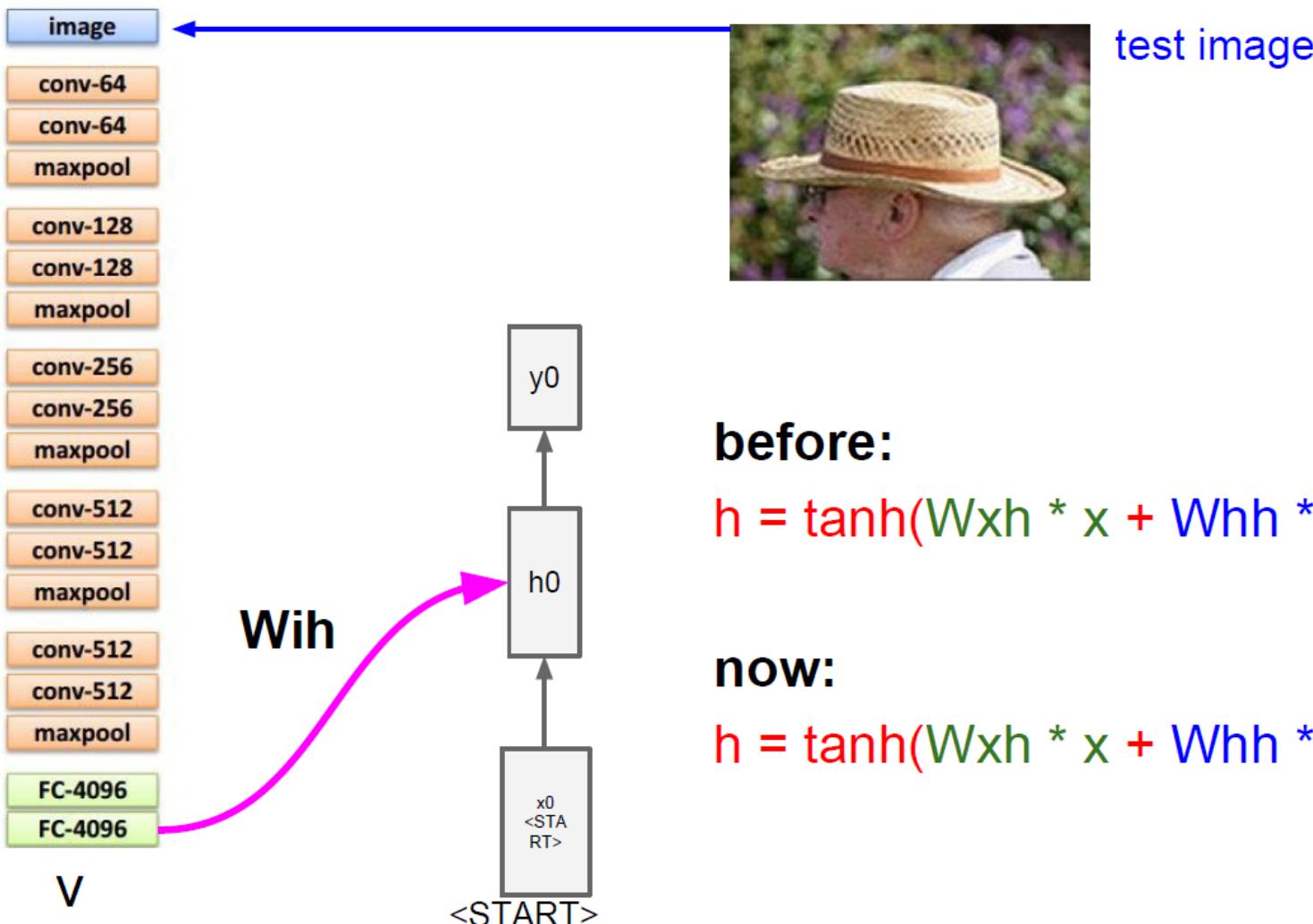
RNN



RNN



RNN



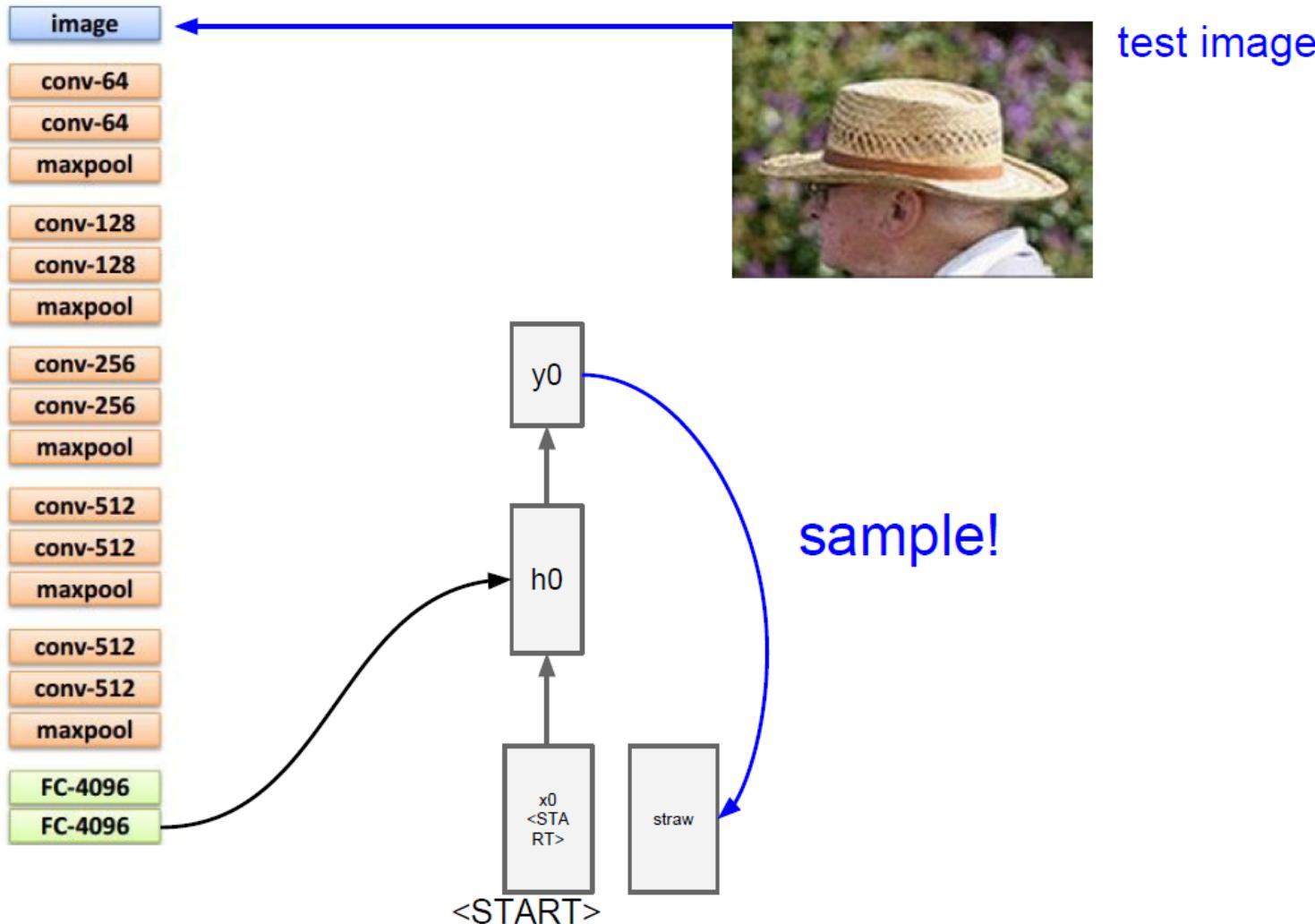
before:

$$h = \tanh(W_{xh} * x + W_{hh} * h)$$

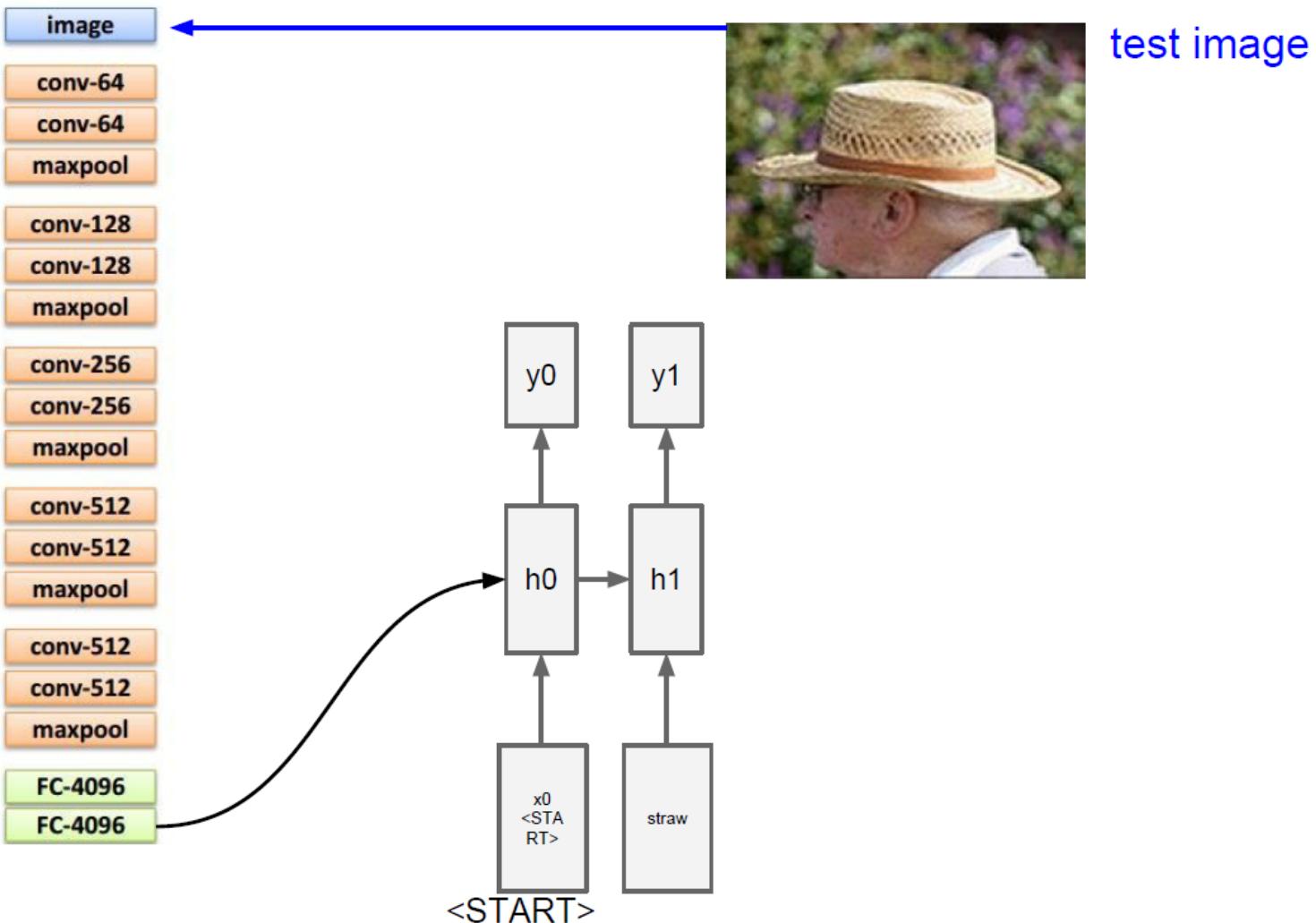
now:

$$h = \tanh(W_{xh} * x + W_{hh} * h + W_{ih} * v)$$

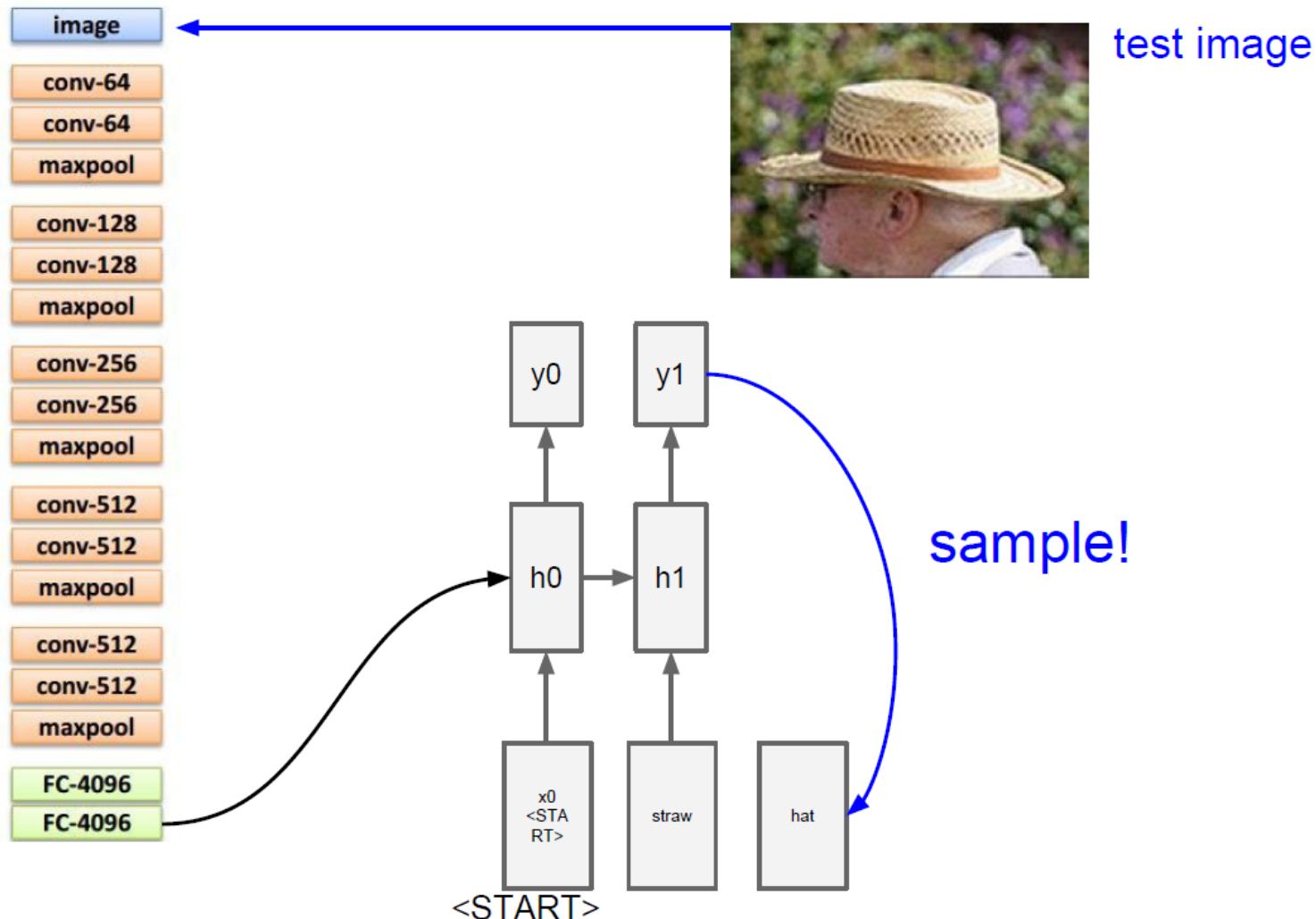
RNN



RNN



RNN



RNN

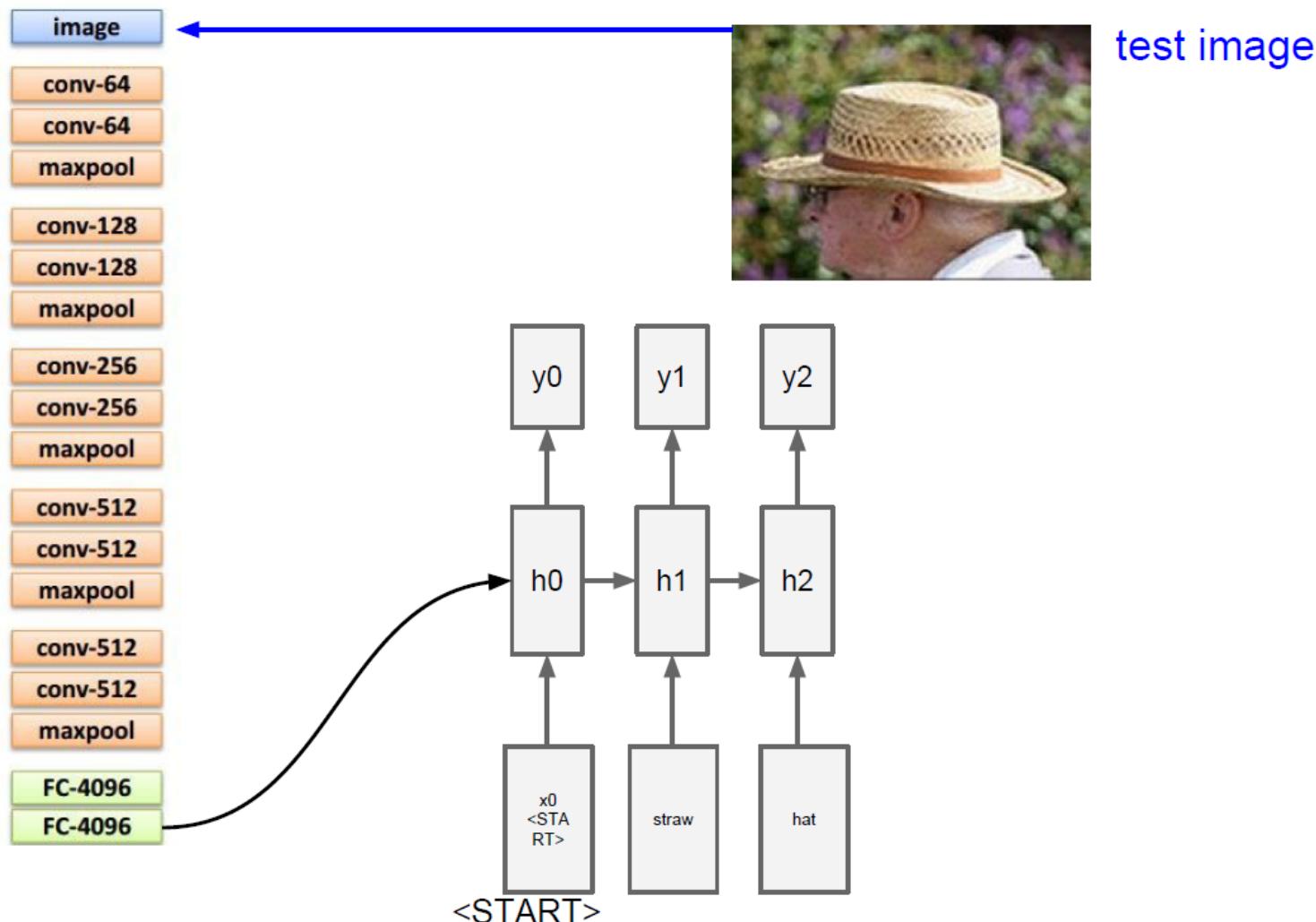


Image Captioning: Example Results

Captions generated using [neuraltalk2](#)
All images are CC0 Public domain
[cat](#) [suitcase](#) [cat](#) [tree](#) [dog](#) [bear](#)
[surfers](#) [tennis](#) [giraffe](#) [motorcycle](#)



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



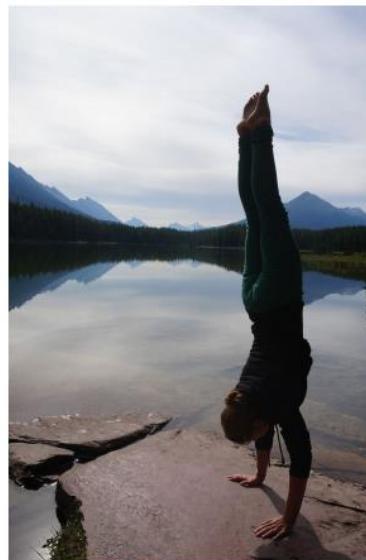
A man riding a dirt bike on a dirt track

Image Captioning: Failure Cases

Captions generated using [neuraltalk2](#)
All images are [CC0 Public domain](#): [fur](#), [coat](#), [handstand](#), [spider web](#), [baseball](#)



A woman is holding a cat in her hand



A woman standing on a beach holding a surfboard



A person holding a computer mouse on a desk



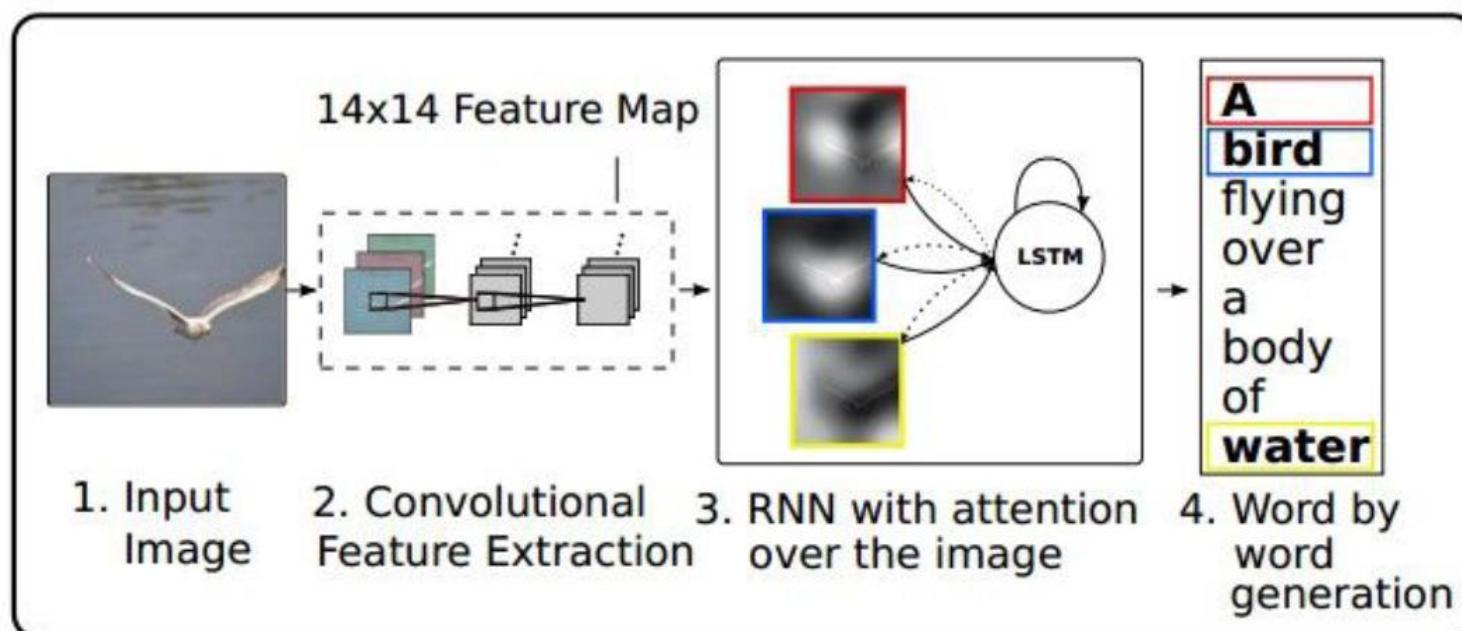
A bird is perched on a tree branch



A man in a baseball uniform throwing a ball

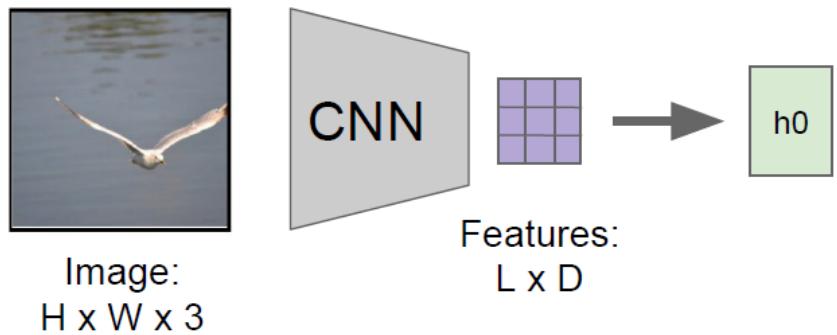
Image Captioning with Attention

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



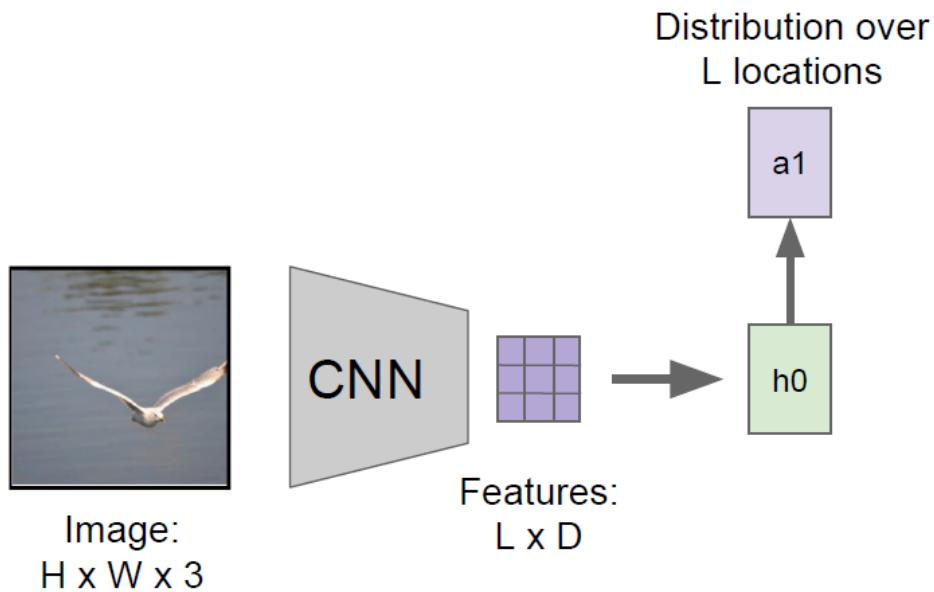
Xu et al., "Show, Attend, and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015
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Image Captioning with Attention



Xu et al, "Show, Attend and Tell: Neural
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Image Captioning with Attention



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Image Captioning with Attention

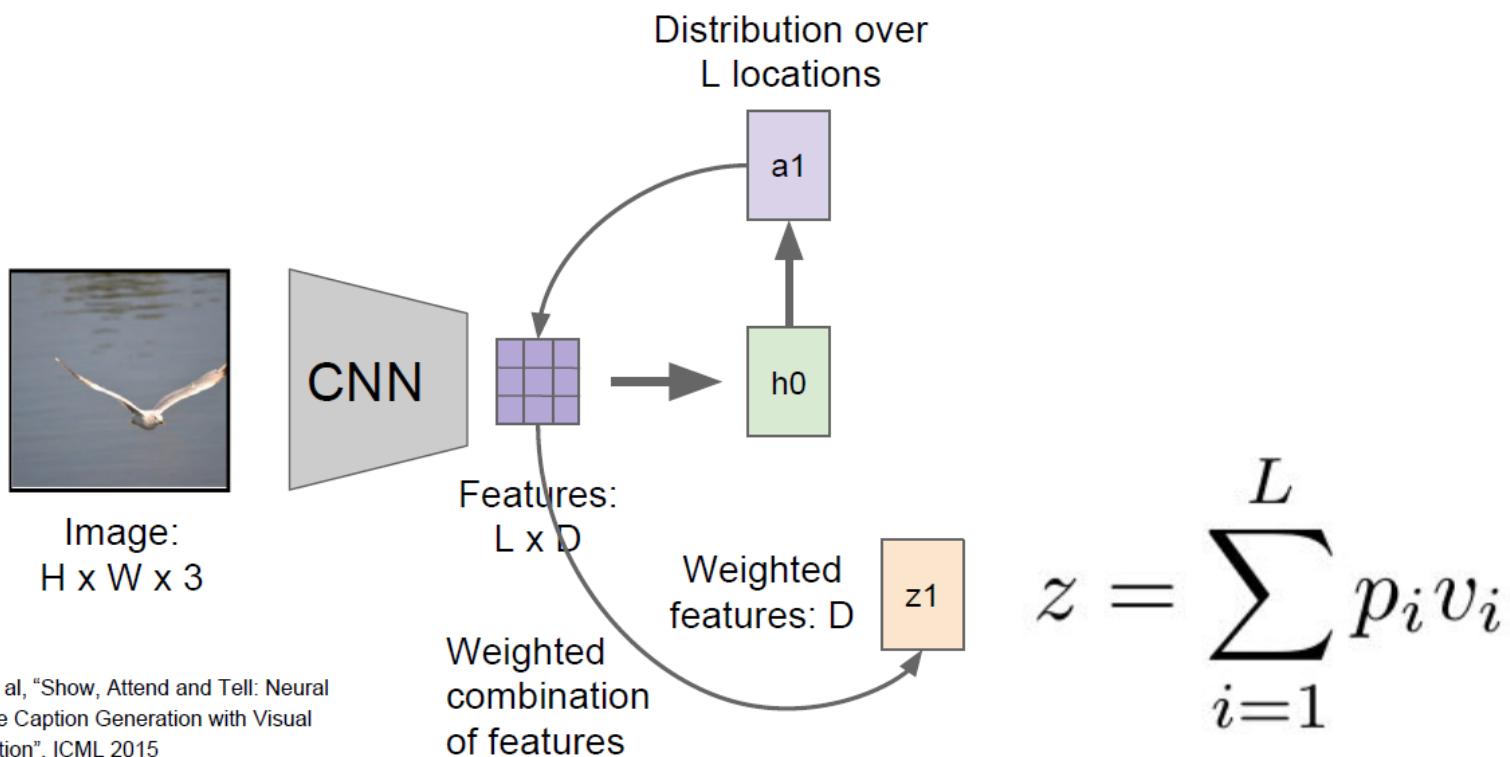


Image Captioning with Attention

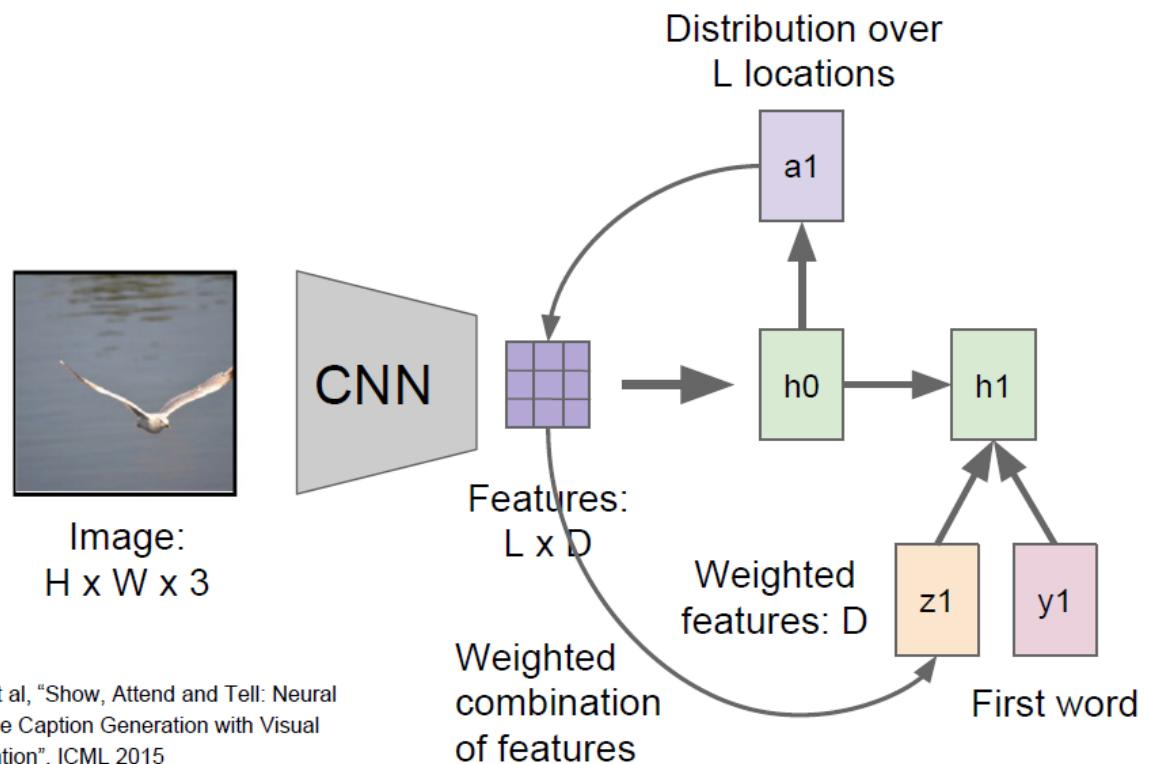


Image Captioning with Attention

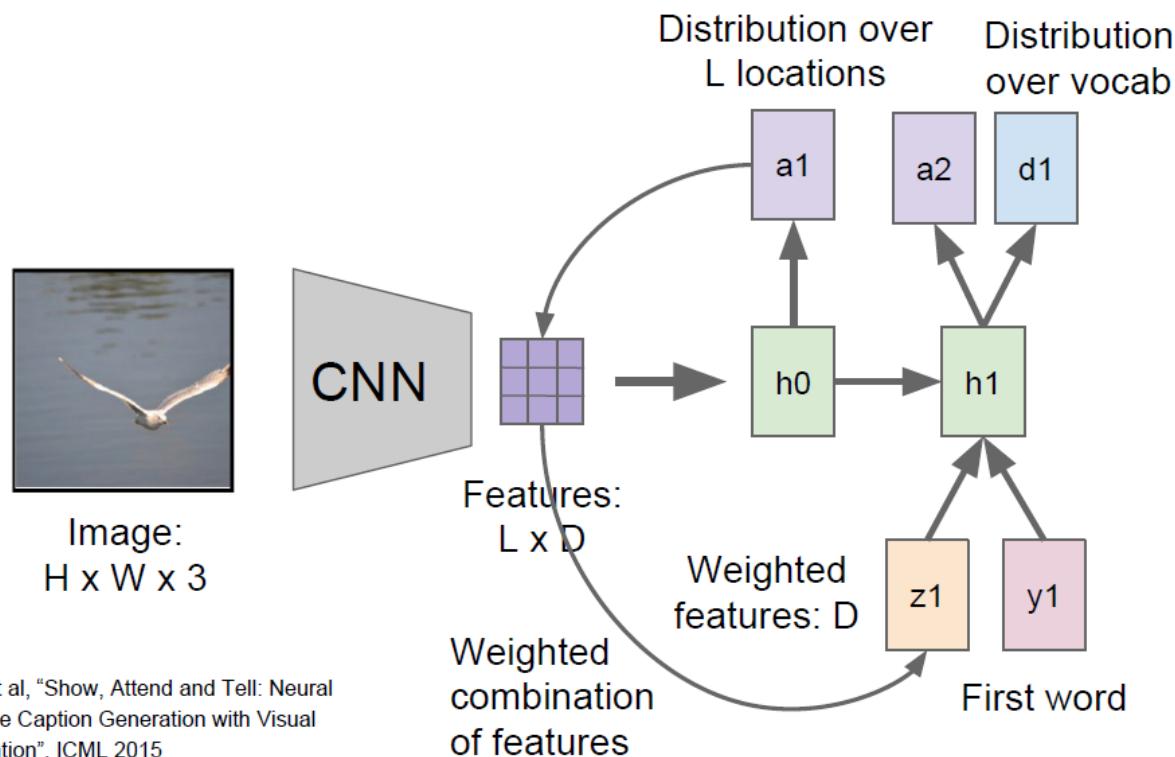


Image Captioning with Attention

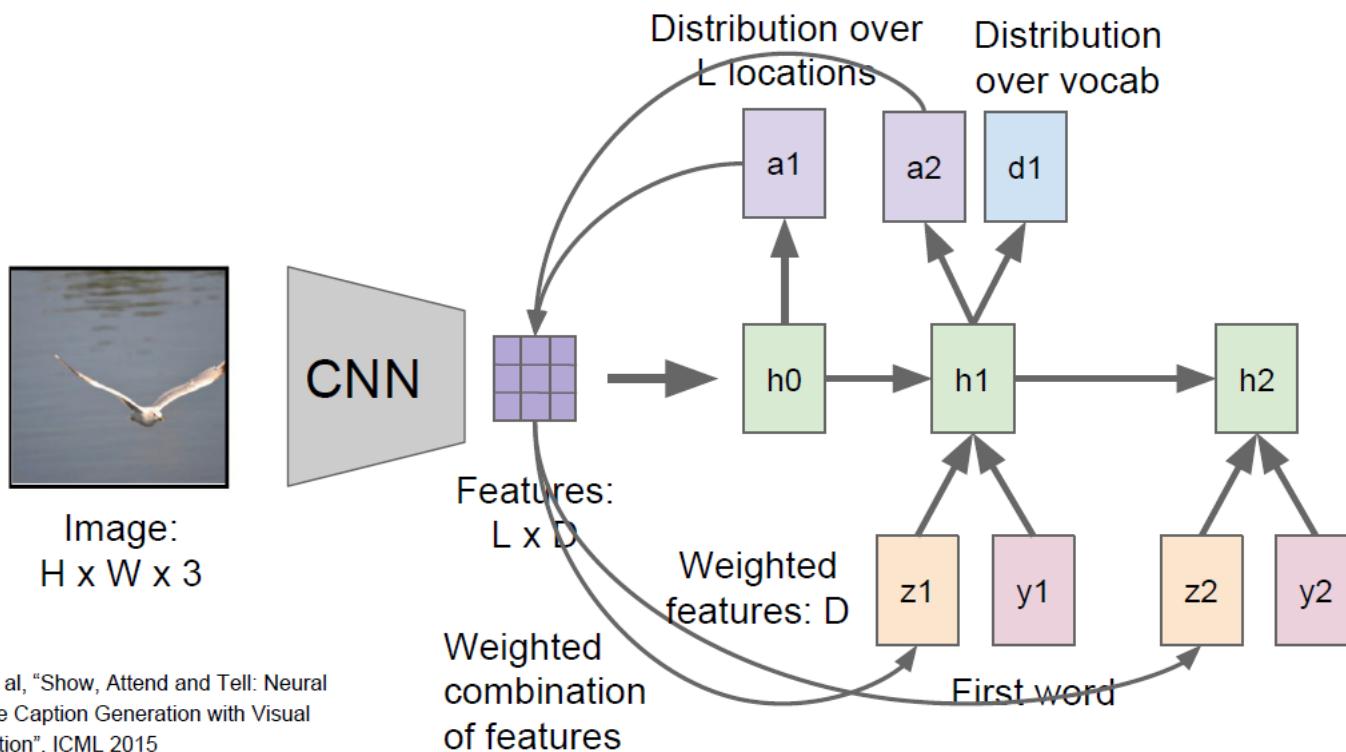


Image Captioning with Attention

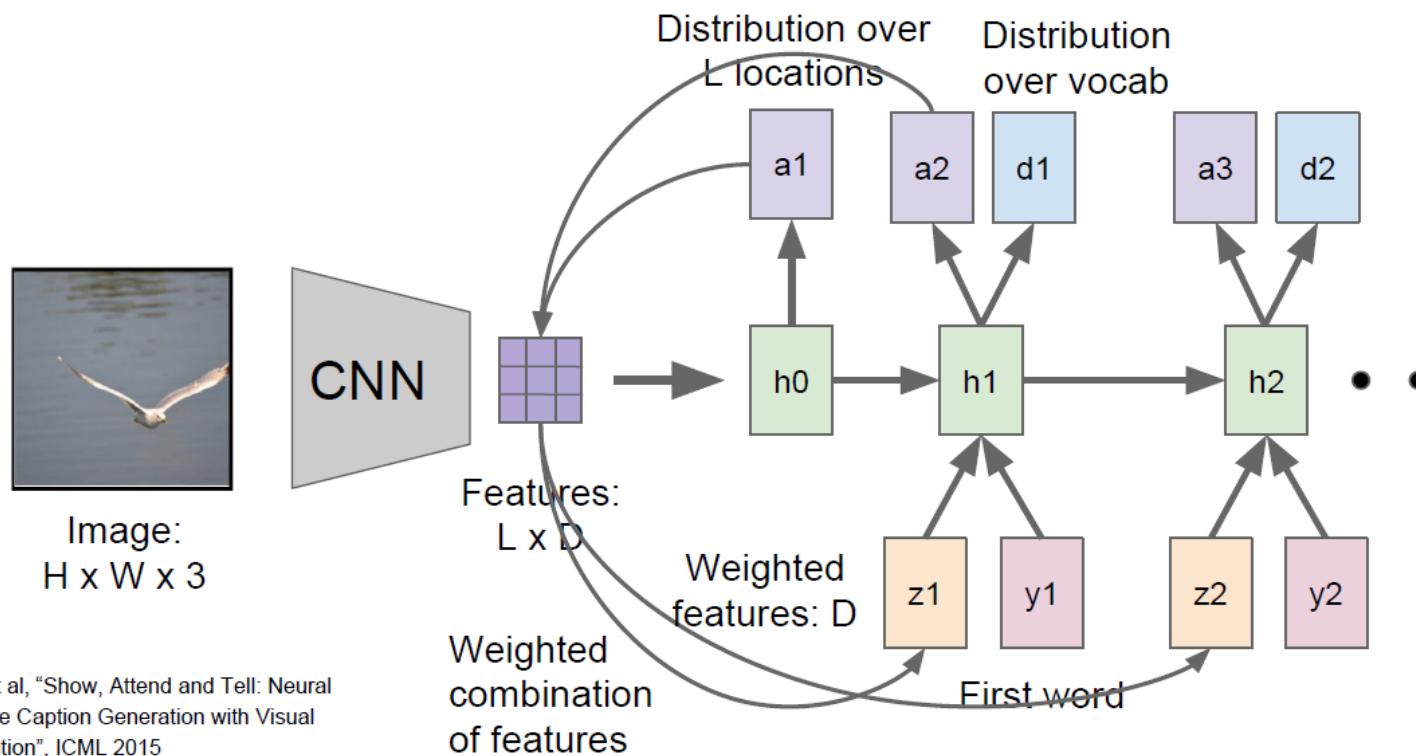
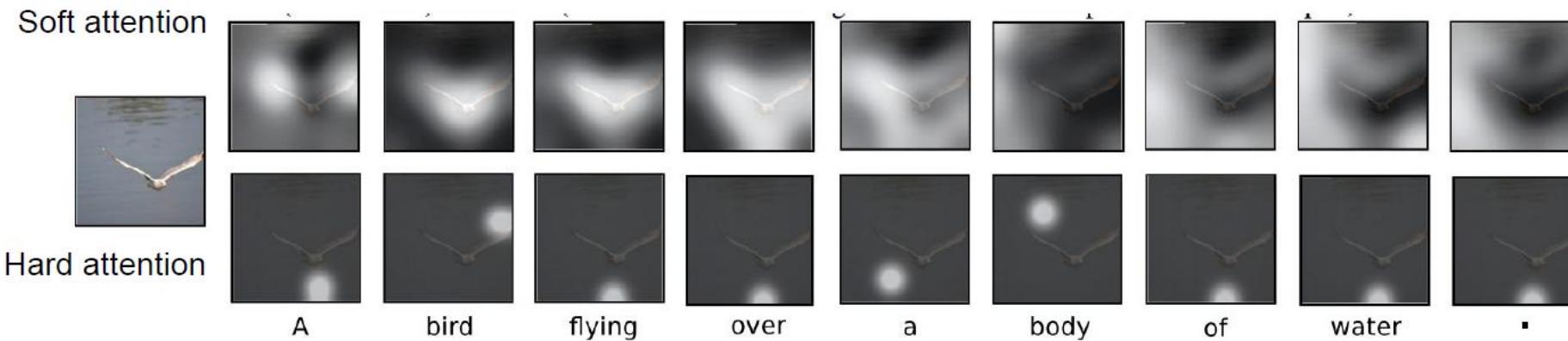


Image Captioning with Attention



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



A woman is throwing a frisbee in a park.



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 giraffe standing in a forest with trees in the background.

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

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Long Short Term Memory (LSTM)

Vanilla RNN

$$h_t = \tanh \left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} \right)$$

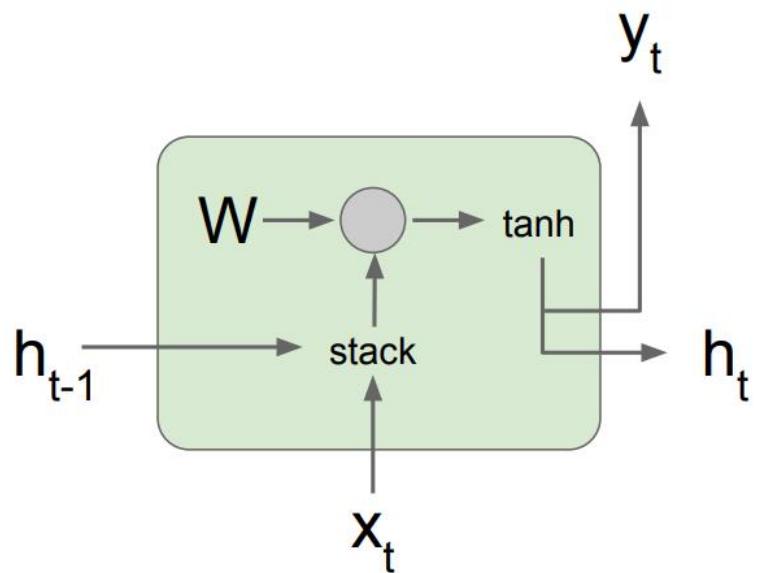
LSTM

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$
$$c_t = f \odot c_{t-1} + i \odot g$$
$$h_t = o \odot \tanh(c_t)$$

Hochreiter and Schmidhuber, "Long Short Term Memory", Neural Computation 1997

Vanilla RNN Gradient Flow

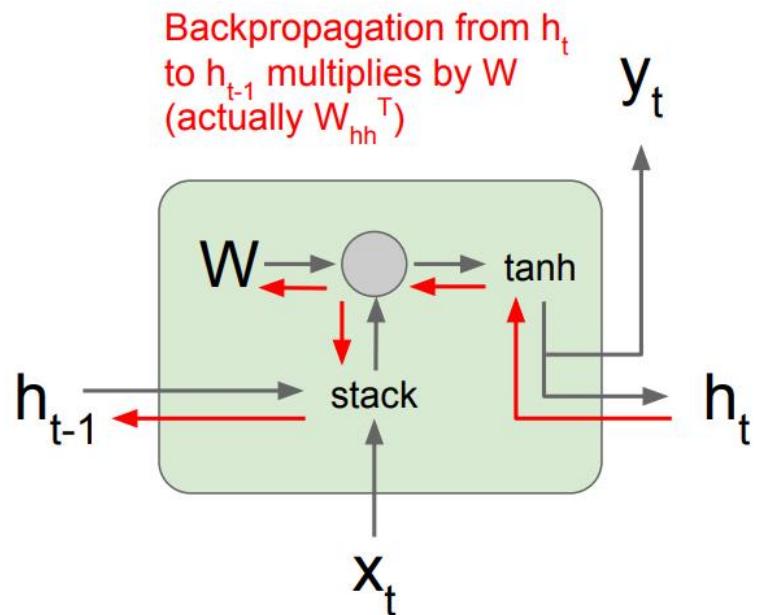
Bengio et al, "Learning long-term dependencies with gradient descent is difficult", IEEE Transactions on Neural Networks, 1994
Pascanu et al, "On the difficulty of training recurrent neural networks", ICML 2013



$$\begin{aligned} h_t &= \tanh(W_{hh}h_{t-1} + W_{xh}x_t) \\ &= \tanh \left(\begin{pmatrix} W_{hh} & W_{hx} \end{pmatrix} \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} \right) \\ &= \tanh \left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} \right) \end{aligned}$$

Vanilla RNN Gradient Flow

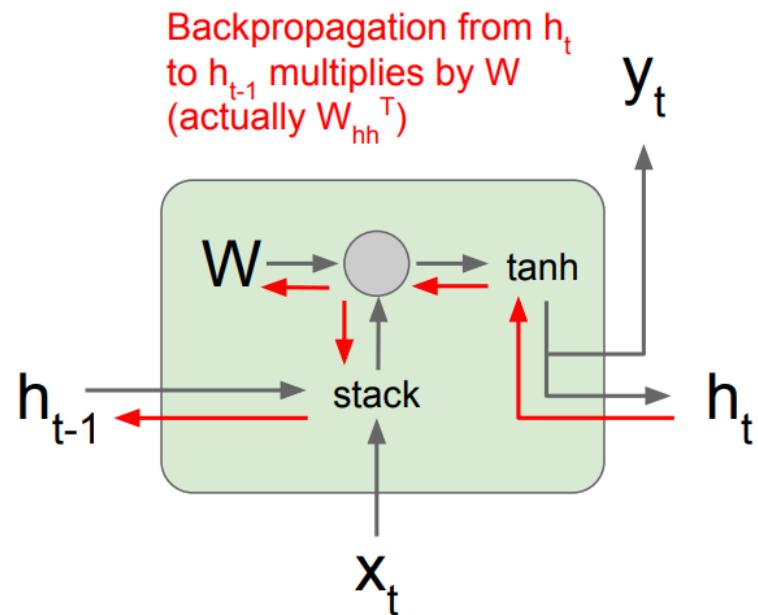
Bengio et al, "Learning long-term dependencies with gradient descent is difficult", IEEE Transactions on Neural Networks, 1994
Pascanu et al, "On the difficulty of training recurrent neural networks", ICML 2013



$$\begin{aligned} h_t &= \tanh(W_{hh}h_{t-1} + W_{xh}x_t) \\ &= \tanh \left(\begin{pmatrix} W_{hh} & W_{hx} \end{pmatrix} \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} \right) \\ &= \tanh \left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} \right) \end{aligned}$$

Vanilla RNN Gradient Flow

Bengio et al, "Learning long-term dependencies with gradient descent is difficult", IEEE Transactions on Neural Networks, 1994
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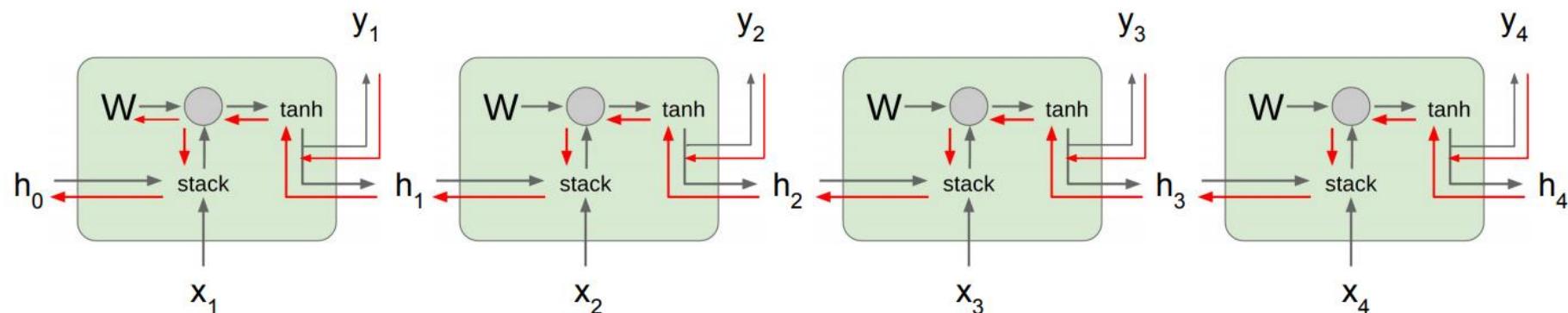


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$$\frac{\partial h_t}{\partial h_{t-1}} = \tanh'(W_{hh}h_{t-1} + W_{xh}x_t)W_{hh}$$

Vanilla RNN Gradient Flow

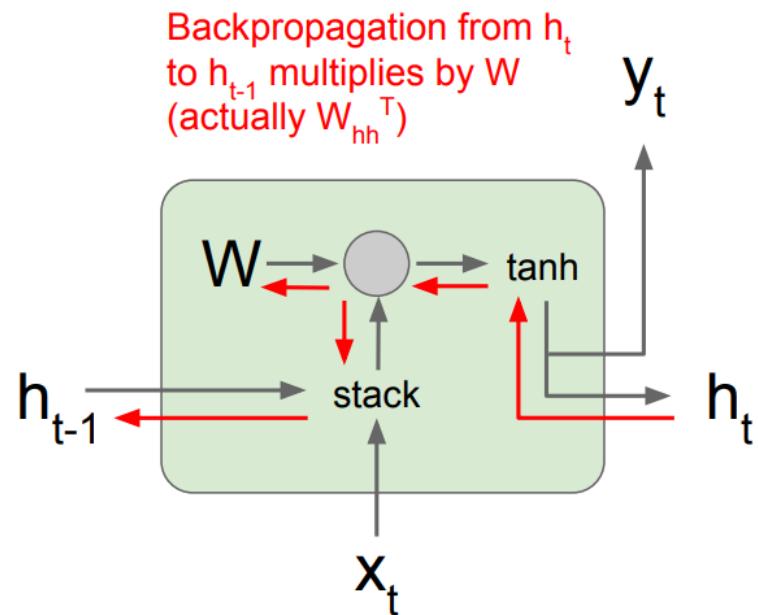
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$$\frac{\partial L}{\partial W} = \sum_{t=1}^T \frac{\partial L_t}{\partial W}$$

Vanilla RNN Gradient Flow

Bengio et al, "Learning long-term dependencies with gradient descent is difficult", IEEE Transactions on Neural Networks, 1994
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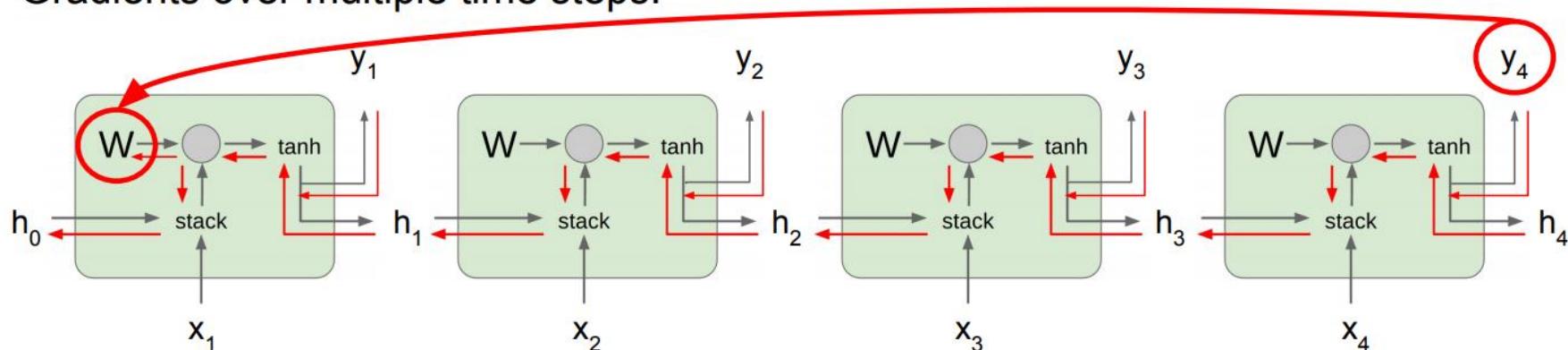
$$\begin{aligned} h_t &= \tanh(W_{hh}h_{t-1} + W_{xh}x_t) \\ &= \tanh \left(\begin{pmatrix} W_{hh} & W_{hx} \end{pmatrix} \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} \right) \\ &= \tanh \left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} \right) \end{aligned}$$

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Vanilla RNN Gradient Flow

Gradients over multiple time steps:

Bengio et al, "Learning long-term dependencies with gradient descent is difficult", IEEE Transactions on Neural Networks, 1994
Pascanu et al, "On the difficulty of training recurrent neural networks", ICML 2013



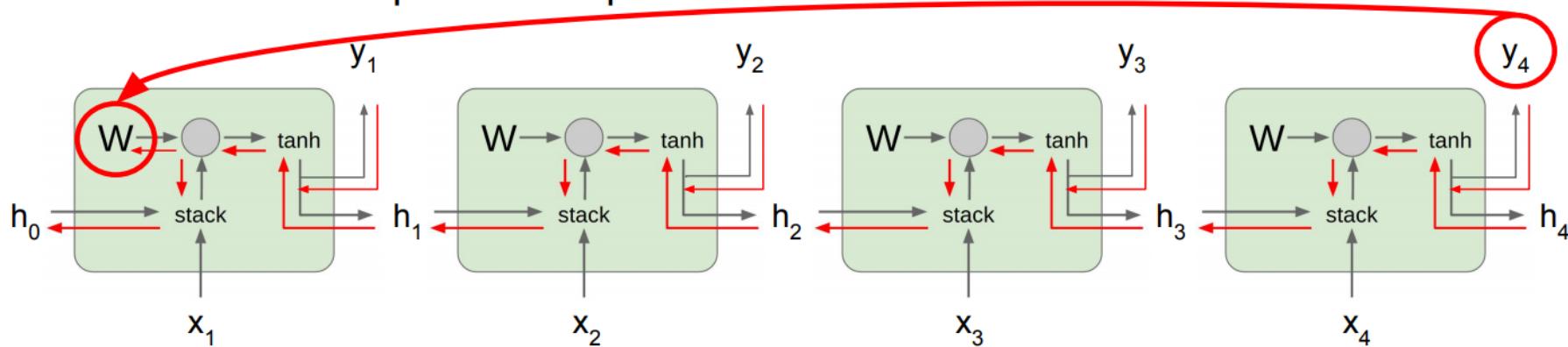
$$\frac{\partial L}{\partial W} = \sum_{t=1}^T \frac{\partial L_t}{\partial W}$$

$$\frac{\partial L_T}{\partial W} = \frac{\partial L_T}{\partial h_T} \frac{\partial h_T}{\partial h_{t-1}} \cdots \frac{\partial h_1}{\partial W}$$

Vanilla RNN Gradient Flow

Gradients over multiple time steps:

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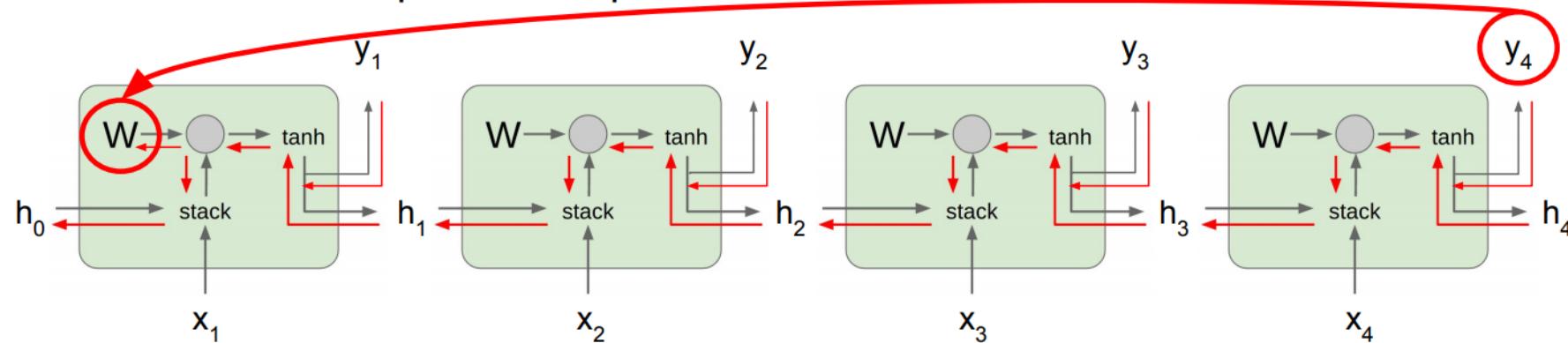
$$\frac{\partial L}{\partial W} = \sum_{t=1}^T \frac{\partial L_t}{\partial W}$$

$$\frac{\partial L_T}{\partial W} = \frac{\partial L_T}{\partial h_T} \frac{\partial h_t}{\partial h_{t-1}} \cdots \frac{\partial h_1}{\partial W} = \frac{\partial L_T}{\partial h_T} \left(\prod_{t=2}^T \frac{\partial h_t}{\partial h_{t-1}} \right) \frac{\partial h_1}{\partial W}$$

Vanilla RNN Gradient Flow

Gradients over multiple time steps:

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 Pascanu et al, "On the difficulty of training recurrent neural networks", ICML 2013



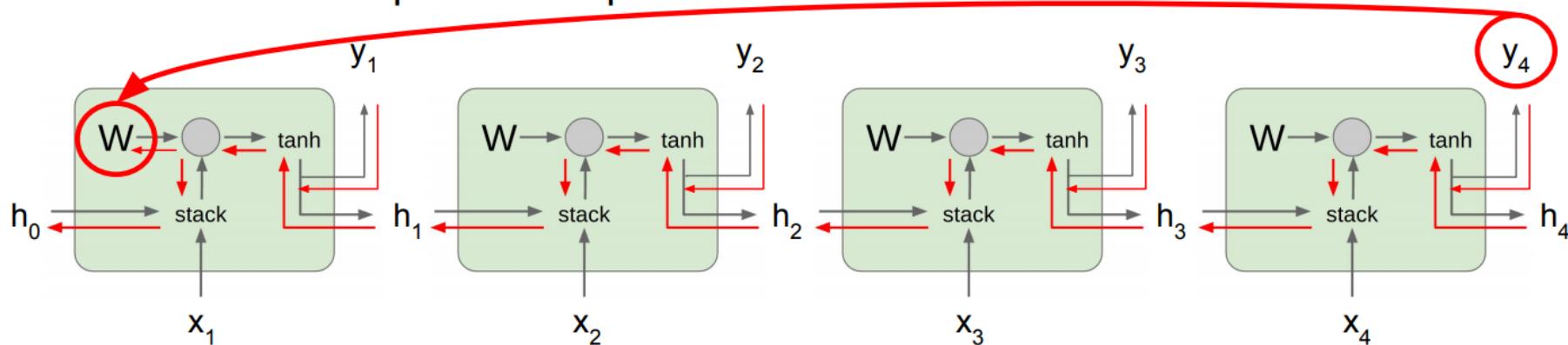
$$\frac{\partial L}{\partial W} = \sum_{t=1}^T \frac{\partial L_t}{\partial W} \quad \boxed{\frac{\partial h_t}{\partial h_{t-1}} = \tanh'(W_{hh}h_{t-1} + W_{xh}x_t)W_{hh}}$$

$$\frac{\partial L_T}{\partial W} = \frac{\partial L_T}{\partial h_T} \frac{\partial h_t}{\partial h_{t-1}} \cdots \frac{\partial h_1}{\partial W} = \frac{\partial L_T}{\partial h_T} \left(\prod_{t=2}^T \boxed{\frac{\partial h_t}{\partial h_{t-1}}} \right) \frac{\partial h_1}{\partial W}$$

Vanilla RNN Gradient Flow

Gradients over multiple time steps:

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$$\frac{\partial L}{\partial W} = \sum_{t=1}^T \frac{\partial L_t}{\partial W}$$

Almost always < 1
Vanishing gradients

$$\frac{\partial L_T}{\partial W} = \frac{\partial L_T}{\partial h_T} \left(\prod_{t=2}^T \boxed{\tanh'(W_{hh}h_{t-1} + W_{xh}x_t)} \right) W_{hh}^{T-1} \frac{\partial h_1}{\partial W}$$

LSTM

Long Short Term Memory (LSTM)

Vanilla RNN

$$h_t = \tanh \left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} \right)$$

LSTM

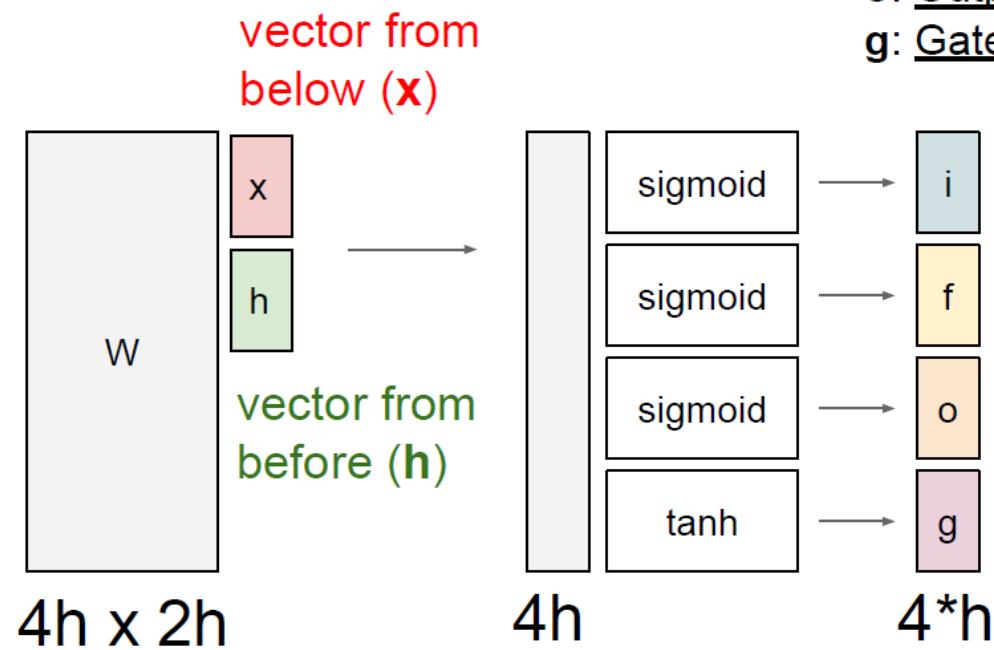
$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$
$$c_t = f \odot c_{t-1} + i \odot g$$
$$h_t = o \odot \tanh(c_t)$$

Hochreiter and Schmidhuber, "Long Short Term Memory", Neural Computation

LSTM

Long Short Term Memory (LSTM)

[Hochreiter et al., 1997]



- i: Input gate, whether to write to cell
- f: Forget gate, Whether to erase cell
- o: Output gate, How much to reveal cell
- g: Gate gate (?), How much to write to cell

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

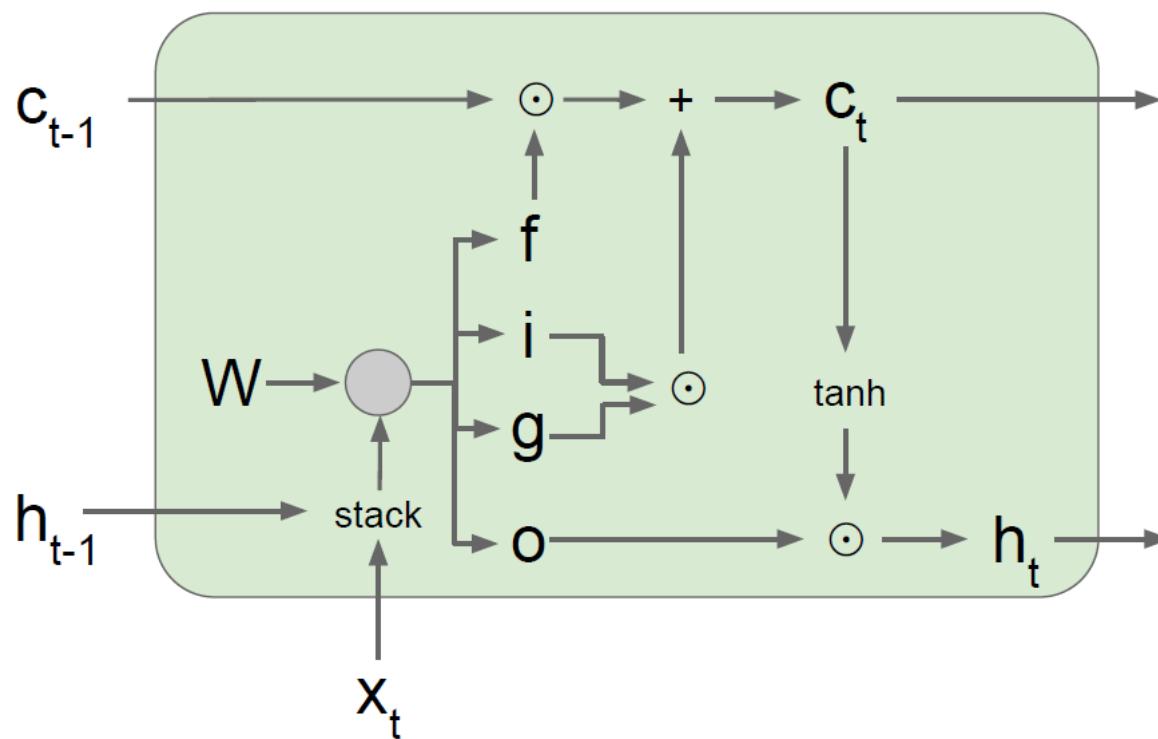
$$c_t = f \odot c_{t-1} + i \odot g$$

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LSTM

Long Short Term Memory (LSTM)

[Hochreiter et al., 1997]



$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

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