# Recurrent Neural Networks

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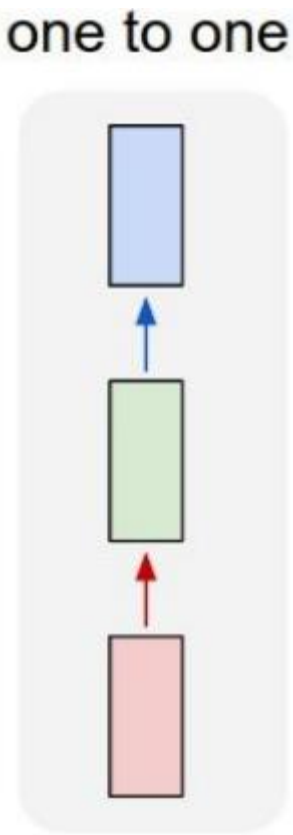
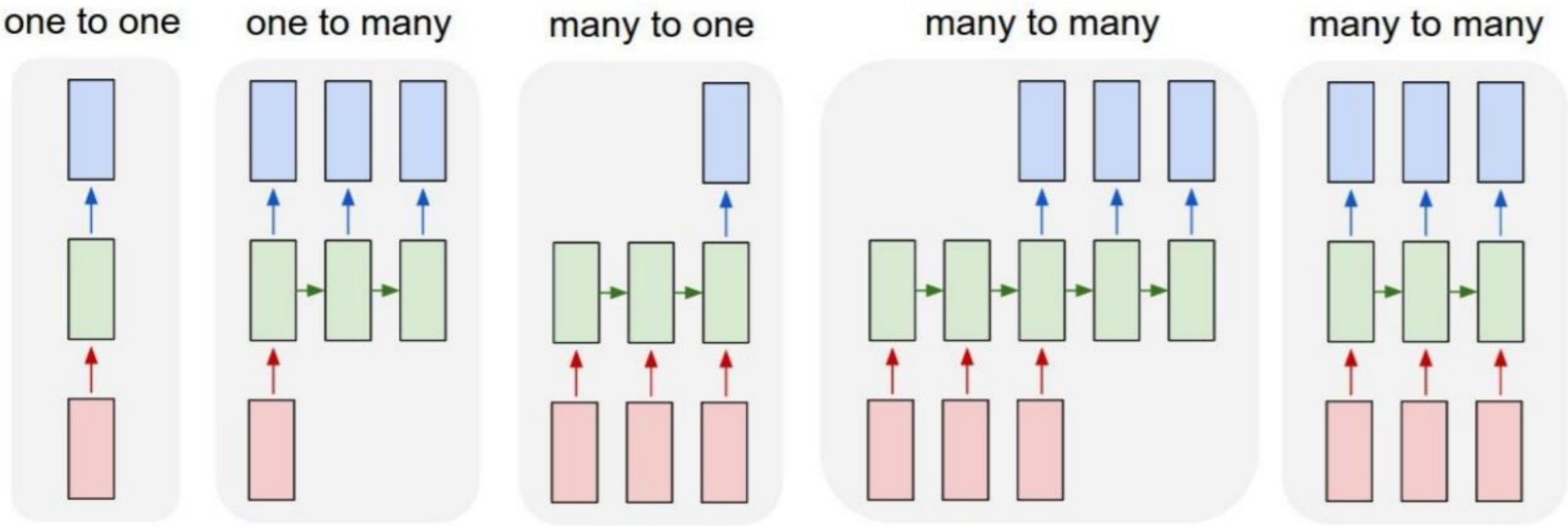
Most slides have been adopted from Fei Fei Li and colleagues lectures, cs231n, Stanford 2017
and some from Socher lectures, cs224d, Stanford, 2017. .

# “Vanilla” Neural Networks




“Vanilla” NN

# Recurrent Neural Networks: Process Sequences




"Vanilla" NN

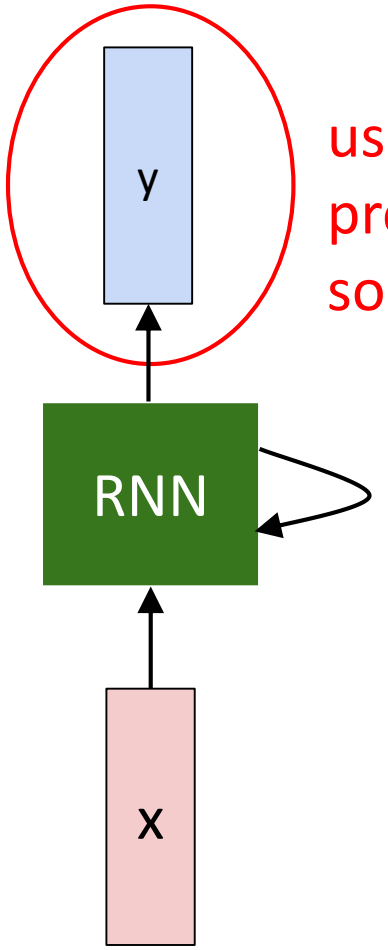
e.g. Image Captioning
image -> seq of words

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

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

e.g. Video classification on frame level

# Recurrent Neural Network




usually want to predict a vector at some time steps

# Recurrent Neural Network

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

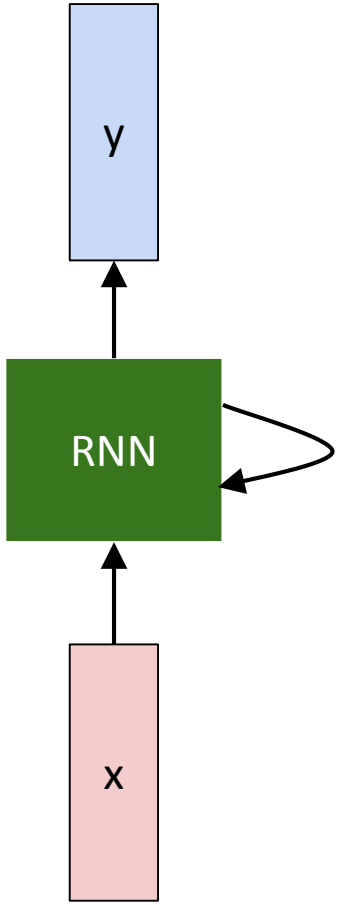
$$h_t = f_W(h_{t-1}, x_t)$$

new state

some function with parameters W

old state

input vector at some time step



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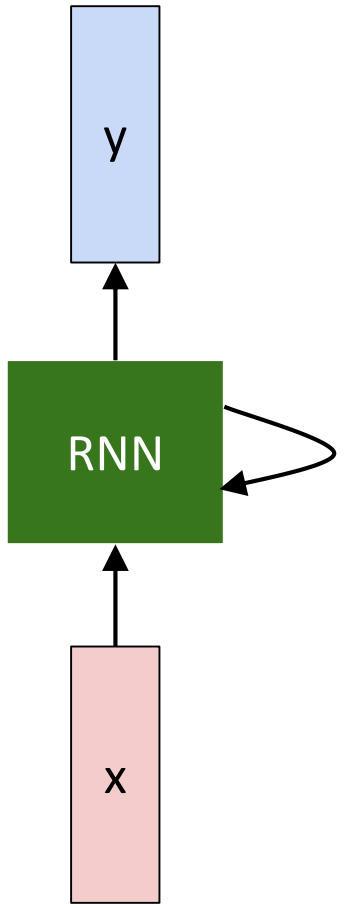
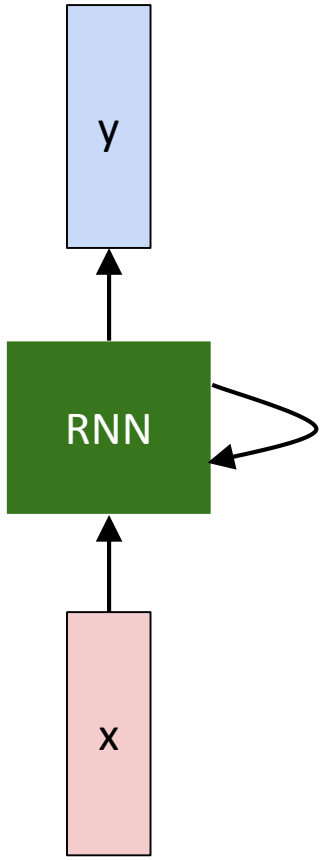



Notice: the same function and the same set of parameters are used at every time step.

# (Vanilla) Recurrent Neural Network

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

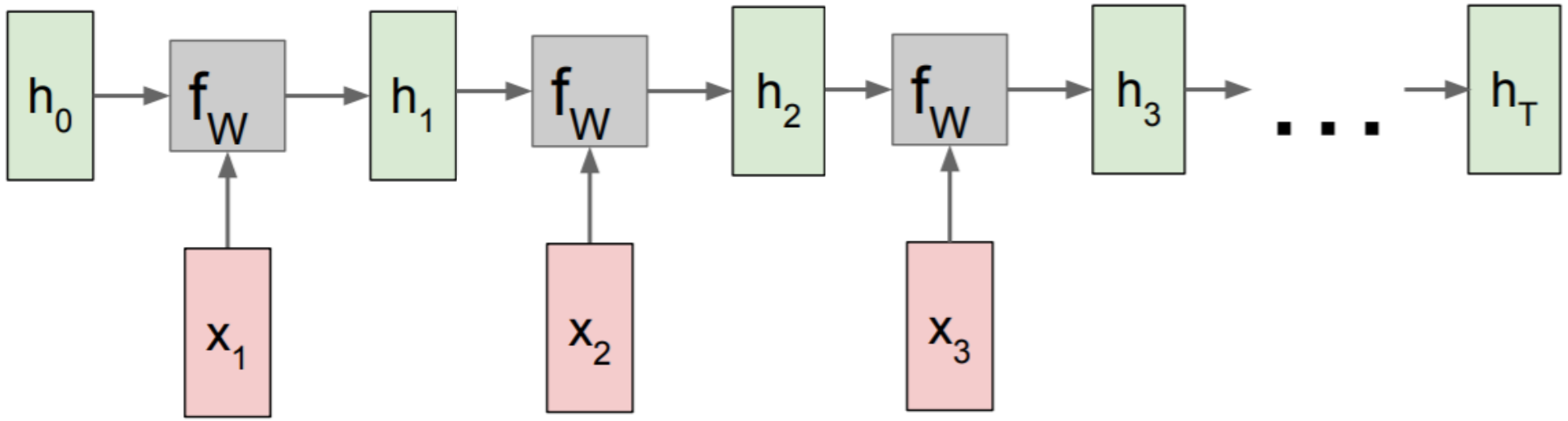



$$h_t = f_W(h_{t-1}, x_t)$$

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

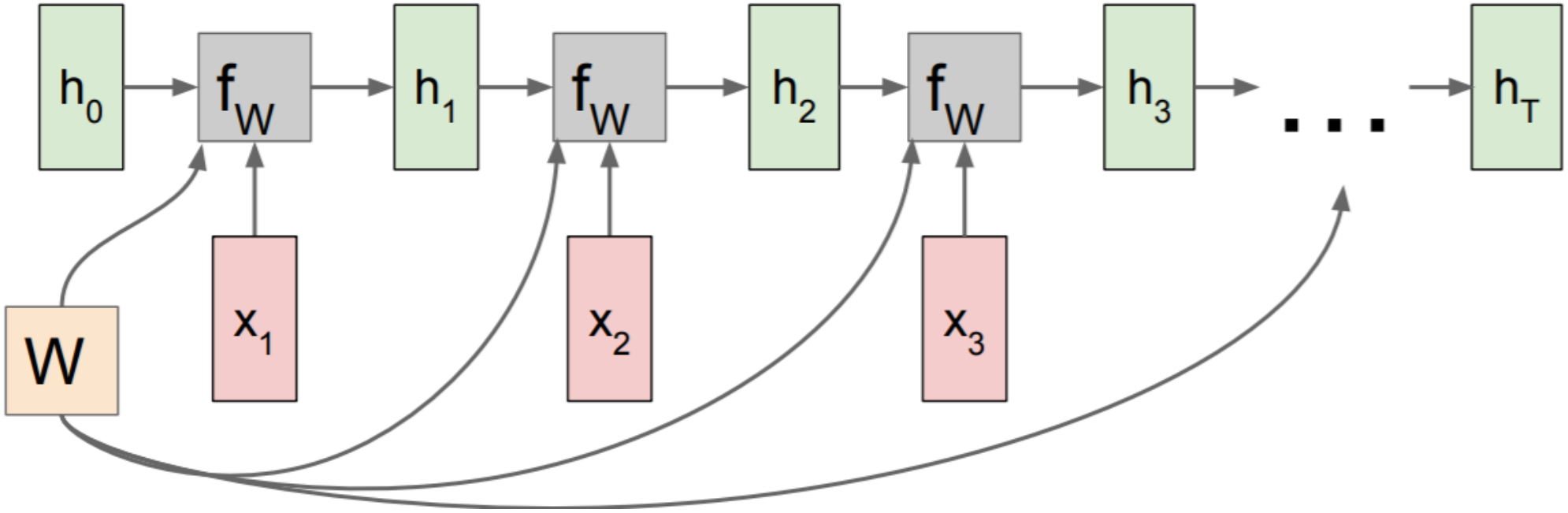
$$y_t = W_{hy}h_t$$

# RNN: Computational Graph

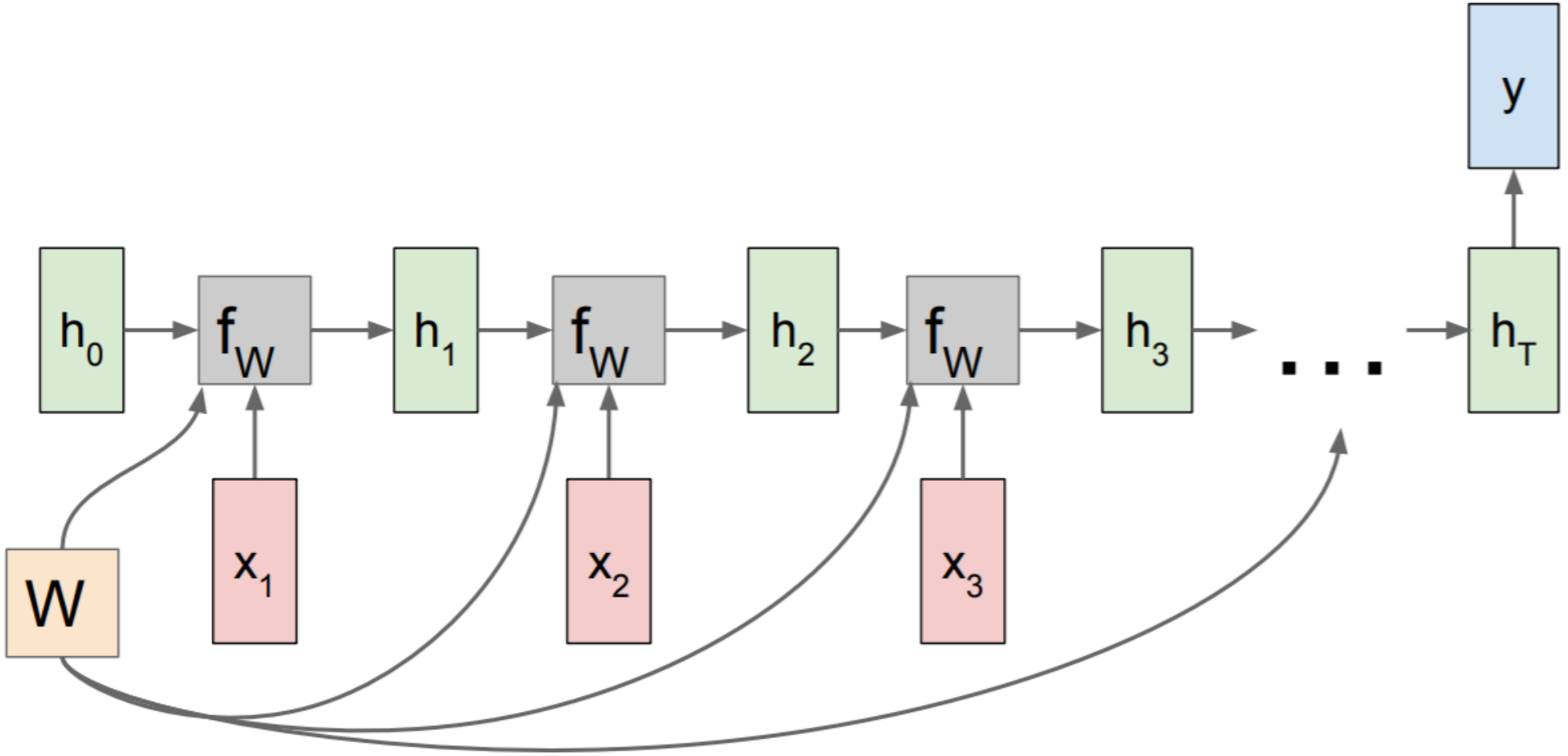


# RNN: Computational Graph

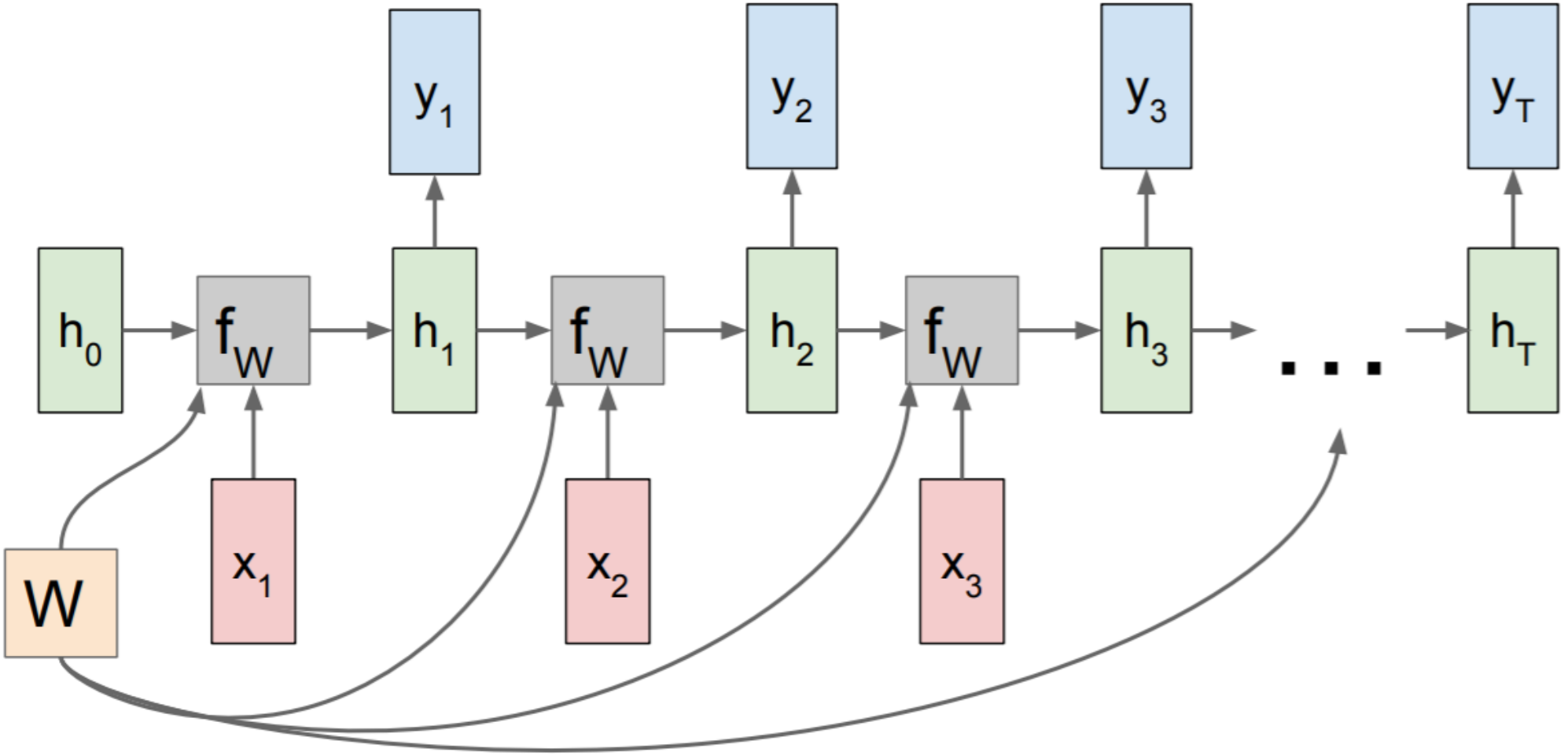
Re-use the same weight matrix at every time-step



# RNN: Computational Graph: Many to One



# RNN: Computational Graph: Many to Many



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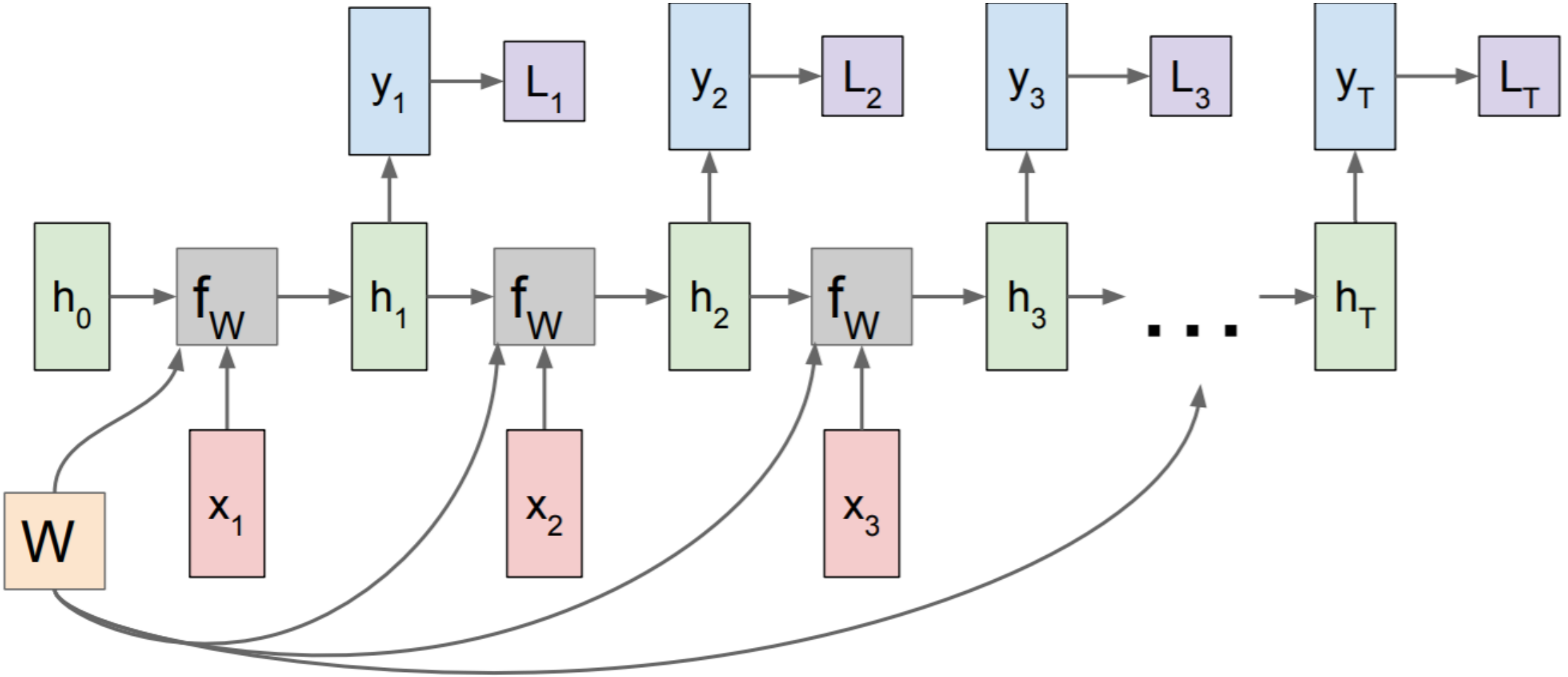

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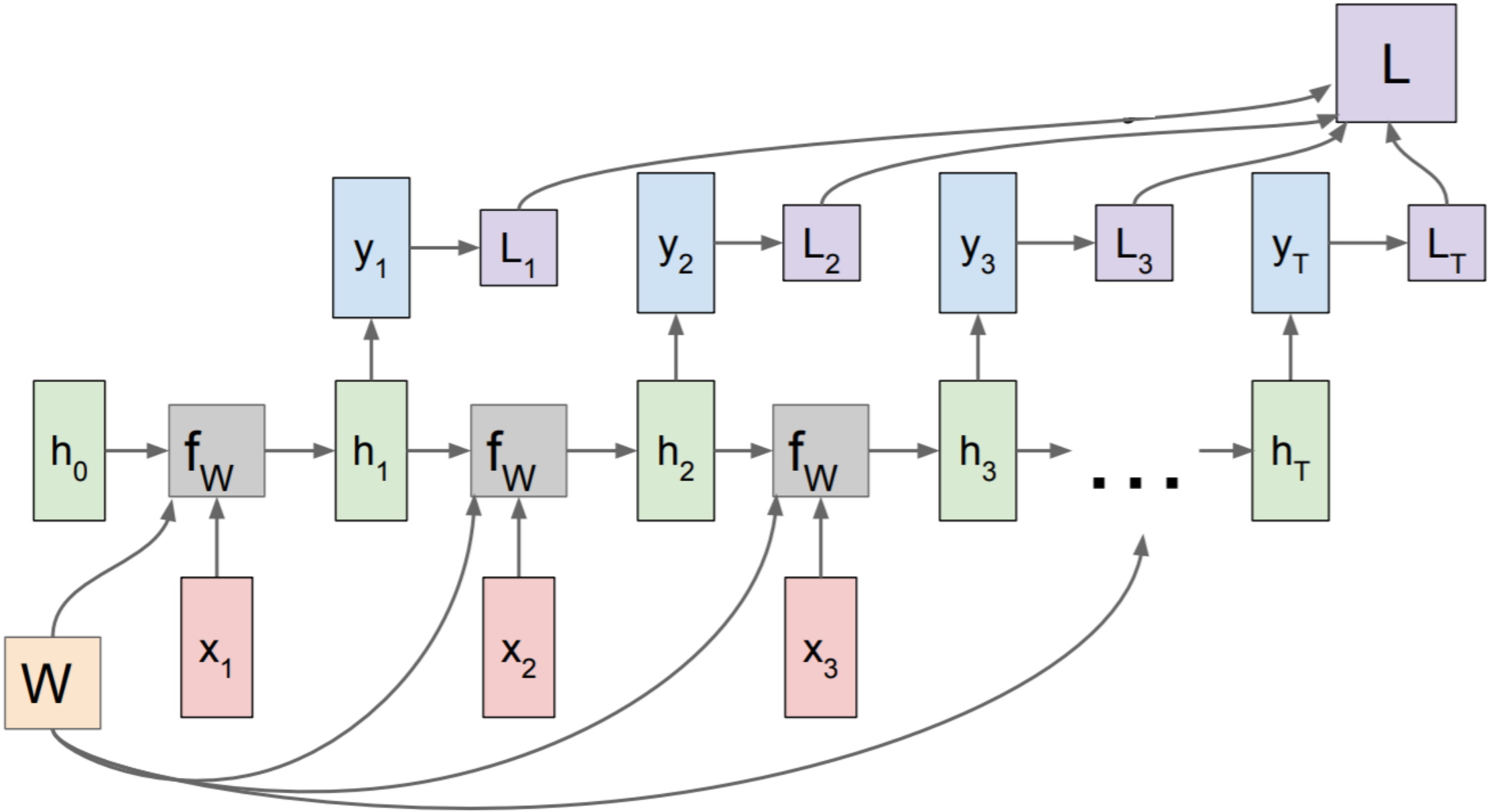
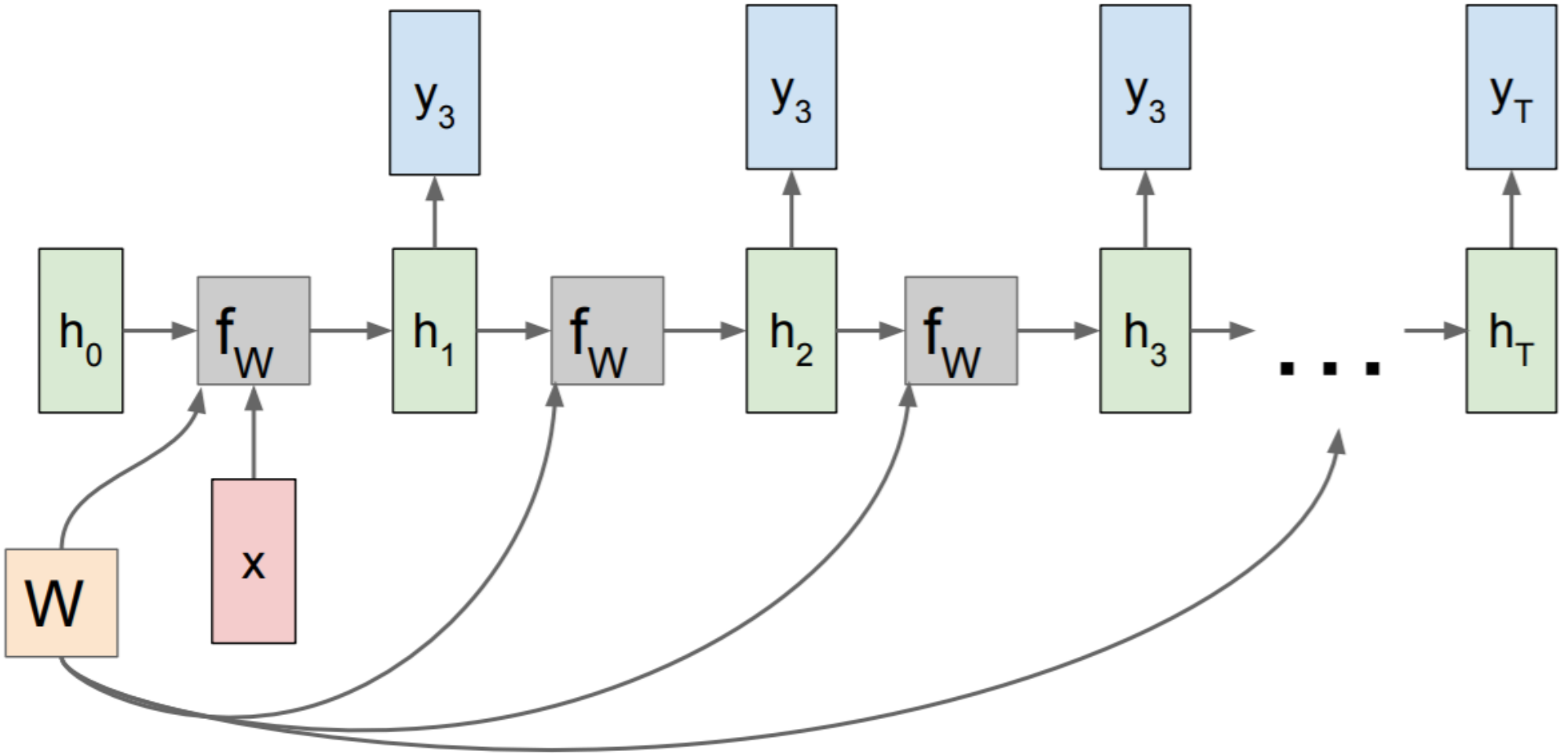


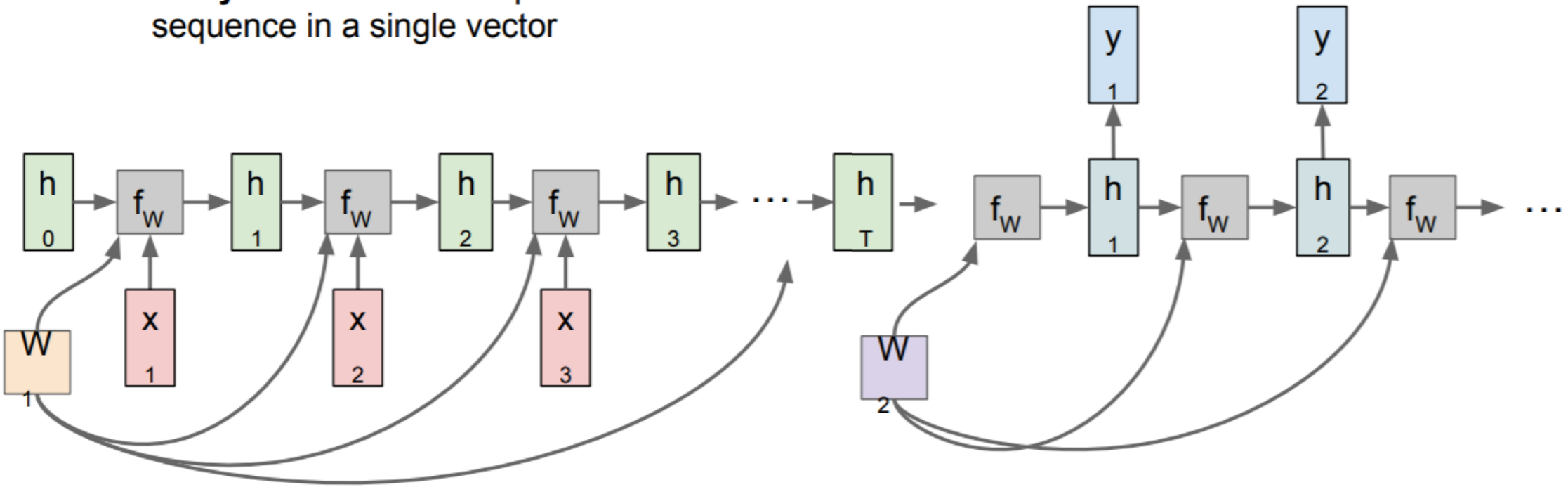
# RNN: Computational Graph: One to Many



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

**Many to one**: Encode input sequence in a single vector

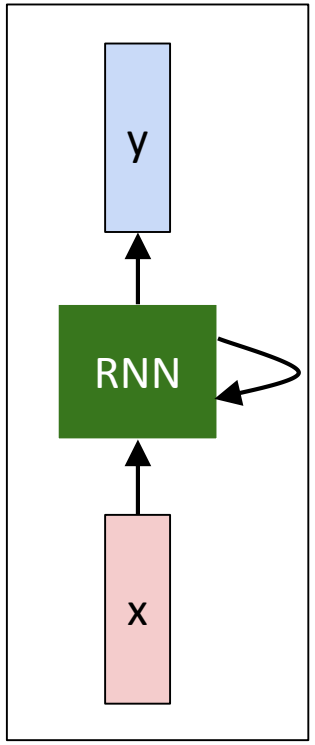
**One to many**: Produce output sequence from single input vector



# Character-level language model example

Vocabulary:
[h,e,l,o]

Example training sequence:
**“hello”**



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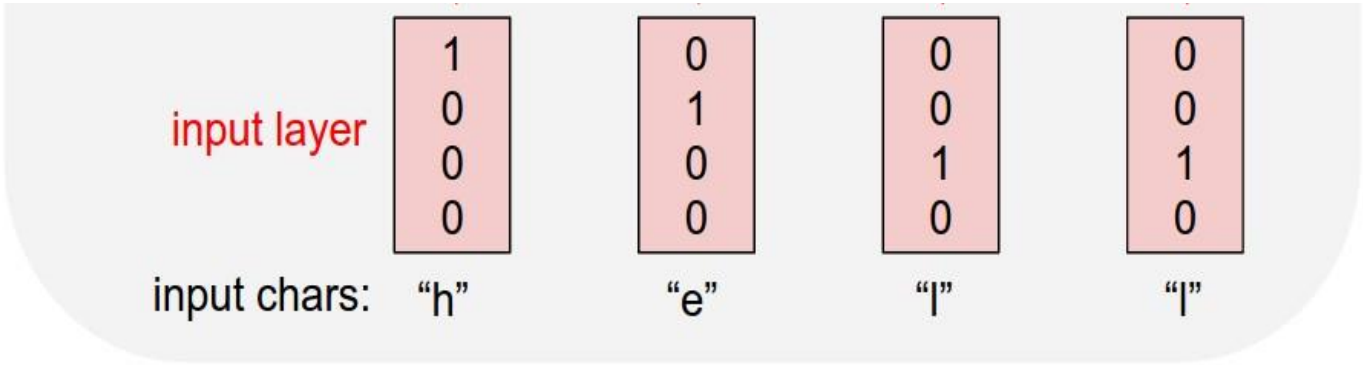

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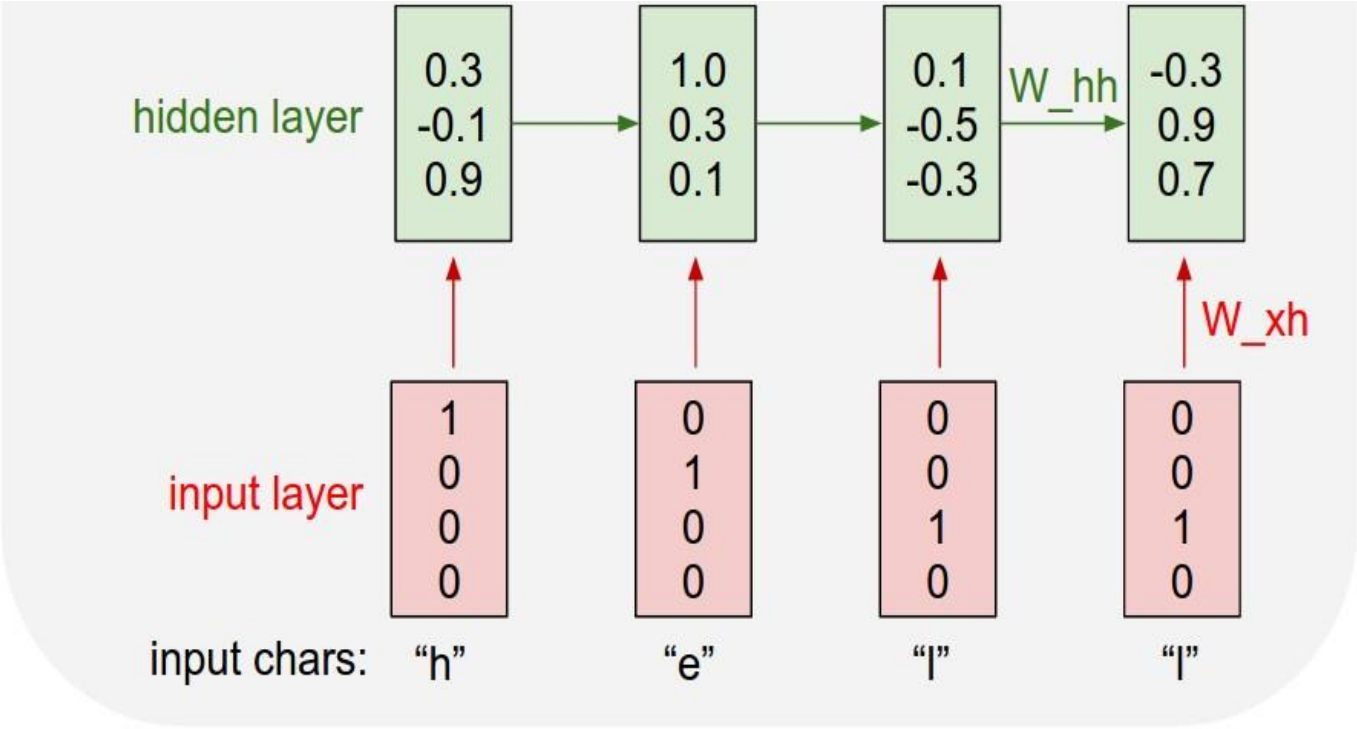

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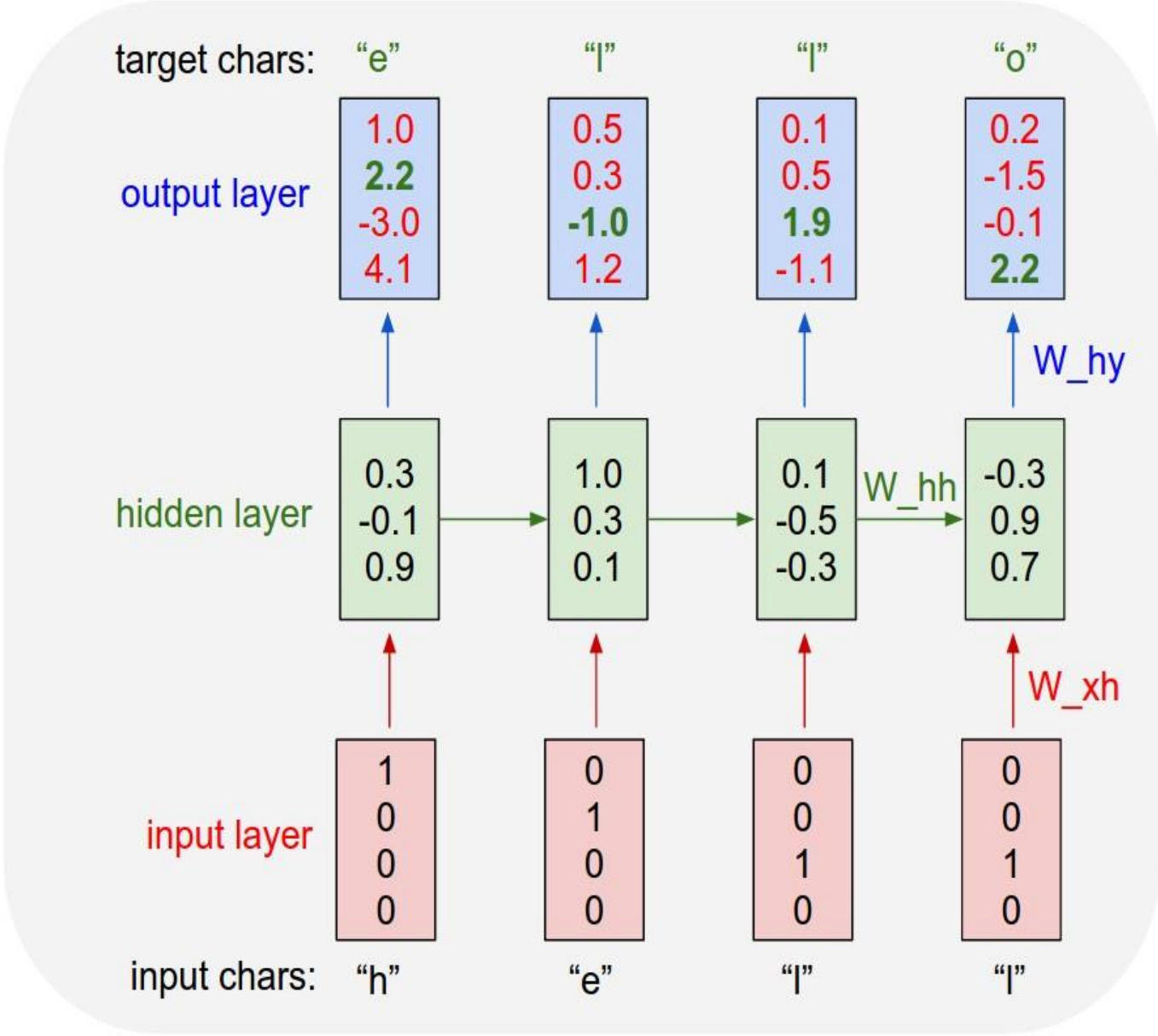
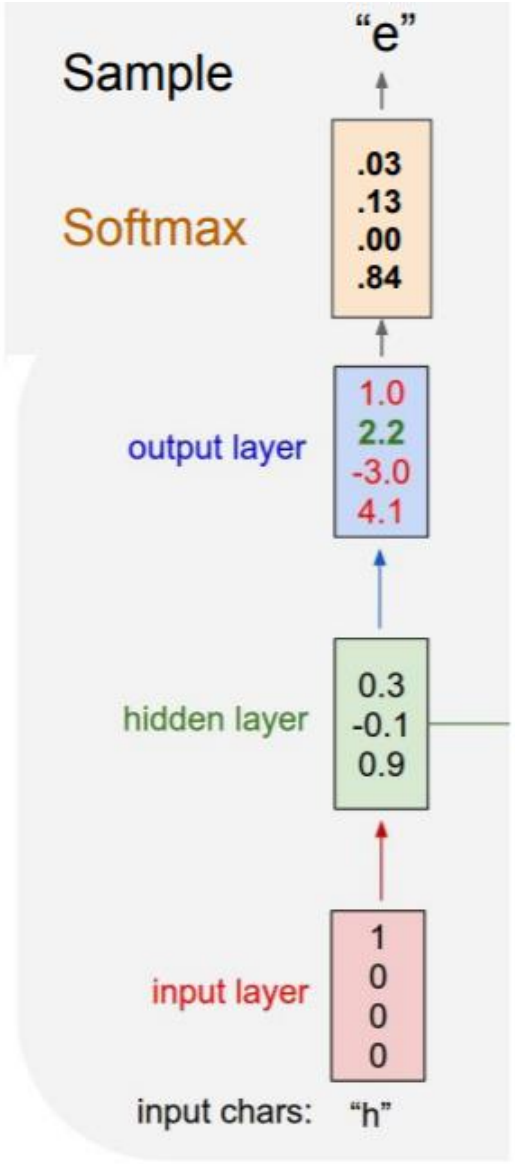


# Example: Character-level Language Model Sampling

- Vocabulary: [h,e,l,o]
- At test-time sample characters one at a time, feed back to model



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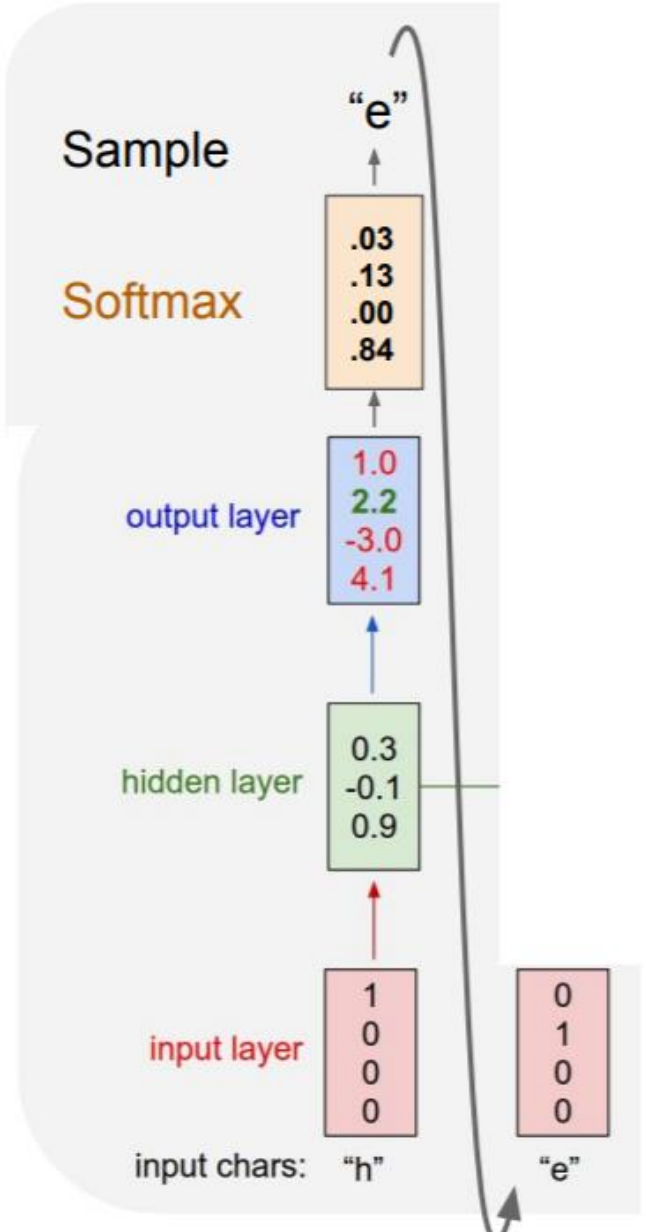

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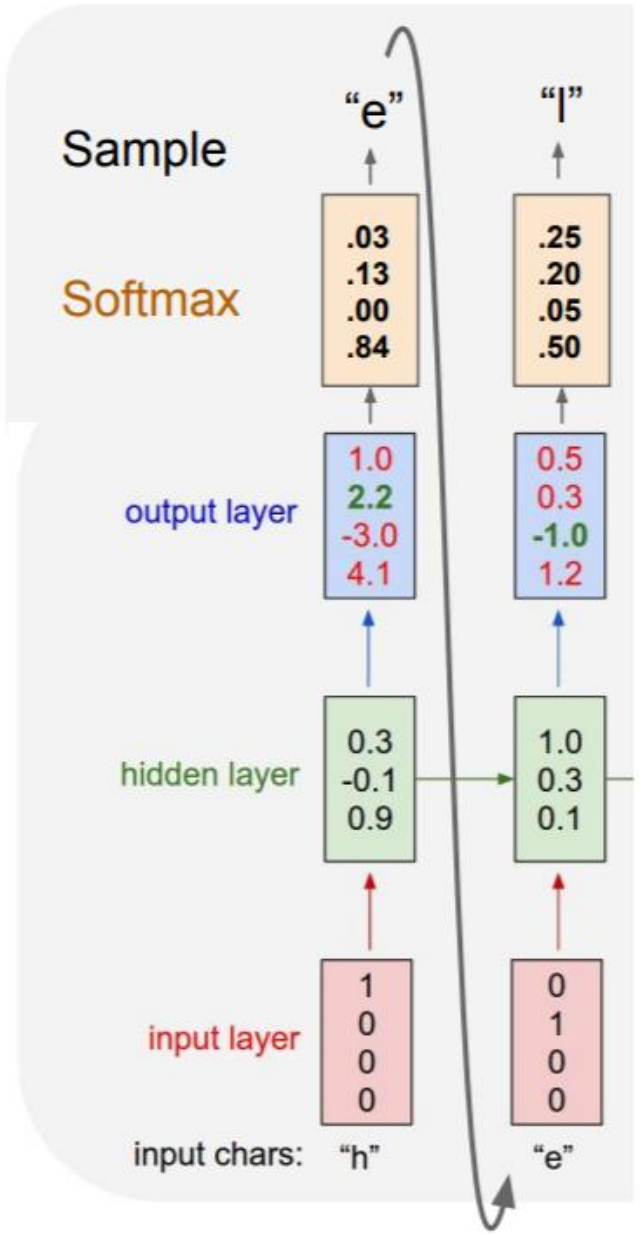

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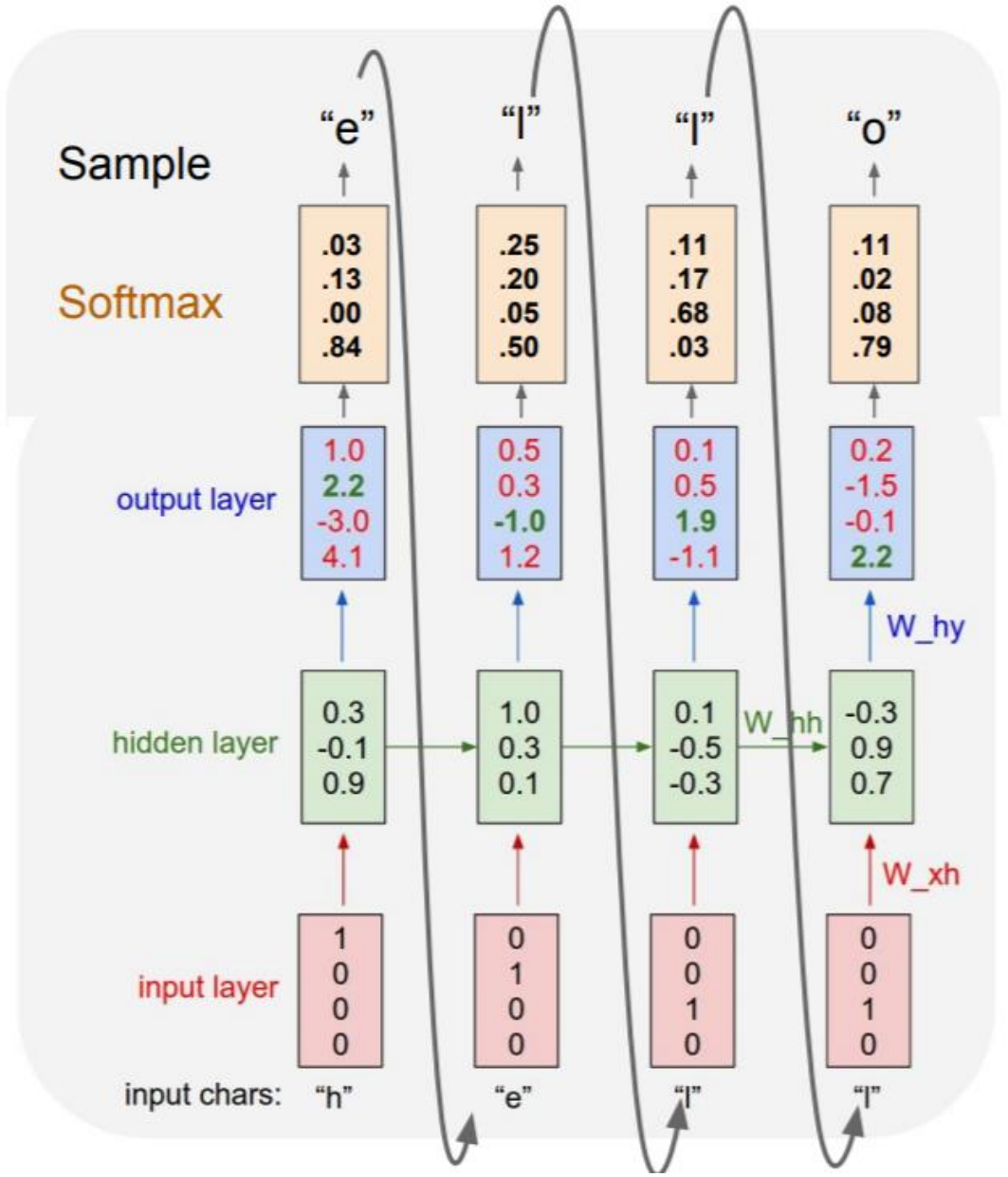


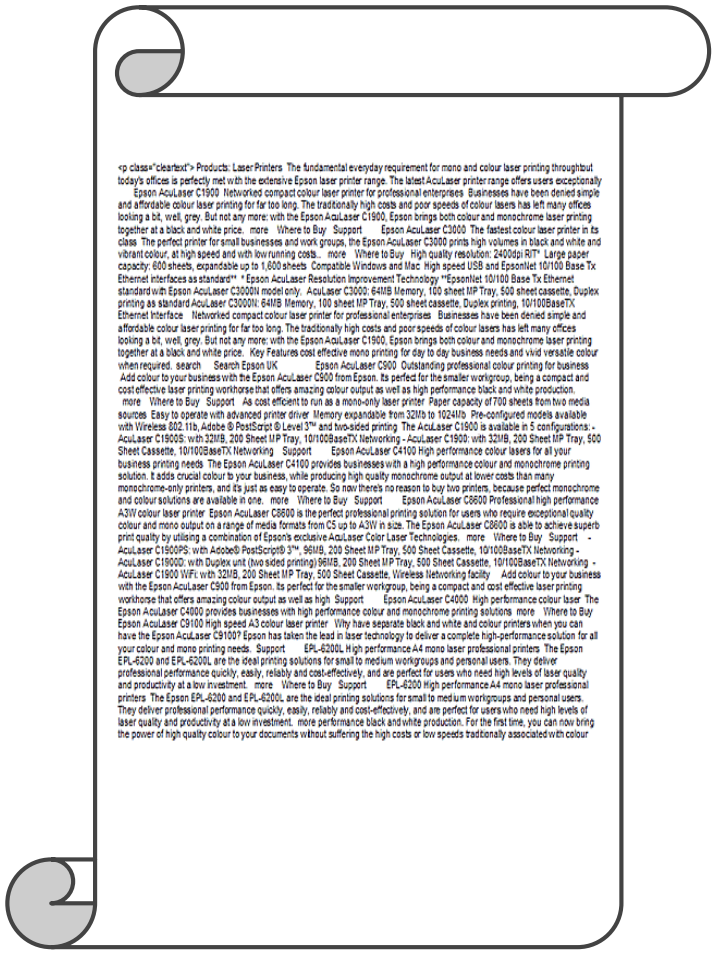
# **min-char-rnn.py** gist:

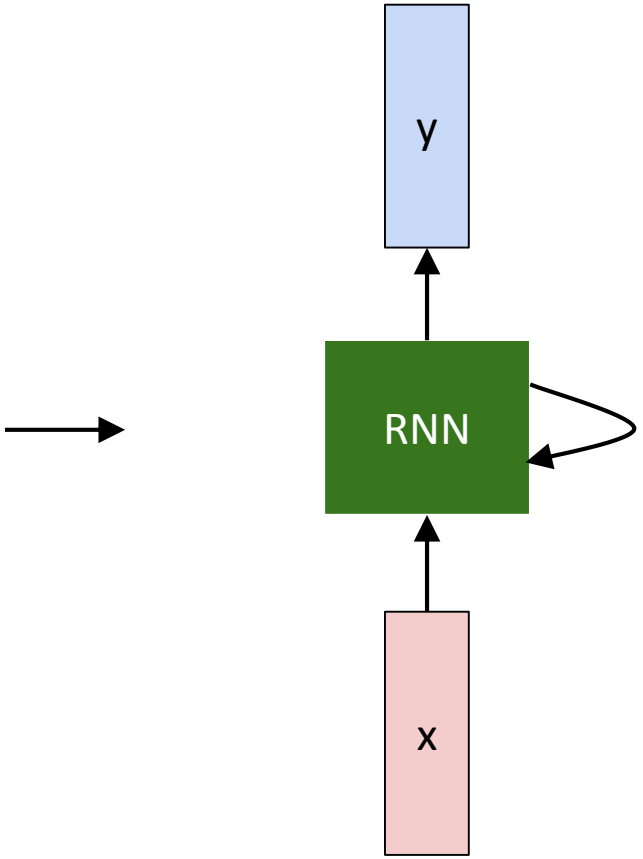
_112 lines of Python

```python
"""
Minimal character-level Vanilla RNN model. Written by Andrej Karpathy (@karpathy)
BSD License
"""
import numpy as np

# data I/O
data = open('input.txt', 'r').read() # should be simple plain text file
chars = list(set(data))
data_size, vocab_size = len(data), len(chars)
print 'data has %d characters, %d unique.' % (data_size, vocab_size)
char_to_ix = { ch:i for i,ch in enumerate(chars) }
ix_to_char = { i:ch for i,ch in enumerate(chars) }

# hyperparameters
hidden_size = 100 # size of hidden layer of neurons
seq_length = 25 # number of steps to unroll the RNN for
learning_rate = 1e-1

# model parameters
Wxh = np.random.randn(hidden_size, vocab_size)*0.01 # input to hidden
Whh = np.random.randn(hidden_size, hidden_size)*0.01 # hidden to hidden
Why = np.random.randn(vocab_size, hidden_size)*0.01 # hidden to output
bh = np.zeros((hidden_size, 1)) # hidden bias
by = np.zeros((vocab_size, 1)) # output bias

def lossFun(inputs, targets, hprev):
  """
  inputs,targets are both list of integers.
  hprev is Hx1 array of initial hidden state
  returns the loss, gradients on model parameters, and last hidden state
  """
  xs, hs, ys, ps = {}, {}, {}, {}
  hs[-1] = np.copy(hprev)
  loss = 0
  # forward pass
  for t in xrange(len(inputs)):
    xs[t] = np.zeros((vocab_size,1)) # encode in 1-of-k representation
    xs[t][inputs[t]] = 1
    hs[t] = np.tanh(np.dot(Wxh, xs[t]) + np.dot(Whh, hs[t-1]) + bh) # hidden state
    ys[t] = np.dot(Why, hs[t]) + by # unnormalized log probabilities for next chars
    ps[t] = np.exp(ys[t]) / np.sum(np.exp(ys[t])) # probabilities for next chars
    loss += -np.log(ps[t][targets[t],0]) # softmax (cross-entropy loss)
  # backward pass: compute gradients going backwards
  dWxh, dWhh, dWhy = np.zeros_like(Wxh), np.zeros_like(Whh), np.zeros_like(Why)
  dbh, dby = np.zeros_like(bh), np.zeros_like(by)
  dhnext = np.zeros_like(hs[0])
  for t in reversed(xrange(len(inputs))):
    dy = np.copy(ps[t])
    dy[targets[t]] -= 1 # backprop into y
    dWhy += np.dot(dy, hs[t].T)
    dby += dy
    dh = np.dot(Why.T, dy) + dhnext # backprop into h
    dhraw = (1 - hs[t] * hs[t]) * dh # backprop through tanh nonlinearity
    dbh += dhraw
    dWxh += np.dot(dhraw, xs[t].T)
    dWhh += np.dot(dhraw, hs[t-1].T)
    dhnext = np.dot(Whh.T, dhraw)
  for dparam in [dWxh, dWhh, dWhy, dbh, dby]:
    np.clip(dparam, -5, 5, out=dparam) # clip to mitigate exploding gradients
  return loss, dWxh, dWhh, dWhy, dbh, dby, hs[len(inputs)-1]

def sample(h, seed_ix, n):
  """
  sample a sequence of integers from the model
  h is memory state, seed_ix is seed letter for first time step
  """
  x = np.zeros((vocab_size, 1))
  x[seed_ix] = 1
  ixes = []
  for t in xrange(n):
    h = np.tanh(np.dot(Wxh, x) + np.dot(Whh, h) + bh)
    y = np.dot(Why, h) + by
    p = np.exp(y) / np.sum(np.exp(y))
    ix = np.random.choice(range(vocab_size), p=p.ravel())
    x = np.zeros((vocab_size, 1))
    x[ix] = 1
    ixes.append(ix)
  return ixes

n, p = 0, 0
mWxh, mWhh, mWhy = np.zeros_like(Wxh), np.zeros_like(Whh), np.zeros_like(Why)
mbh, mby = np.zeros_like(bh), np.zeros_like(by) # memory variables for Adagrad
smooth_loss = -np.log(1.0/vocab_size)*seq_length # loss at iteration 0
while True:
  # prepare inputs (we're sweeping from left to right in steps seq_length long)
  if p+seq_length+1 >= len(data) or n == 0:
    hprev = np.zeros((hidden_size,1)) # reset RNN memory
    p = 0 # go from start of data
  inputs = [char_to_ix[ch] for ch in data[p:p+seq_length]]
  targets = [char_to_ix[ch] for ch in data[p+1:p+seq_length+1]]

  # sample from the model now and then
  if n % 100 == 0:
    sample_ix = sample(hprev, inputs[0], 200)
    txt = ''.join(ix_to_char[ix] for ix in sample_ix)
    print '----\n %s \n----' % (txt, )

  # forward seq_length characters through the net and fetch gradient
  loss, dWxh, dWhh, dWhy, dbh, dby, hprev = lossFun(inputs, targets, hprev)
  smooth_loss = smooth_loss * 0.999 + loss * 0.001
  if n % 100 == 0: print 'iter %d, loss: %f' % (n, smooth_loss) # print progress

  # perform parameter update with Adagrad
  for param, dparam, mem in zip([Wxh, Whh, Why, bh, by],
                                [dWxh, dWhh, dWhy, dbh, dby],
                                [mWxh, mWhh, mWhy, mbh, mby]):
    mem += dparam * dparam
    param += -learning_rate * dparam / np.sqrt(mem + 1e-8) # adagrad update

  p += seq_length # move data pointer
  n += 1 # iteration counter
```

([https://gist.github.com/karpathy/d4dee566867f8291f086](https://gist.github.com/karpathy/d4dee566867f8291f086))

# Language Modeling: Example I



# 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-iafhatawiaoihrdemot  lytdws  e ,tfti, astai f ogoh eoase rrranbyne 'nhthnee e
plia tklrgd 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 shuwy 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 srain 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.

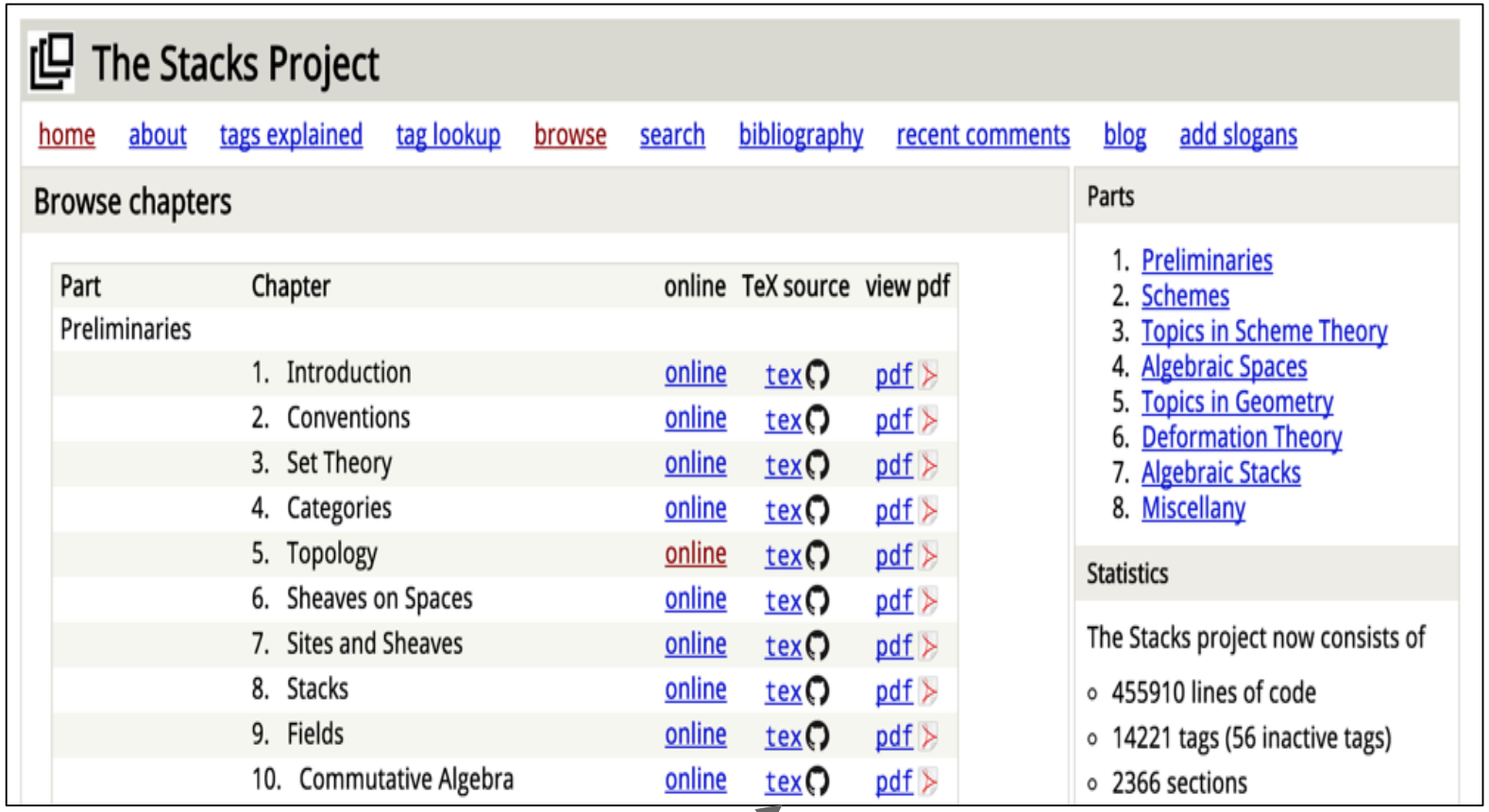
Second Lord:
They would be ruled after this chamber, and
my fair nues begun out of the fact, to be conveyed,
Whose noble souls I'll have the heart of the wars.

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.




Latex source

For $\bigoplus_{n=1,\ldots,m}$ where $\mathcal{L}_{m_\bullet} = 0$, 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 $U \to T$ is a separated algebraic space.

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

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

and the comparicoly in the fibre product covering we have to prove the lemma generated by $\coprod Z \times_U U \to V$. Consider the maps $M$ along the set of points $Sch_{fppf}$ and $U \to U$ 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 $Sh(G)$ such that $\mathrm{Spec}(R') \to S$ 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 $\mathcal{O}_{X,x'} \to \mathcal{O}'_{X',x'}$ is separated. By Algebra, Lemma **??** we can define a map of complexes $\mathrm{GL}_{S'}(x'/S'')$ and we win. □

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

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

is a unique morphism of algebraic stacks. Note that

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

and

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

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. □

The result for prove any open covering follows from the less of Example **??**. It may replace $S$ by $X_{spaces,étale}$ 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* $\underline{Proj}_X(\mathcal{A}) = \mathrm{Spec}(B)$ *over* $U$ *compatible with the complex*

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

*When in this case of to show that* $\mathcal{Q} \to \mathcal{C}_{Z/X}$ *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* $S = \mathrm{Spec}(R)$ *and* $Y = \mathrm{Spec}(R)$.

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

The following lemma surjective restrocomposes of this implies that $\mathcal{F}_{x_0} = \mathcal{F}_{x_0} = \mathcal{F}_{\mathcal{X},\ldots,0}$.

**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* $i_0 \leq \mathfrak{p}$ *is a subset of* $\mathcal{J}_{n,0} \circ \overline{A}_2$ *works.*

**Lemma 0.3.** *In Situation* **??**. *Hence we may assume* $\mathfrak{q}' = 0$.

*Proof.* We will use the property we see that $\mathfrak{p}$ is the mext 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 $\delta_{n+1}$ is a scheme over $S$. □

*Proof.* Omitted. □

**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 $X_{\acute{e}tale}$ we have

$$\mathcal{O}_X(\mathcal{F}) = \{morph_1 \times_{\mathcal{O}_X} (\mathcal{G}, \mathcal{F})\}$$

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

**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 $\mathcal{U} \subset \mathcal{X}$ 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*

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

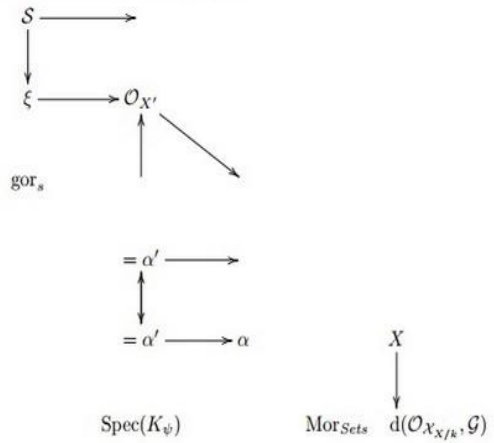
*be a morphism of algebraic spaces over $S$ and $Y$.*

*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. □

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




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.

□

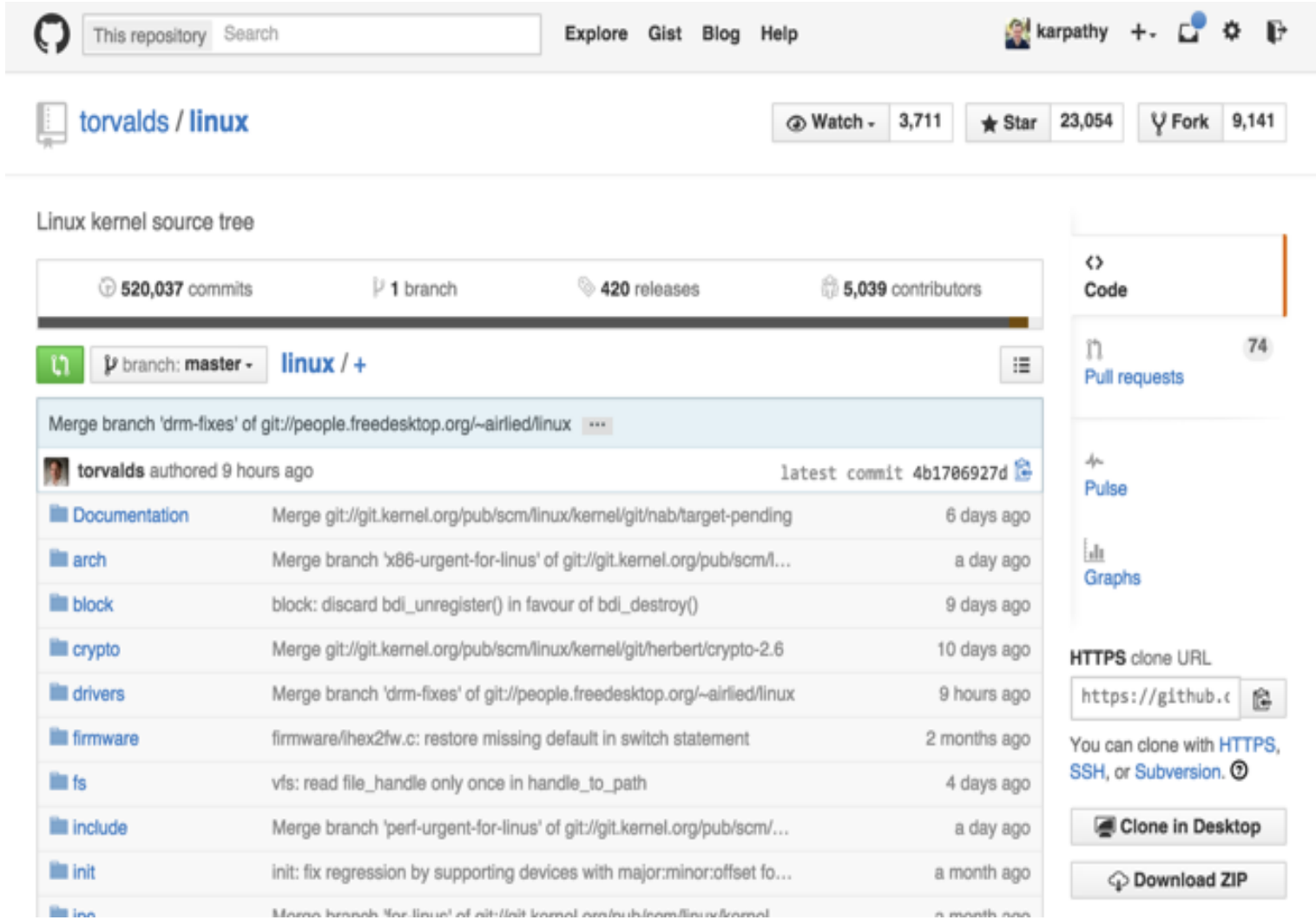
*Proof.* We have see that $X = \mathrm{Spec}(R)$ and $\mathcal{F}$ is a finite type representable by algebraic space. The property $\mathcal{F}$ is a finite morphism of algebraic stacks. Then the cohomology of $X$ is an open neighbourhood of $U$. □

*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

$$\mathcal{O}_{X,x} \longrightarrow \mathcal{F}_{\overline{x}} \quad \text{-1}(\mathcal{O}_{X_{\acute{e}tale}}) \longrightarrow \mathcal{O}_{X_\acute{e}}^{-1}\mathcal{O}_{X_\lambda}(\mathcal{O}_{X_\eta}^{\overline{v}})$$

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. □

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.


This repository
Search
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karpathy
torvalds / linux
Watch 3,711
Star 23,054
Fork 9,141
Linux kernel source tree
520,037 commits
1 branch
420 releases
5,039 contributors
branch: master
linux / +
Merge branch 'drm-fixes' of git://people.freedesktop.org/~airlied/linux
torvalds authored 9 hours ago
latest commit 4b1706927d
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/ihex2fw.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
Code
74
Pull requests
Pulse
Graphs
HTTPS clone URL
https://github.c
You can clone with HTTPS, SSH, or Subversion.
Clone in Desktop
Download ZIP

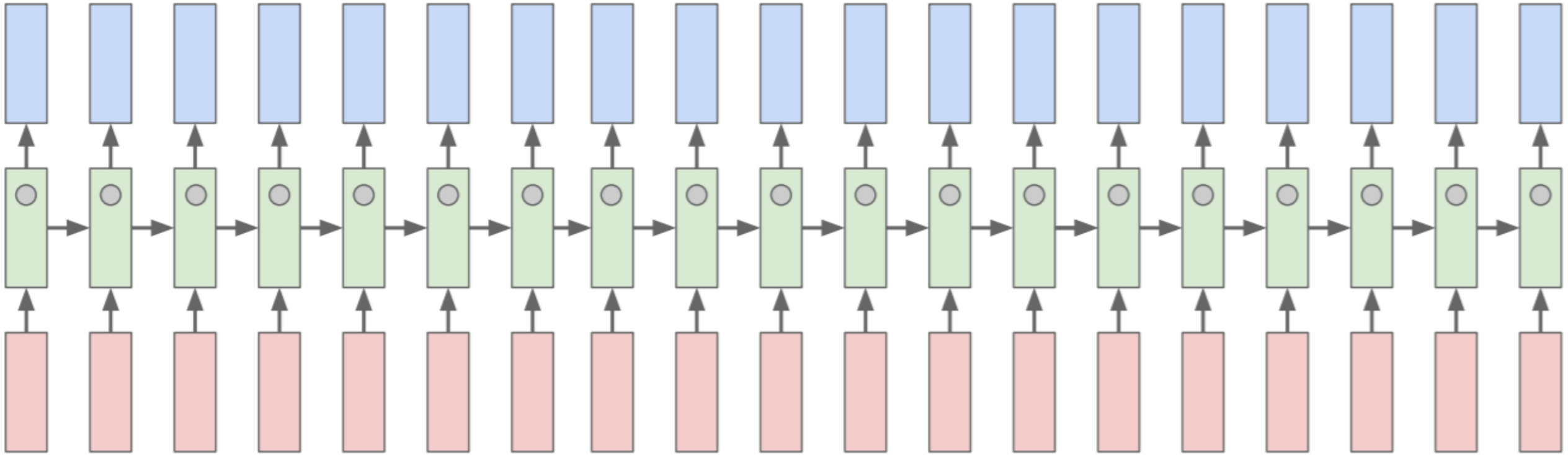
```
static void do_command(struct seq_file *m, void *v)
{
  int column = 32 << (cmd[2] & 0x80);
  if (state)
    cmd = (int)(int_state ^ (in_8(&ch->ch_flags) & Cmd) ? 2 : 1);
  else
    seq = 1;
  for (i = 0; i < 16; i++) {
    if (k & (1 << 1))
      pipe = (in_use & UMXTHREAD_UNCCA) +
        ((count & 0x00000000ffffffff8) & 0x000000f) << 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/setew.h>
#include <asm/pgproto.h>
```

```
#include <asm/io.h>
#include <asm/prom.h>
#include <asm/e820.h>
#include <asm/system_info.h>
#include <asm/setew.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;
}
```

# Searching for interpretable cells



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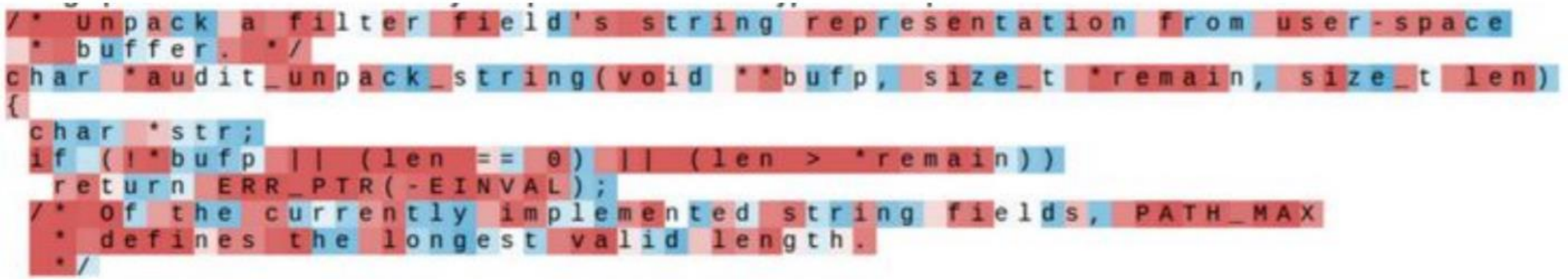
# Searching for interpretable cells



```
/*  Unpack a filter field's string representation from user-space
 *  buffer.  */
char *audit_unpack_string(void **bufp, size_t *remain, size_t len)
{
  char *str;
  if (!*bufp || (len == 0) || (len > *remain))
    return ERR_PTR(-EINVAL);
  /*  Of the currently implemented string fields, PATH_MAX
   *  defines the longest valid length.
   */
```

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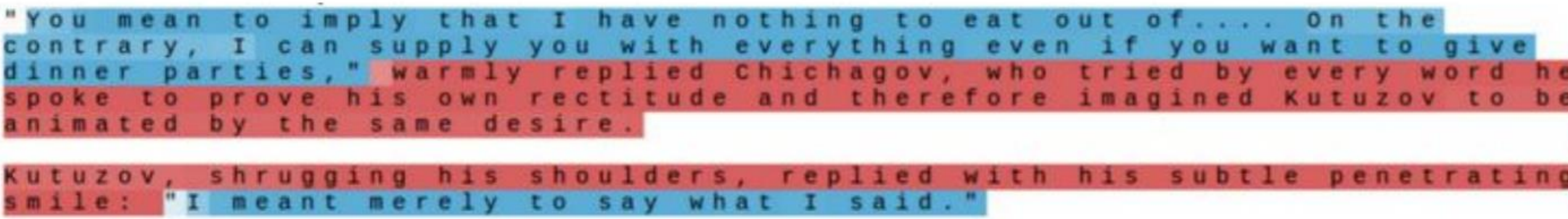
# Searching for interpretable cells




quote detection cell

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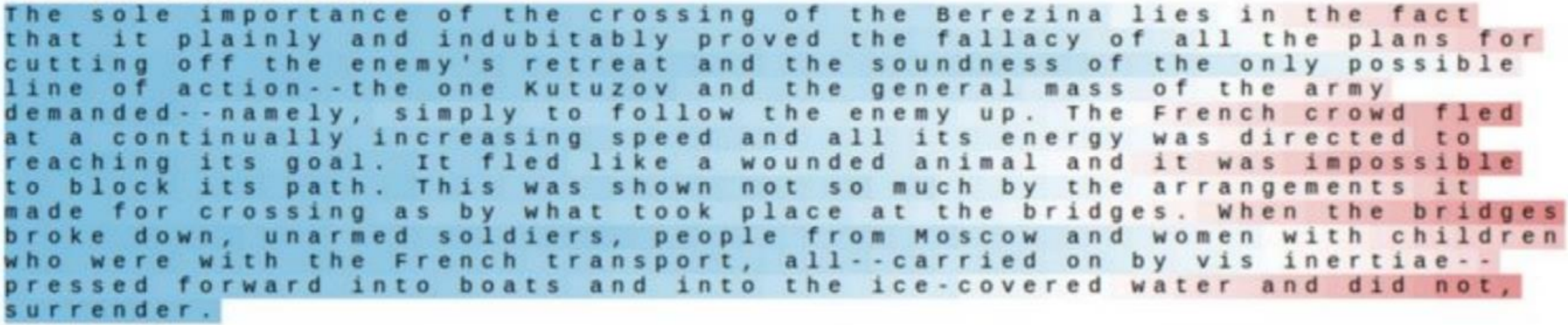
# Searching for interpretable cells

Cell sensitive to position in line:




line length tracking cell

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# Searching for interpretable cells

```
static int __dequeue_signal(struct sigpending *pending, sigset_t *mask,
        siginfo_t *info)
{
  int sig = next_signal(pending, mask);
  if (sig) {
    if (current->notifier) {
      if (sigismember(current->notifier_mask, sig)) {
        if (!(current->notifier)(current->notifier_data)) {
          clear_thread_flag(TIF_SIGPENDING);
          return 0;
        }
      }
    }
    collect_signal(sig, pending, info);
  }
  return sig;
}
```

if statement cell

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# Searching for interpretable cells

Cell that turns on inside comments and quotes:

```
/* Duplicate LSM field information.  The lsm_rule is opaque, so
 * re-initialized. */
static inline int audit_dupe_lsm_field(struct audit_field *df,
                                       struct audit_field *sf)
{
  int ret = 0;
  char *lsm_str;
  /* our own copy of lsm_str */
  lsm_str = kstrdup(sf->lsm_str, GFP_KERNEL);
  if (unlikely(!lsm_str))
    return -ENOMEM;
  df->lsm_str = lsm_str;
  /* our own (refreshed) copy of lsm_rule */
  ret = security_audit_rule_init(df->type, df->op, df->lsm_str,
                                 (void **)&df->lsm_rule);
  /* Keep currently invalid fields around in case they
   * become valid after a policy reload. */
  if (ret == -EINVAL) {
    pr_warn("audit rule for LSM \'%s\' is invalid\n",
            df->lsm_str);
    ret = 0;
  }
  return ret;
}
```

quote/comment cell

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# Searching for interpretable cells

```
#ifdef CONFIG_AUDITSYSCALL
static inline int audit_match_class_bits(int class, u32 *mask)
{
  int i;
  if (classes[class]) {
    for (i = 0; i < AUDIT_BITMASK_SIZE; i++)
      if (mask[i] & classes[class][i])
        return 0;
  }
  return 1;
}
```

code depth cell

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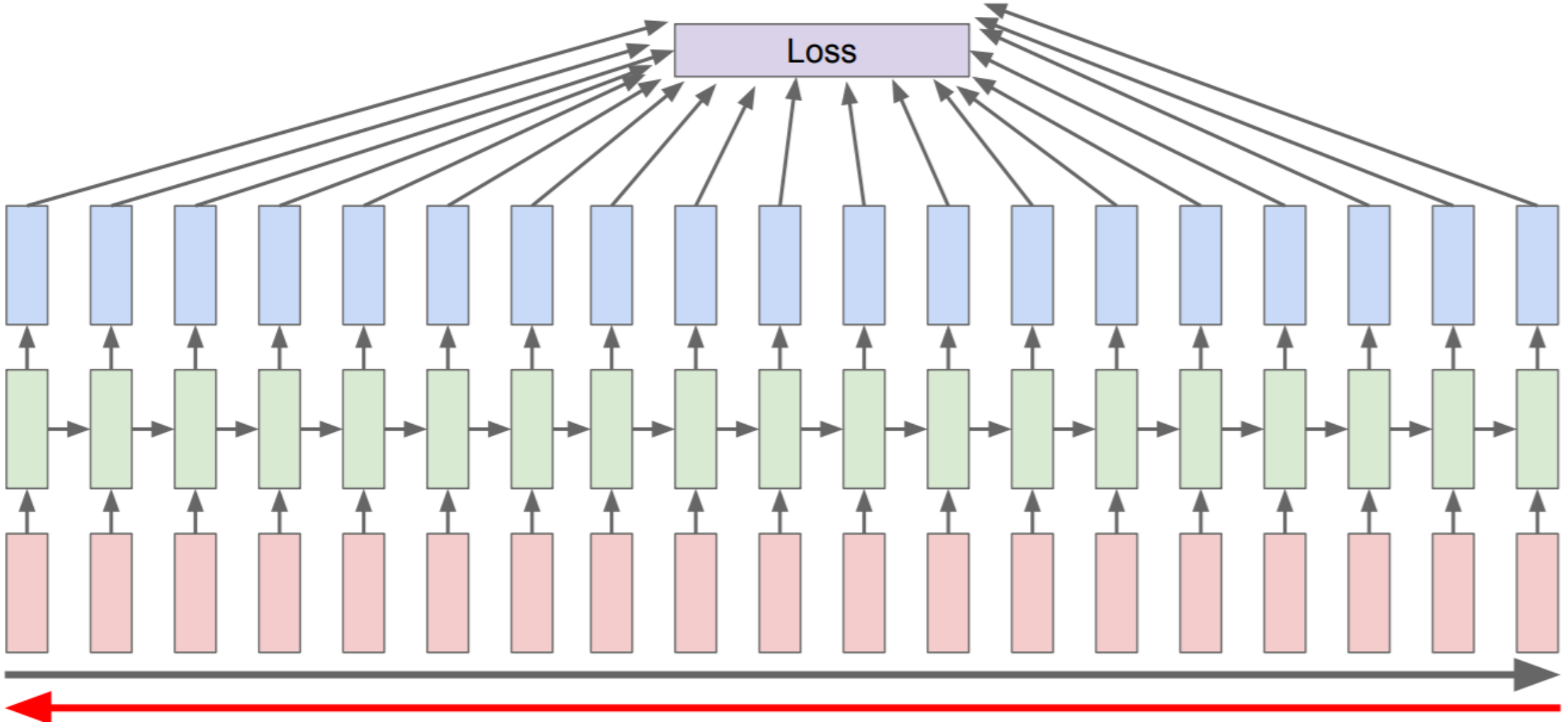
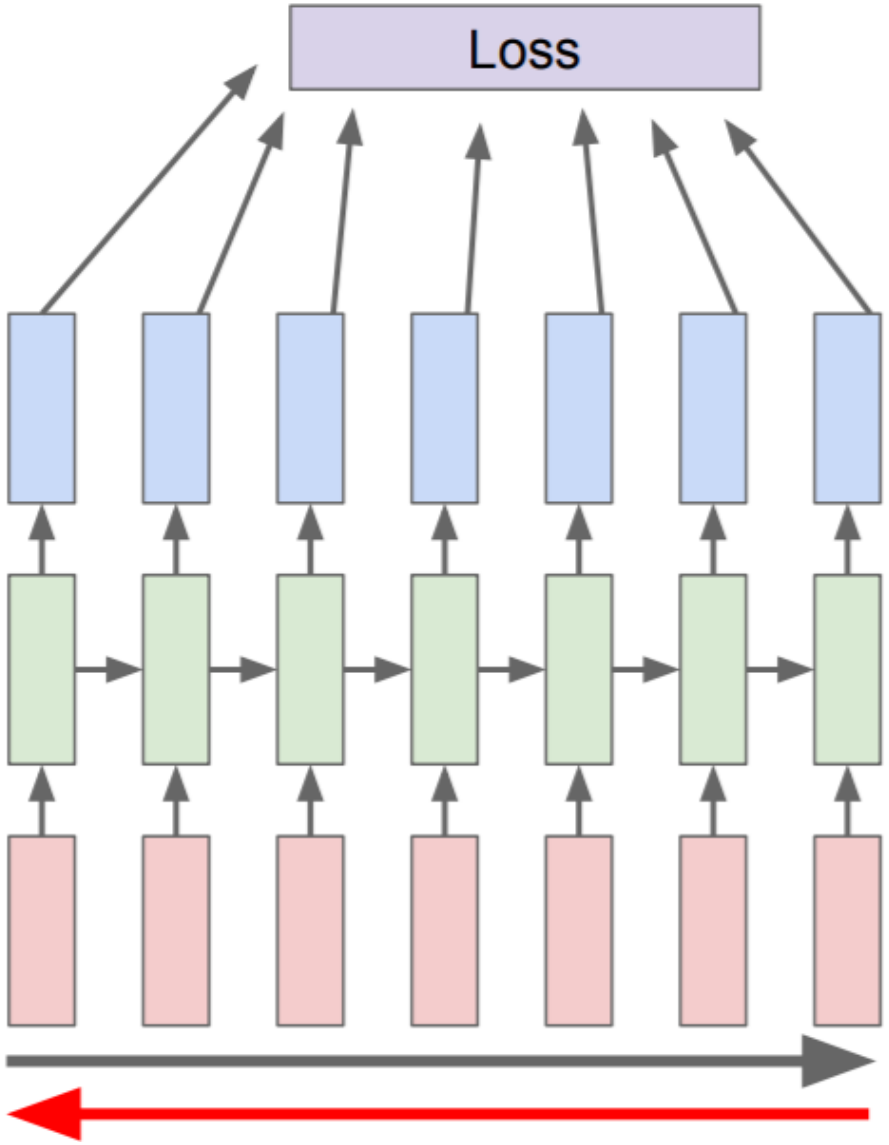
# Backpropagation through time

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

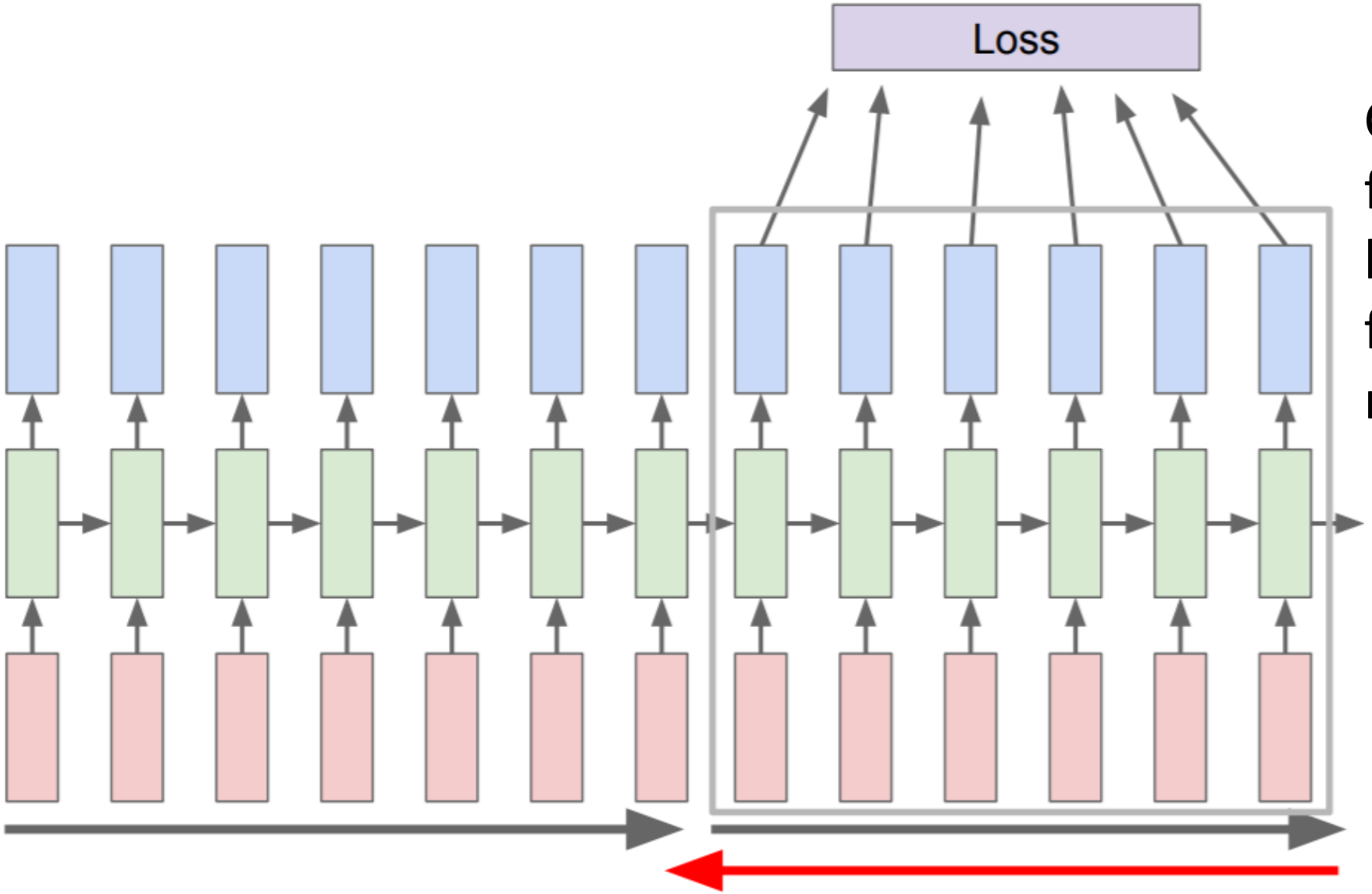


# **Truncated** Backpropagation through time



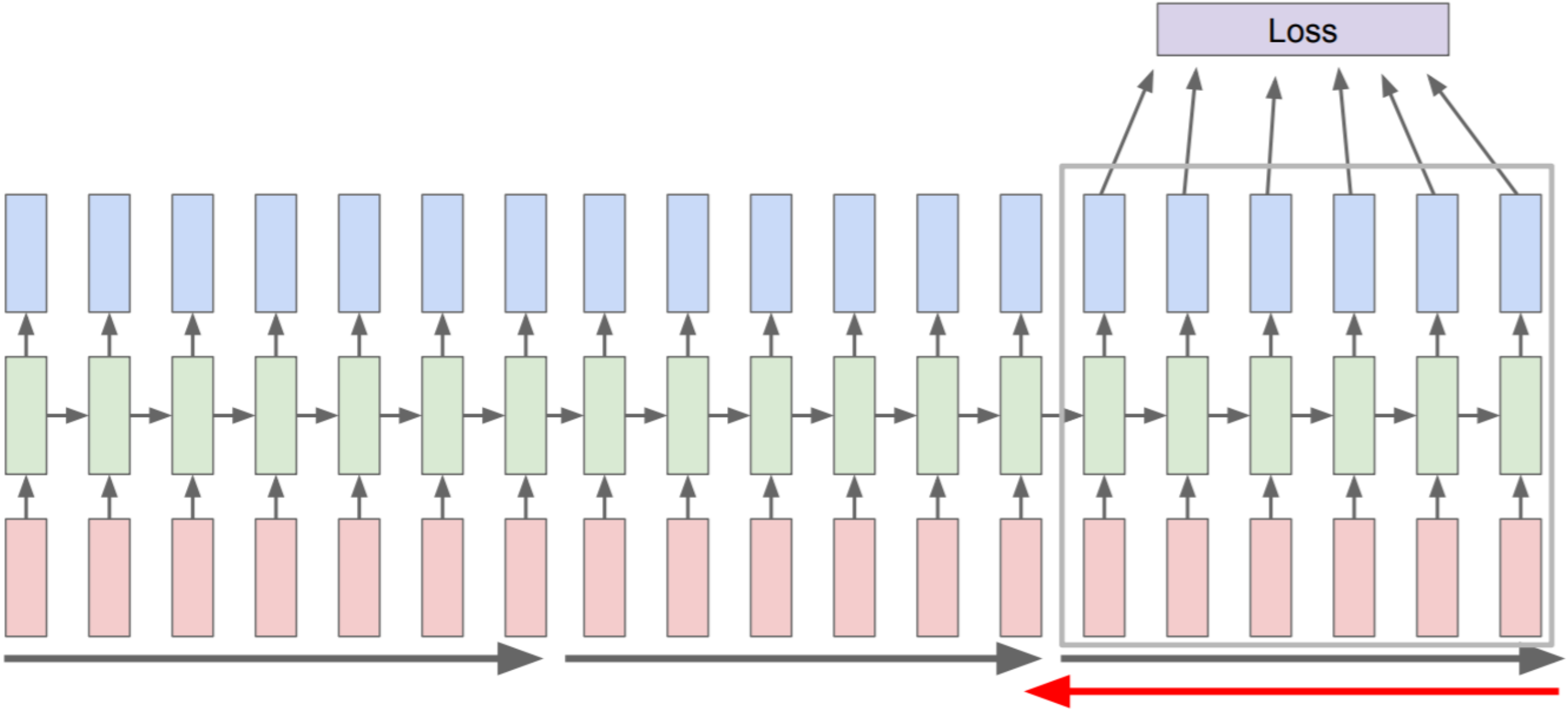

Run forward and backward through chunks of the sequence instead of whole sequence

# **Truncated** Backpropagation through time




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

# **Truncated** Backpropagation through time



# Example: Language Models

- A language model computes a probability for a sequence of words: $P(w_1, \ldots, w_T)$

- Useful for machine translation, spelling correction, and …
  - Word ordering: p(the cat is small) > p(small the is cat)
  - Word choice: p(walking home after school) > p(walking house after school)

# Example: RNN language model

- Given list of word vectors:

$$x_1, x_2, \ldots, x_T$$

- At a single time step:

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

- Output:

$$\hat{y}_t = \text{softmax}\left(W_{hy} h_t\right)$$

$$P(y_t = v_j | x_1, \ldots, x_t) \approx \hat{y}_{t,j}$$

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$$P(y_t = v_j | x_1, \ldots, x_t) \approx \hat{y}_{t,j}$$

$h_0$ is some initialization vector for the hidden layer at time step 0

$x_t$ is the column vector at time step t

# Example: RNN language model loss

- $\hat{y} \in \mathbb{R}^{|V|}$ is a probability distribution over the vocabulary
- Cross entropy loss function at location t of the sequence:

$$E_t = -\sum_{j=1}^{|V|} y_{t,j} \log \hat{y}_{t,j}$$

$y_{t,j} = 1$ when $w_t$ must be the word $j$ of vocabulary

- Cost function over the entire sequence:

$$E = -\frac{1}{T} \sum_{t=1}^{T} \sum_{j=1}^{|V|} y_{t,j} \log \hat{y}_{t,j}$$

# Training RNN

- Total error is the sum of each error at time steps t

$$\frac{\partial E}{\partial W} = \sum_{t=1}^{T} \frac{\partial E_t}{\partial W}$$

# Training RNN

- Total error is the sum of each error at time steps t

$$\frac{\partial E}{\partial W} = \sum_{t=1}^{T} \frac{\partial E_t}{\partial W}$$

- Hardcore chain rule application:

$$\frac{\partial E_t}{\partial W} = \sum_{k=1}^{t} \frac{\partial E_t}{\partial y_t} \frac{\partial y_t}{\partial h_t} \frac{\partial h_t}{\partial h_k} \frac{\partial h_k}{\partial W}$$

$$\frac{\partial h_t}{\partial h_k} = \prod_{j=k+1}^{t} \frac{\partial h_j}{\partial h_{j-1}}$$

# Training RNN

$$h_j = W_{hh} f\left(h_{j-1}\right) + W_{xh} x_j$$

$$\frac{\partial h_j}{\partial h_{j-1}} = W_{hh}^T \mathrm{diag}\left(f'\left(h_{j-1}\right)\right) \qquad \frac{\partial h_{j,m}}{\partial h_{j-1,n}} = \left(W_{hh}^T\right)_{n,\cdot} (f')_m$$

$$\left\|\frac{\partial h_j}{\partial h_{j-1}}\right\| \leq \left\|W_{hh}^T\right\| \left\|f'\left(h_{j-1}\right)\right\| \leq \beta_W \beta_h$$

$$\left\|\frac{\partial h_t}{\partial h_k}\right\| = \left\|\prod_{j=k+1}^{t} \frac{\partial h_j}{\partial h_{j-1}}\right\| = \left\|\prod_{j=k+1}^{t} W_{hh}^T \mathrm{diag}\left(f'\left(h_{j-1}\right)\right)\right\| \leq \left(\beta_W \beta_h\right)^{t-k}$$

- This can become very small or very large quickly (vanishing/exploding gradients) [Bengio et al 1994].

# Training RNNs is hard

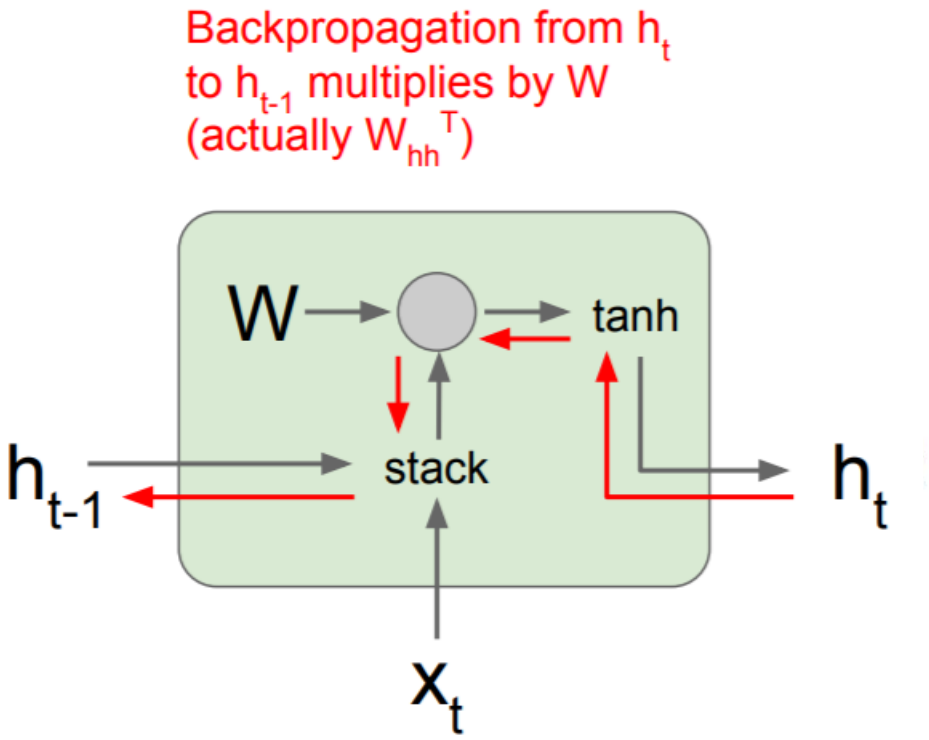
- Multiply the same matrix at each time step during forward prop
- Ideally inputs from many time steps ago can modify output y

# The vanishing gradient problem: Example

- In the case of language modeling words from time steps far away are not taken into consideration when training to predict the next word

- Example: Jane walked into the room. John walked in too. It was late in the day. Jane said hi to ____

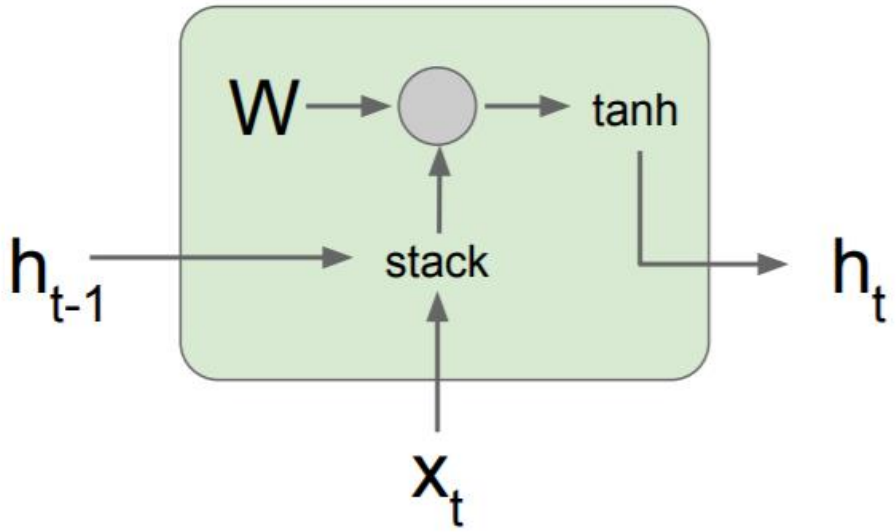
# Vanilla RNN Gradient Flow




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

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

# Vanilla RNN Gradient Flow




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

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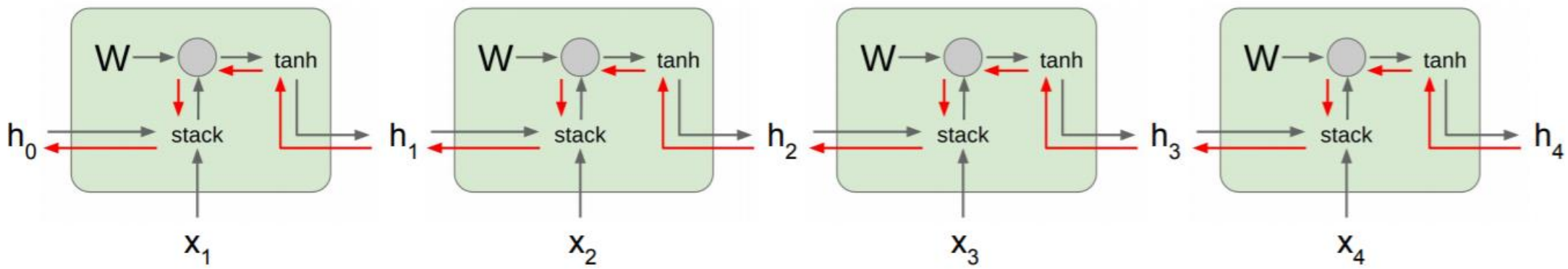
# Vanilla RNN Gradient Flow




Computing gradient of h0 involves many factors of W (and repeated tanh)

Largest singular value > 1: Exploding gradients
Largest singular value < 1: Vanishing gradients

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

# Trick for exploding gradient: clipping trick

- The solution first introduced by Mikolov is to clip gradients to a maximum value.

**Algorithm 1** Pseudo-code for norm clipping the gradients whenever they explode

$\hat{\mathbf{g}} \leftarrow \frac{\partial \mathcal{E}}{\partial \theta}$
**if** $\|\hat{\mathbf{g}}\| \geq threshold$ **then**
  $\hat{\mathbf{g}} \leftarrow \frac{threshold}{\|\hat{\mathbf{g}}\|}\hat{\mathbf{g}}$
**end if**

- Makes a big difference in RNNs.

# Gradient clipping intuition

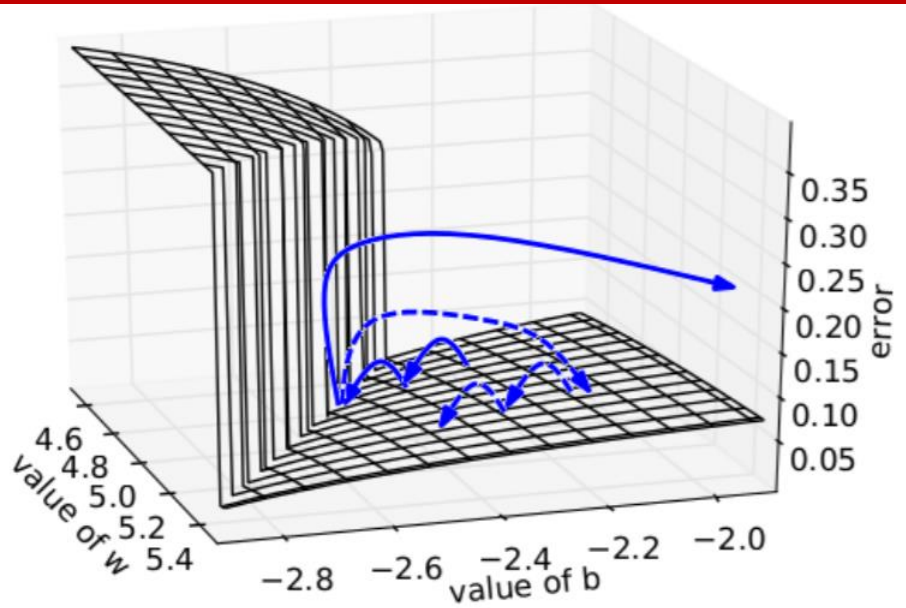
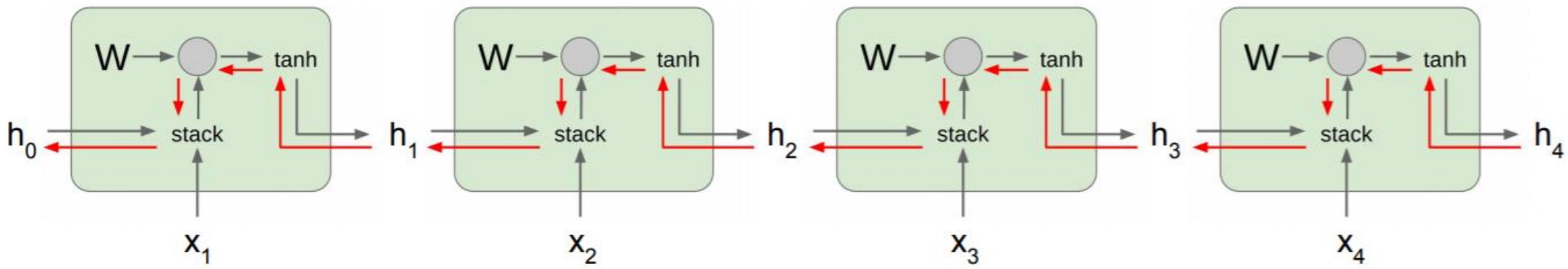



Figure from paper:
On the difficulty of training Recurrent Neural Networks, Pascanu et al. 2013

- Error surface of a single hidden unit RNN
  - High curvature walls
- Solid lines: standard gradient descent trajectories
- Dashed lines gradients rescaled to fixed size

# Vanilla RNN Gradient Flow




Computing gradient of h0 involves many factors of W (and repeated tanh)

Largest singular value > 1: Exploding gradients

Largest singular value < 1: Vanishing gradients

Gradient clipping: Scale Computing gradient if its norm is too big

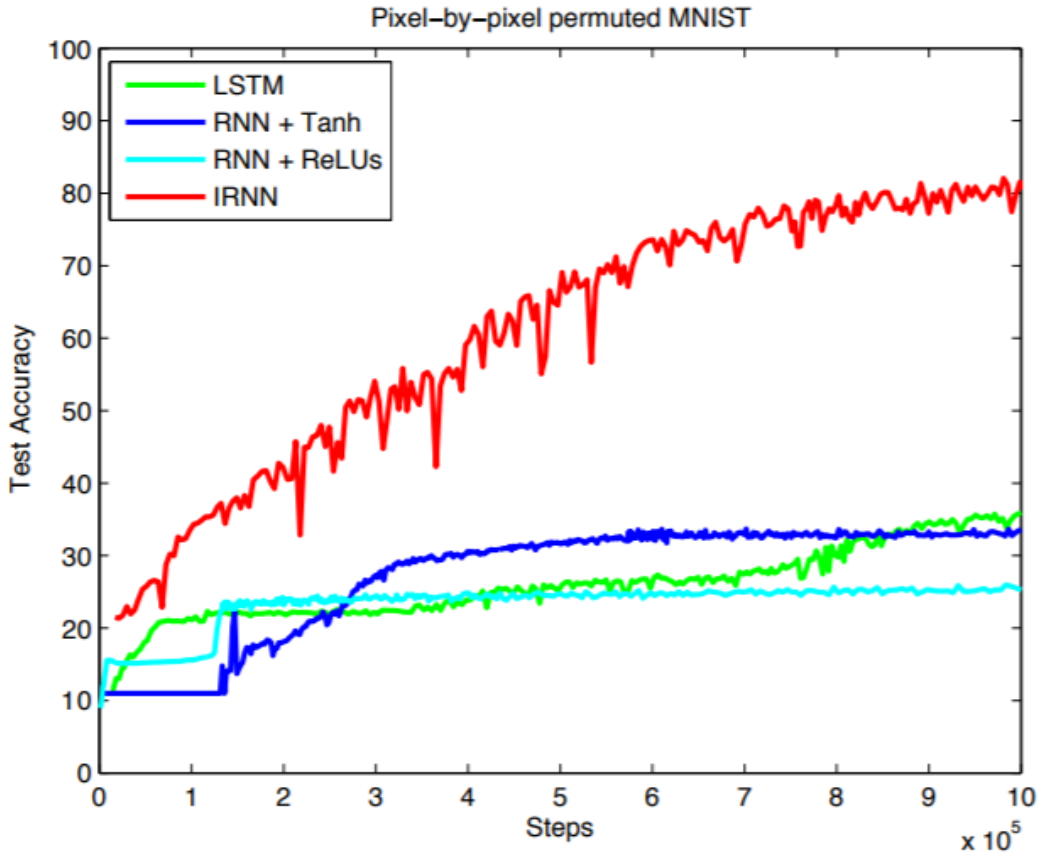
```
grad_norm = np.sum(grad * grad)
if grad_norm > threshold:
  grad *= (threshold / grad_norm)
```

Change RNN architecture

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

# For vanishing gradients: Initialization + ReLus!

- Initialize Ws to identity matrix I and activations to RelU
- New experiments with recurrent neural nets.




Le et al. A Simple Way to Initialize Recurrent Networks of Rectified Linear Unit, 2015.

# Better units for recurrent models

- More complex hidden unit computation in recurrence!
  - $h_t = LSTM(x_t, h_{t-1})$
  - $h_t = GRU(x_t, h_{t-1})$
- Main ideas:
  - keep around memories to capture long distance dependencies
  - allow error messages to flow at different strengths depending on the inputs

# Long Short Term Memory (LSTM)

## Vanilla RNN

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

## LSTM

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

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

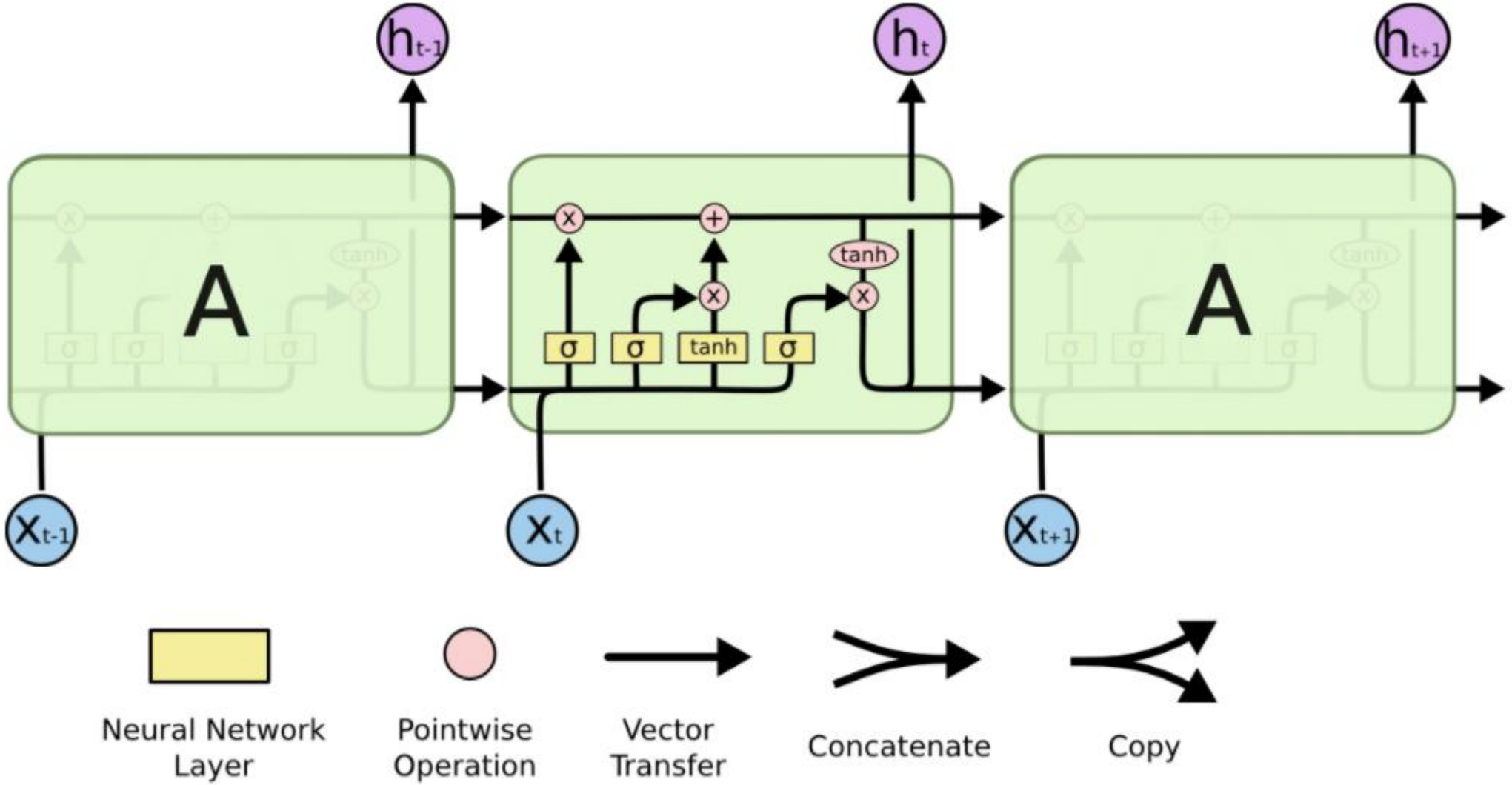
$$h_t = o \odot \tanh(c_t)$$

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

# Long-short-term-memories (LSTMs)

- Input gate (current cell matterst $i_t = \sigma\left(W_i \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} + b_i\right)$
- Forget (gate 0, forget past): $f_t = \sigma\left(W_f \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} + b_f\right)$
- Output (how much cell is exposed): $o_t = \sigma\left(W_o \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} + b_o\right)$
- New memory cell: $g_t = \tanh\left(W_g \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} + b_g\right)$
- Final memory cell: $c_t = i_t \circ g_t + f_t \circ c_{t-1}$
- Final hidden state: $h_t = o_t \circ \tanh(c_t)$

# Some visualization




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

# LSTM Gates

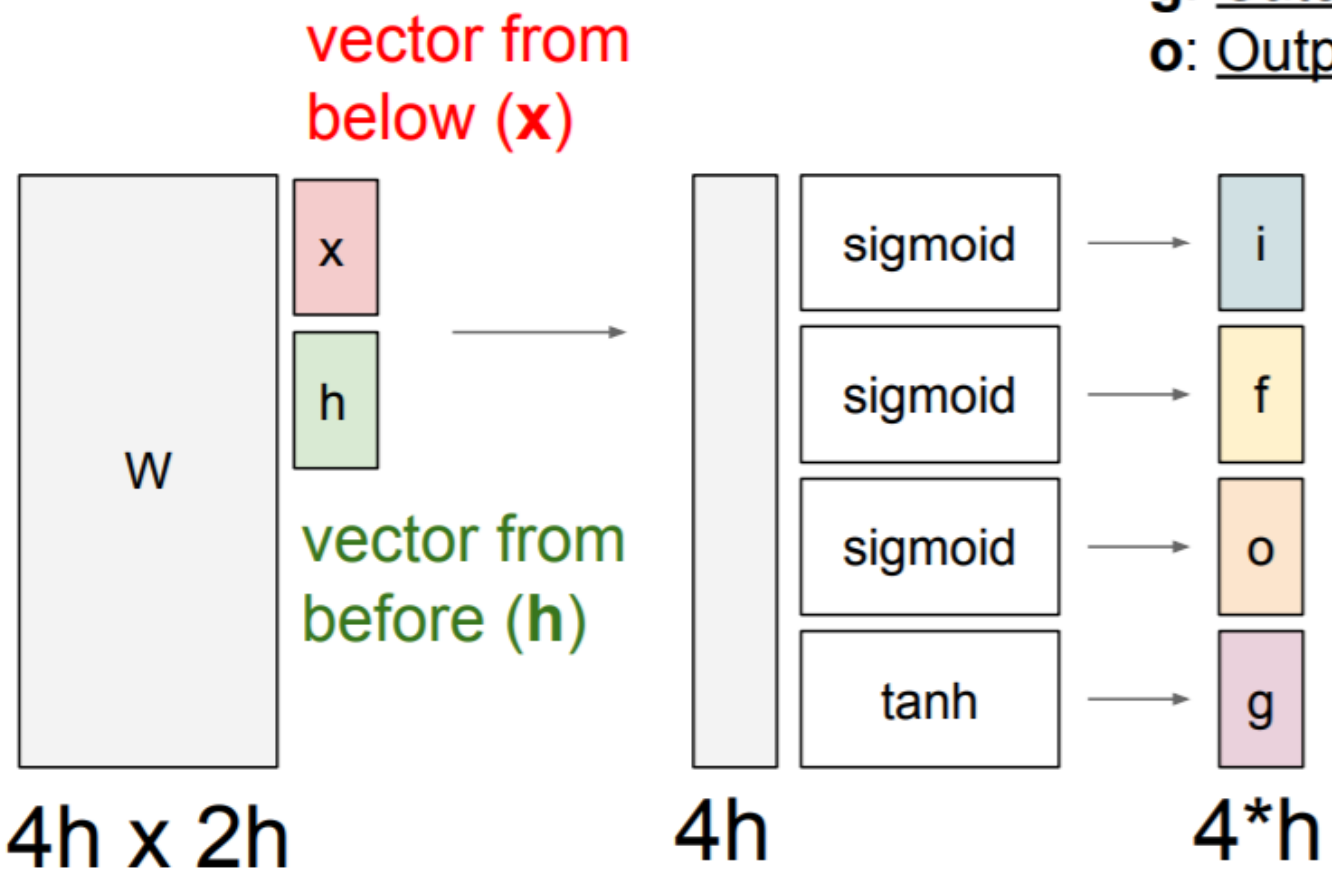
- Gates are ways to let information through (or not):
  - Forget gate: look at previous cell state and current input, and decide which information to throw away.
  - Input gate: see which information in the current state we want to update.
  - Output: Filter cell state and output the filtered result.
  - Gate or update gate: propose new values for the cell state.

- For instance: store gender of subject until another subject is seen.

# Long Short Term Memory (LSTM)

*[Hochreiter et al., 1997]*

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



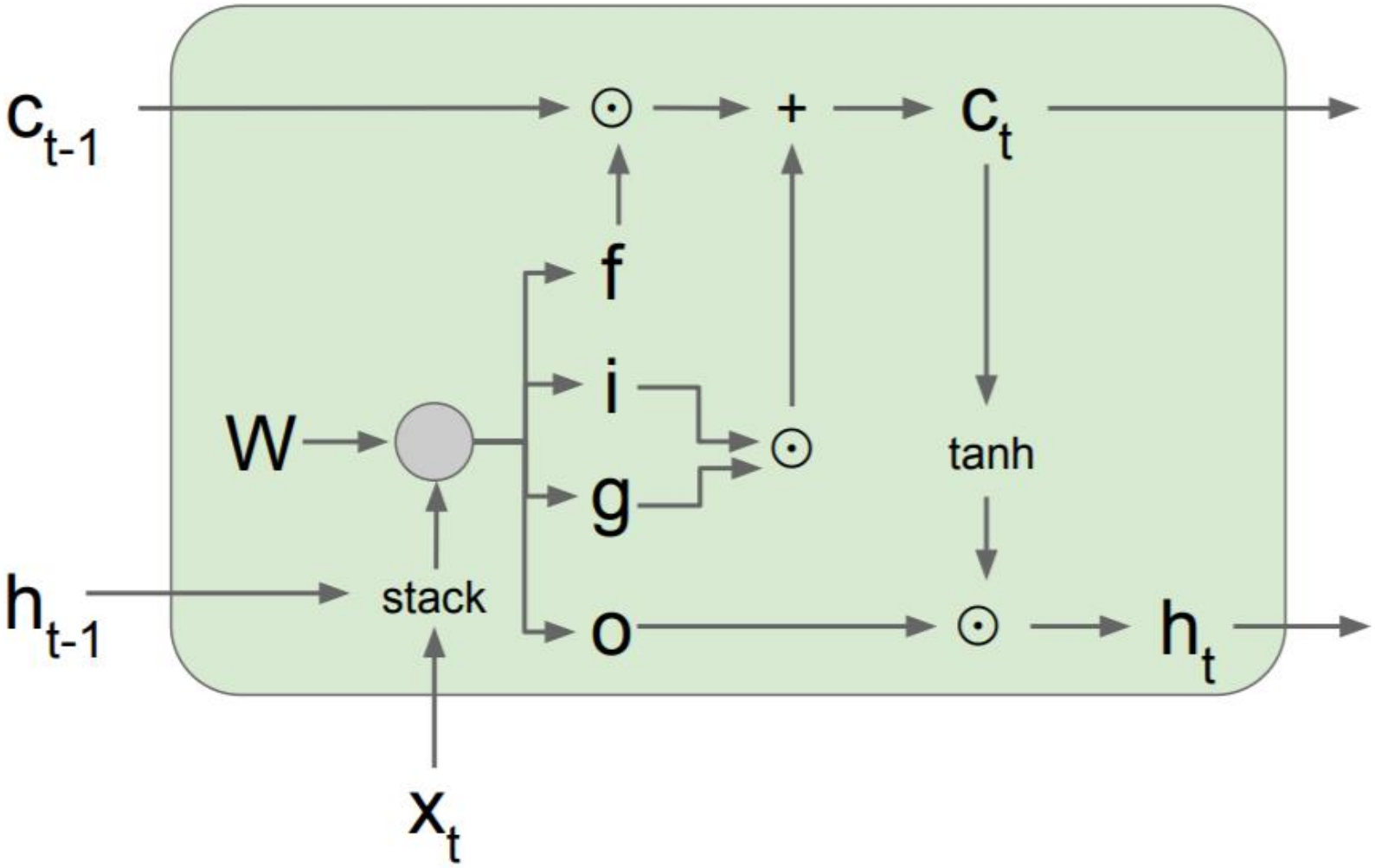

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

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

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

# Long Short Term Memory (LSTM)

[Hochreiter et al., 1997]



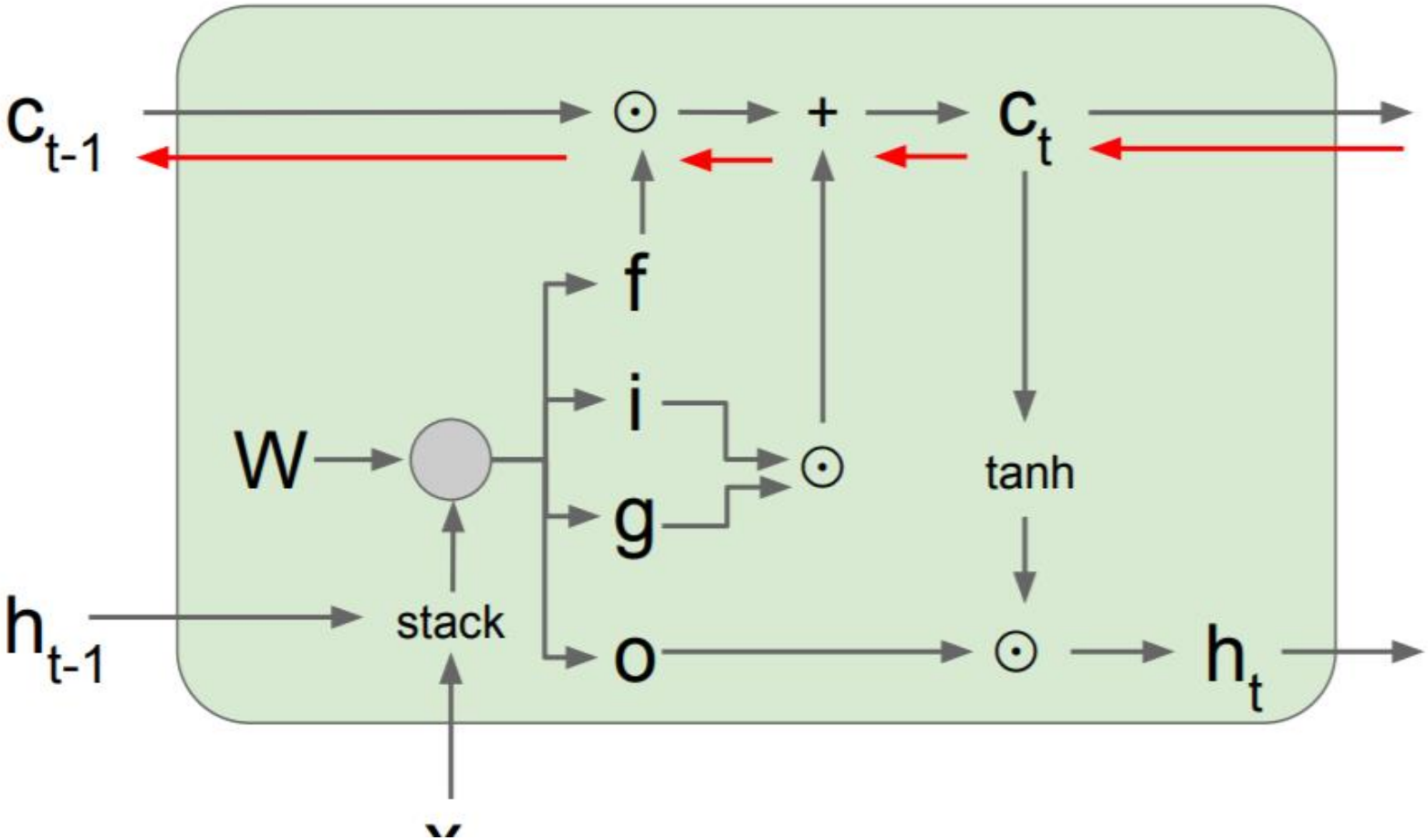

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

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

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

# Long Short Term Memory (LSTM)

[Hochreiter et al., 1997]




Backpropagation from $c_t$ to $c_{t-1}$ only elementwise multiplication by f, no matrix multiply by W

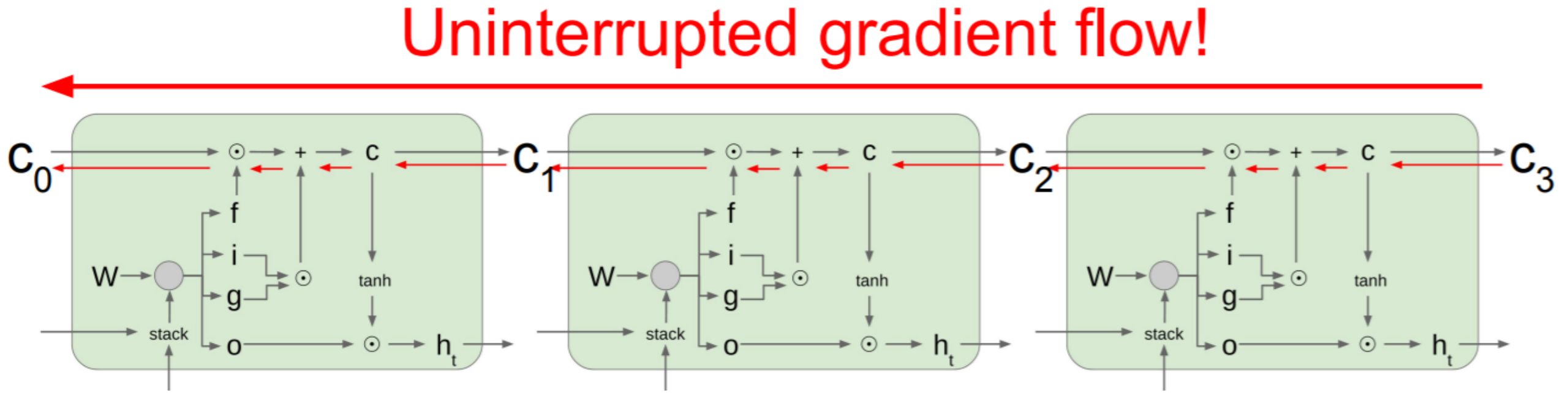
$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

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

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

# Long Short Term Memory (LSTM)

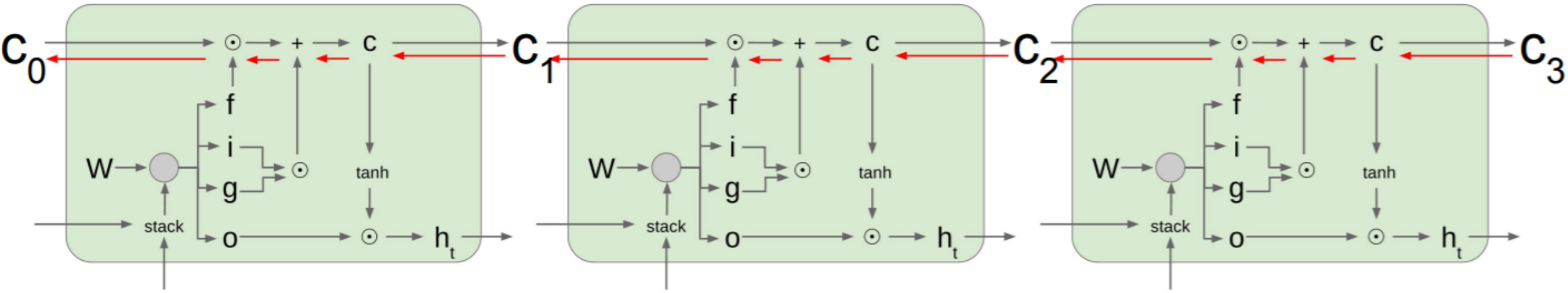
[Hochreiter et al., 1997]



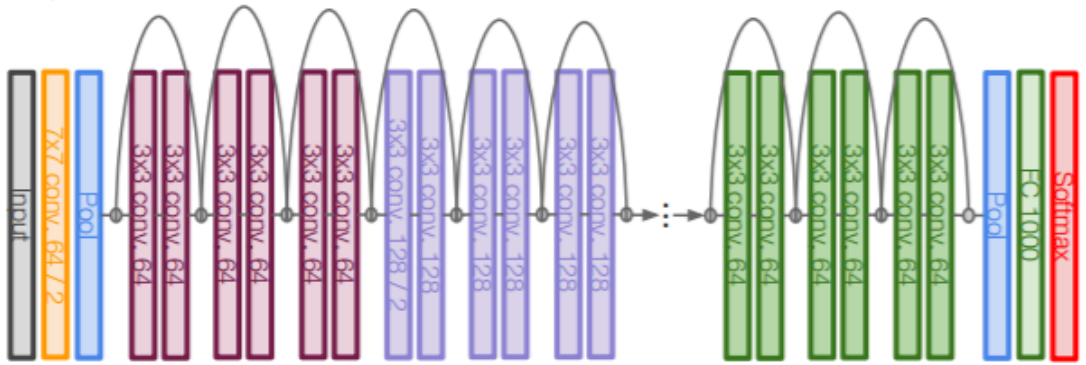
# Long Short Term Memory (LSTM)

[Hochreiter et al., 1997]

Uninterrupted gradient flow!




Similar to ResNet!




In between:

**Highway Networks**

$$g = T(x, W_T)$$

$$y = g \odot H(x, W_H) + (1 - g) \odot x$$

Srivastava et al, "Highway Networks", ICML DL Workshop 2015

# Derivatives for LSTM

$$z = f(x_1, x_2) = x_1 \circ x_2$$

$$\frac{\partial E}{\partial x_1} = \frac{\partial E}{\partial z}\frac{\partial z}{\partial x_1}$$

$$= \frac{\partial E}{\partial z} \circ x_2$$

# GRUs

- Gated Recurrent Units (GRU) introduced by Cho et al. 2014
- **Update gate**

$$z_t = \sigma\left(W_z \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} + b_z\right)$$

- **Reset gate**

$$r_t = \sigma\left(W_r \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} + b_r\right)$$

- **Memory**

$$\hat{h}_t = \tanh\left(W_m \begin{bmatrix} r_t \circ h_{t-1} \\ x_t \end{bmatrix} + b_m\right)$$

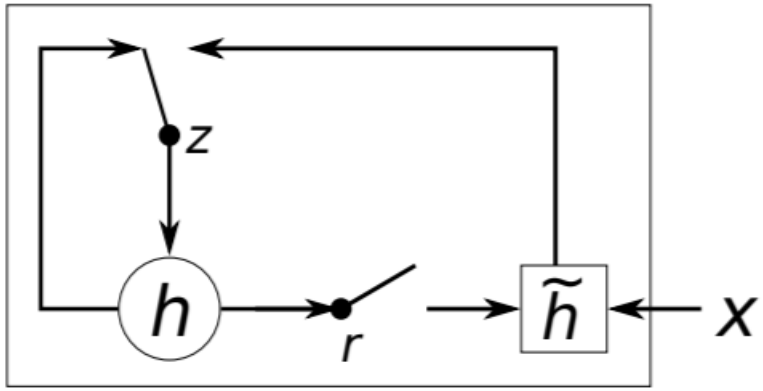
- **Final Memory**

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

If reset gate unit is ~0, then this ignores previous memory and only stores the new input

# GRU intuition

- Units with long term dependencies have active update gates z
- Illustration:



# GRU intuition

- If reset is close to 0, ignore previous hidden state
  → Allows model to drop information that is irrelevant in the future

- Update gate z controls how much of past state should matter now.
  – If z close to 1, then we can copy information in that unit through many time steps! Less vanishing gradient!

- Units with short-term dependencies often have reset gates very active

# Other RNN Varients

**GRU** [*Learning phrase representations using rnn encoder-decoder for statistical machine translation*, Cho et al. 2014]

$$r_t = \sigma(W_{xr}x_t + W_{hr}h_{t-1} + b_r)$$
$$z_t = \sigma(W_{xz}x_t + W_{hz}h_{t-1} + b_z)$$
$$\tilde{h}_t = \tanh(W_{xh}x_t + W_{hh}(r_t \odot h_{t-1}) + b_h)$$
$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \tilde{h}_t$$

[*LSTM: A Search Space Odyssey*, Greff et al., 2015]

[*An Empirical Exploration of Recurrent Network Architectures*, Jozefowicz et al., 2015]

MUT1:

$$\begin{aligned} z &= \text{sigm}(W_{xz}x_t + b_z) \\ r &= \text{sigm}(W_{xr}x_t + W_{hr}h_t + b_r) \\ h_{t+1} &= \tanh(W_{hh}(r \odot h_t) + \tanh(x_t) + b_h) \odot z \\ &+ h_t \odot (1 - z) \end{aligned}$$

MUT2:

$$\begin{aligned} z &= \text{sigm}(W_{xz}x_t + W_{hz}h_t + b_z) \\ r &= \text{sigm}(x_t + W_{hr}h_t + b_r) \\ h_{t+1} &= \tanh(W_{hh}(r \odot h_t) + W_{xh}x_t + b_h) \odot z \\ &+ h_t \odot (1 - z) \end{aligned}$$

MUT3:

$$\begin{aligned} z &= \text{sigm}(W_{xz}x_t + W_{hz}\tanh(h_t) + b_z) \\ r &= \text{sigm}(W_{xr}x_t + W_{hr}h_t + b_r) \\ h_{t+1} &= \tanh(W_{hh}(r \odot h_t) + W_{xh}x_t + b_h) \odot z \\ &+ h_t \odot (1 - z) \end{aligned}$$

# Which of these variants is best?

- Do the differences matter?
  - Greff et al. (2015), perform comparison of popular variants, finding that they're all about the same.
  - Jozefowicz et al. (2015) tested more than ten thousand RNN architectures, finding some that worked better than LSTMs on certain tasks.

# LSTM Achievements

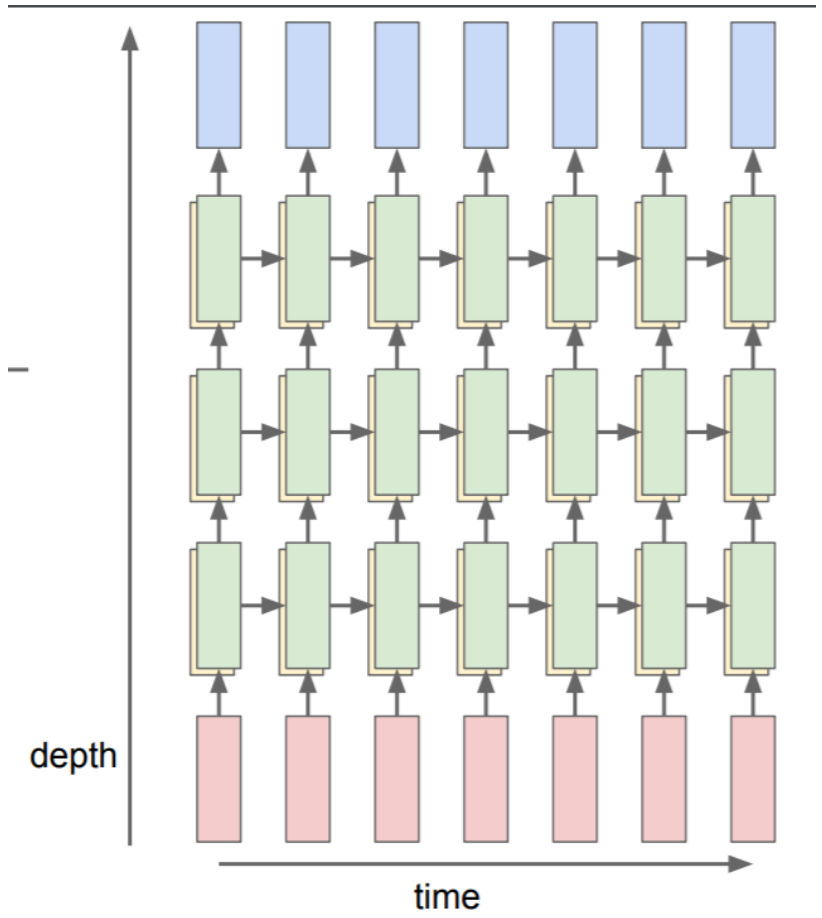
- LSTMs have essentially replaced n-grams as language models for **speech**.
- **Image captioning** and other multi-modal tasks which were very difficult with previous methods are now feasible.
- Many **traditional NLP tasks** work very well with LSTMs, but not necessarily the top performers: e.g., POS tagging and NER: Choi 2016.
- **Neural MT**: broken away from plateau of SMT, especially for grammaticality (partly because of characters/subwords), but not yet industry strength.

[Ann Copestake, Overview of LSTMs and word2vec, 2016.]
https://arxiv.org/ftp/arxiv/papers/1611/1611.00068.pdf

# Multi-layer RNN

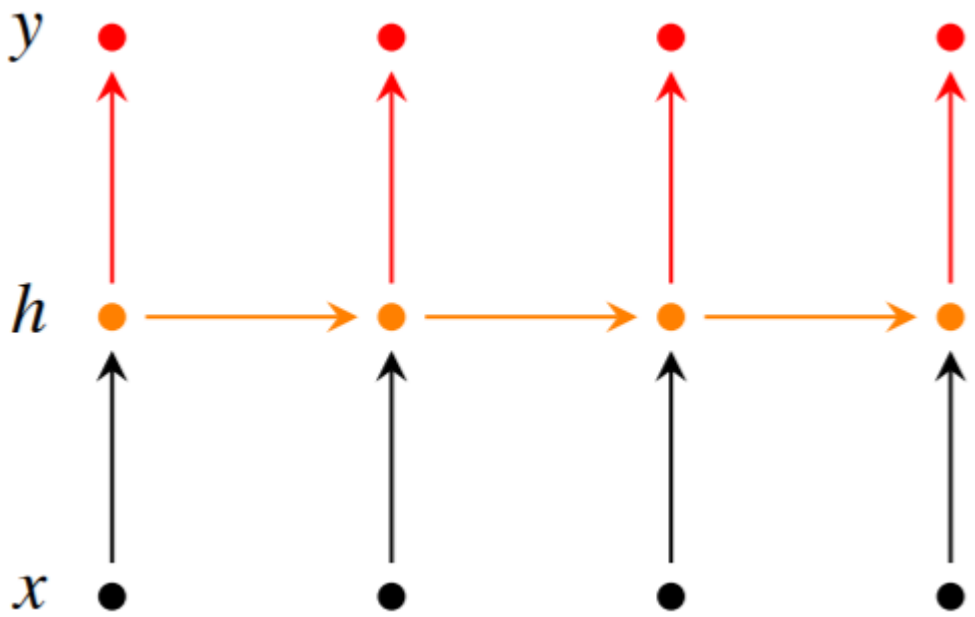
$$h_t^l = \tanh W^l \begin{pmatrix} h_t^{l-1} \\ h_{t-1}^l \end{pmatrix}$$

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



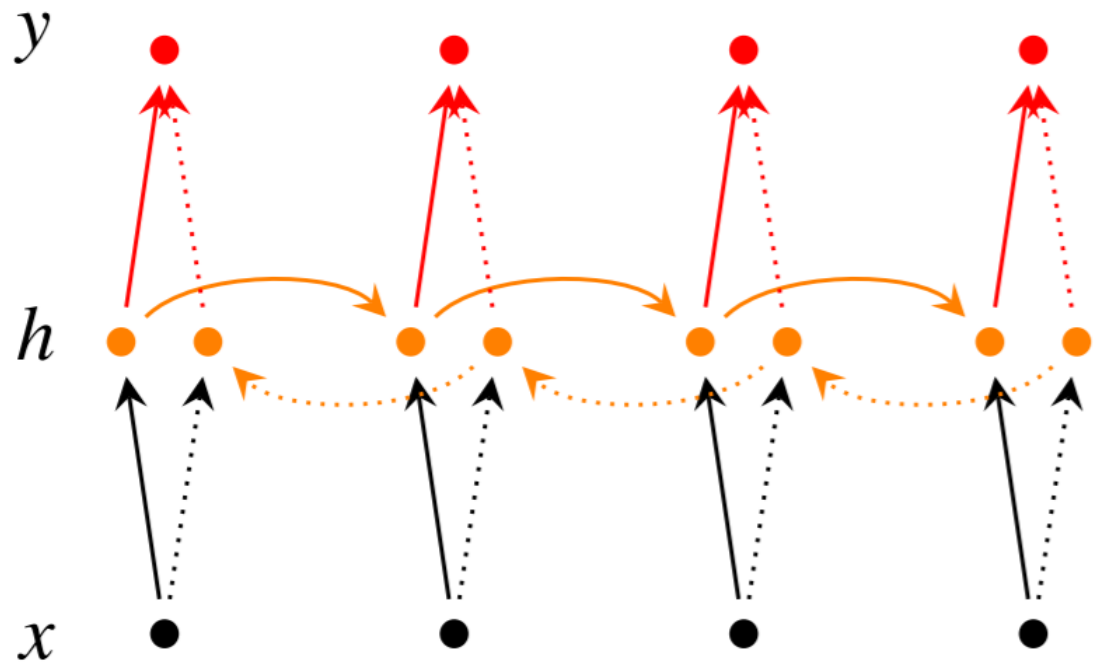
# Bidirectional RNN

- h is the memory, computed from the past memory and current word. It summarizes the sentence up to that time.



# Bidirectional RNN

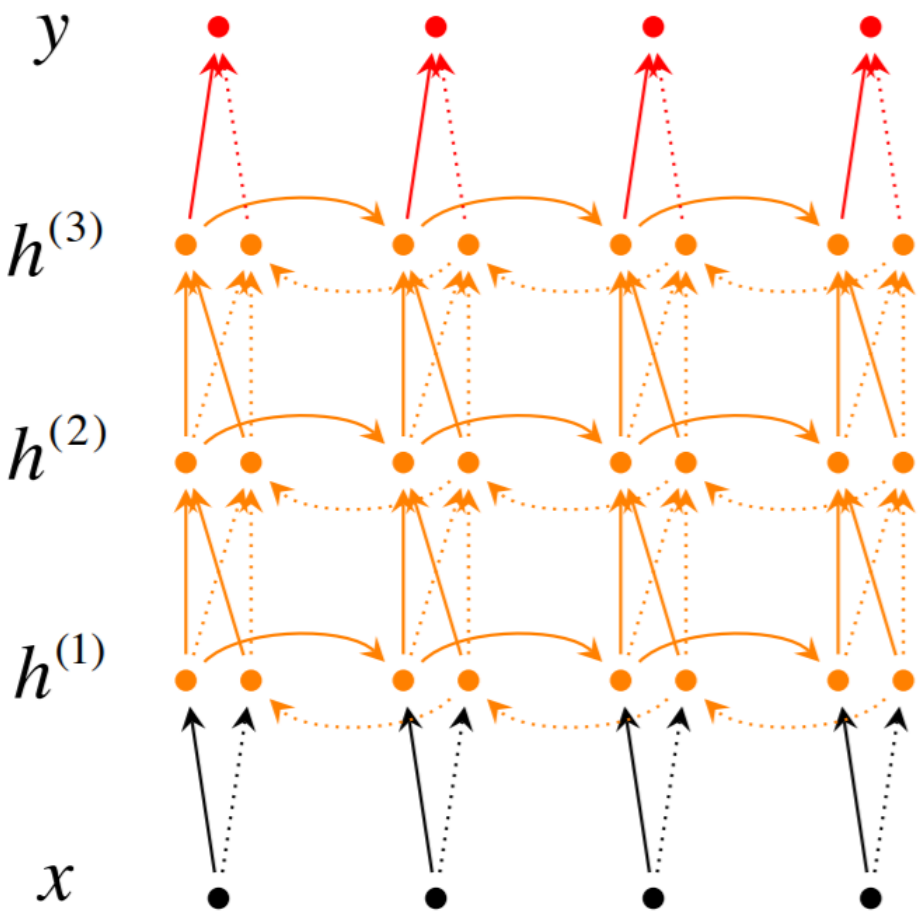
- Problem: For classification you want to incorporate information from words both preceding and following



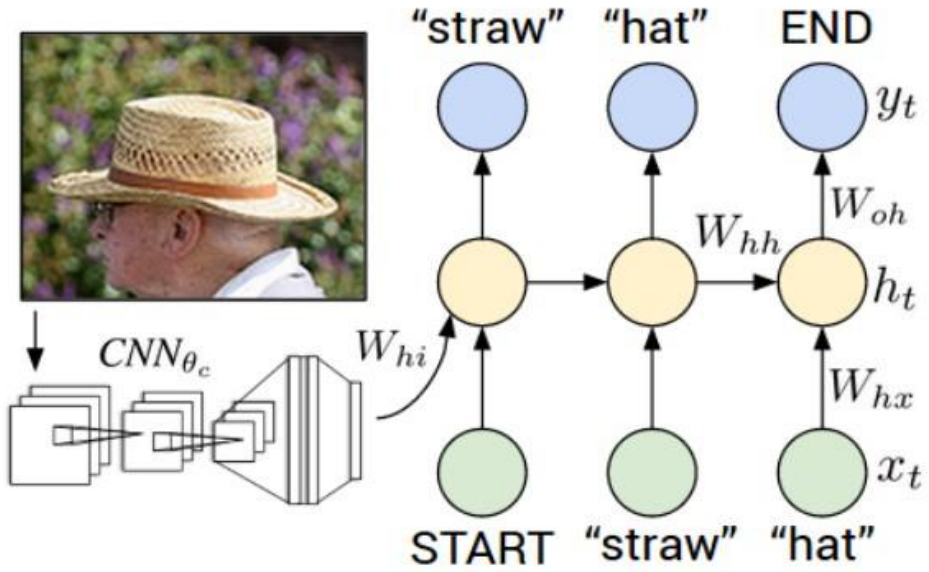

$h = [\overrightarrow{h}; \overleftarrow{h}]$ now represents (summarizes) the past and future around a single token.

# Multilayer bidirectional RNN

- Each memory layer passes an intermediate sequential representation to the next.

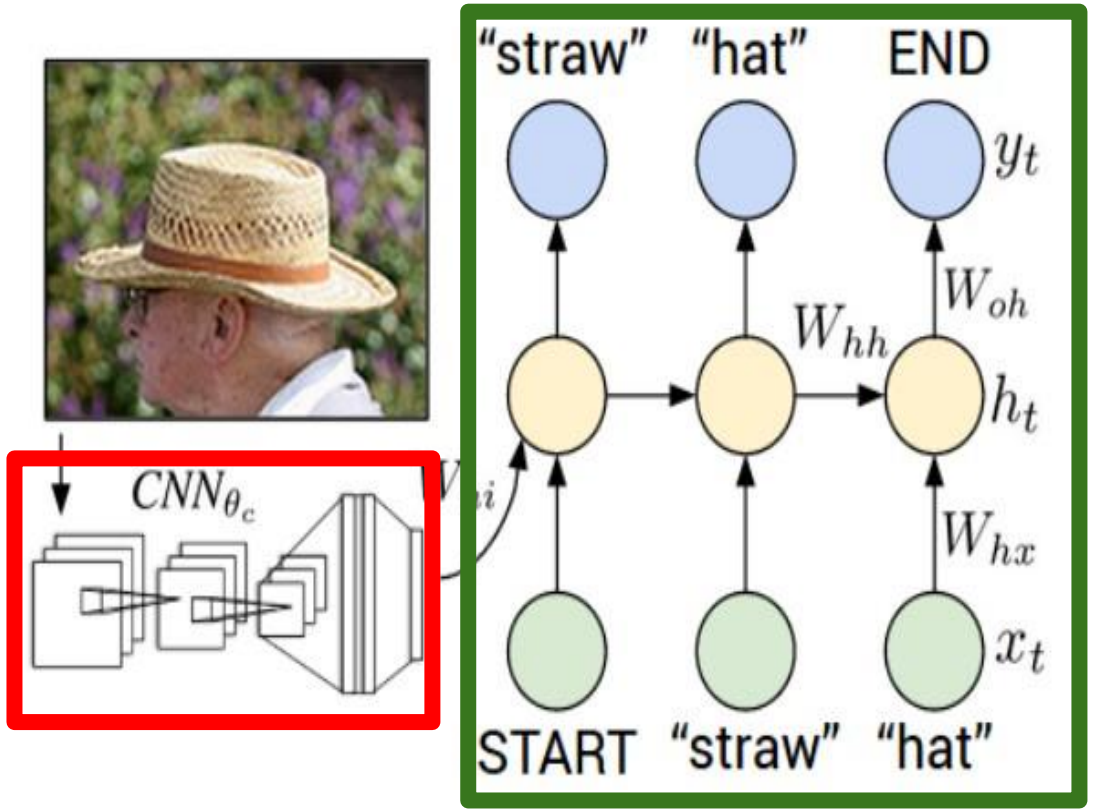


# Image Captioning




- 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

image

conv-64

conv-64

maxpool

conv-128

conv-128

maxpool

conv-256

conv-256

maxpool

conv-512

conv-512

maxpool

conv-512

conv-512

maxpool

FC-4096

FC-4096

FC-1000

softmax

test image

image

conv-64

conv-64

maxpool

conv-128

conv-128

maxpool

conv-256

conv-256

maxpool

conv-512

conv-512

maxpool

conv-512

conv-512

maxpool

FC-4096

FC-4096

FC-1000

softmax

X

test image

image

conv-64

conv-64

maxpool

conv-128

conv-128

maxpool

conv-256

conv-256

maxpool

conv-512

conv-512

maxpool

conv-512

conv-512

maxpool

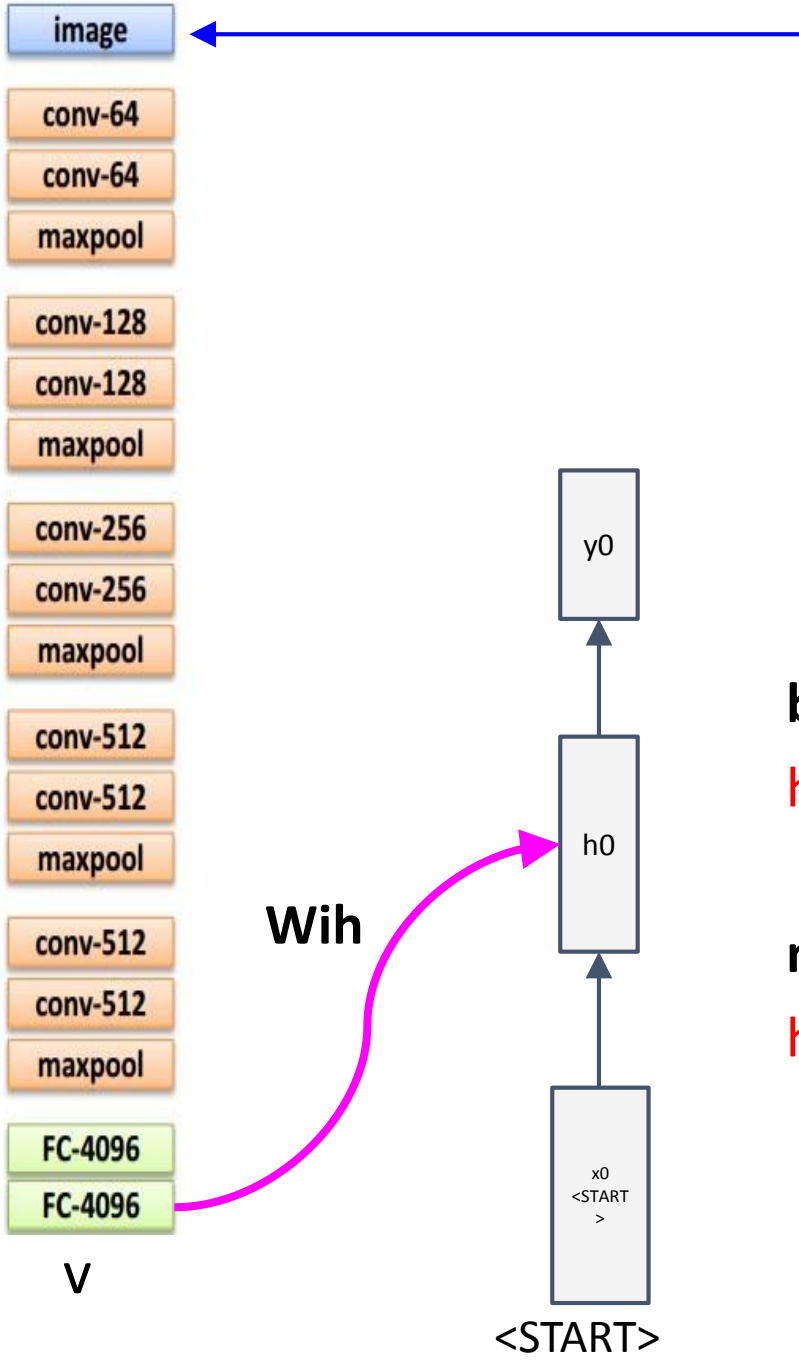
FC-4096

FC-4096

test image

x0
<START
>

<START>



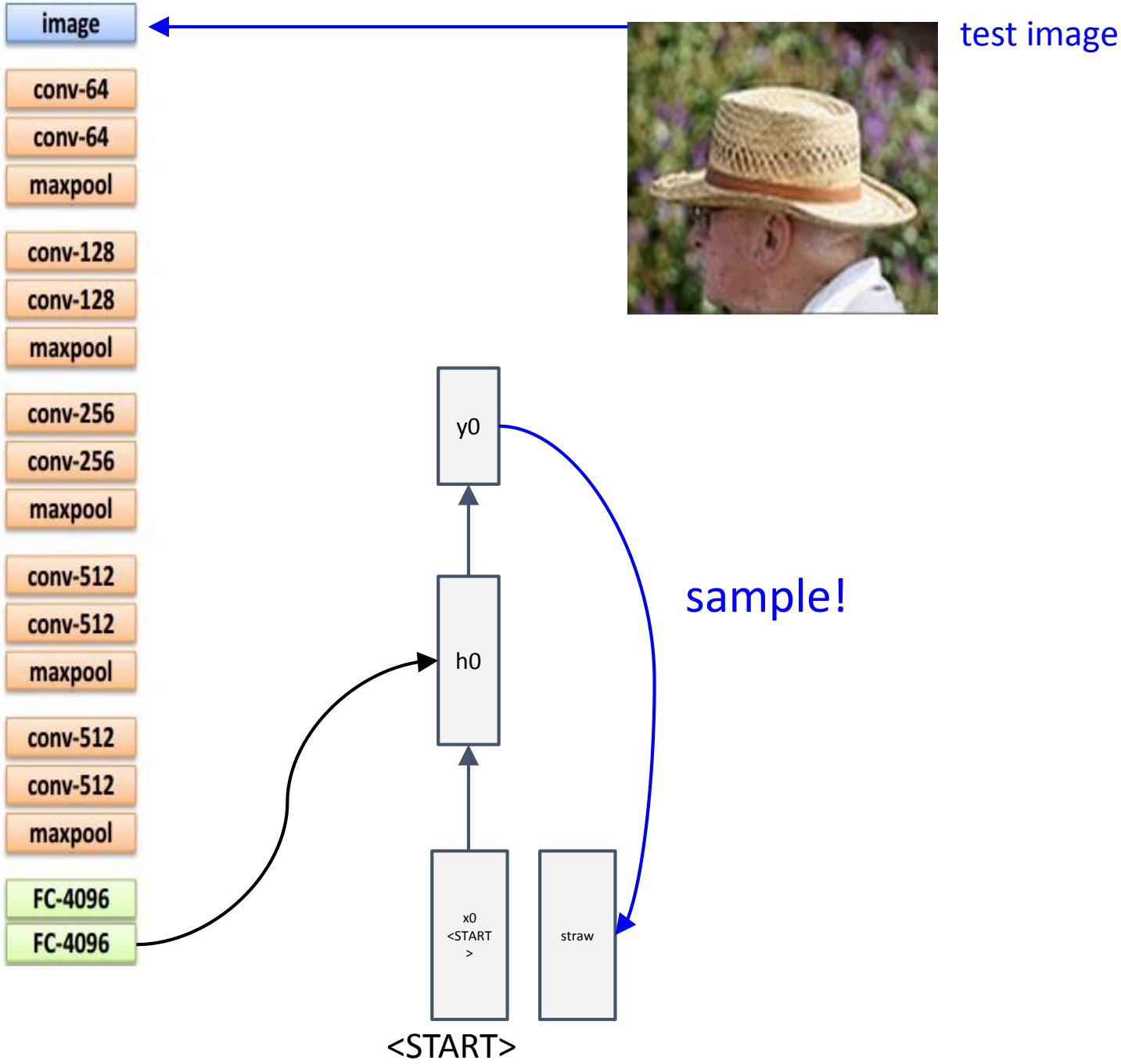

test image

**before:**

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

**now:**

h = tanh(Wxh * x + Whh * h + **Wih * v**)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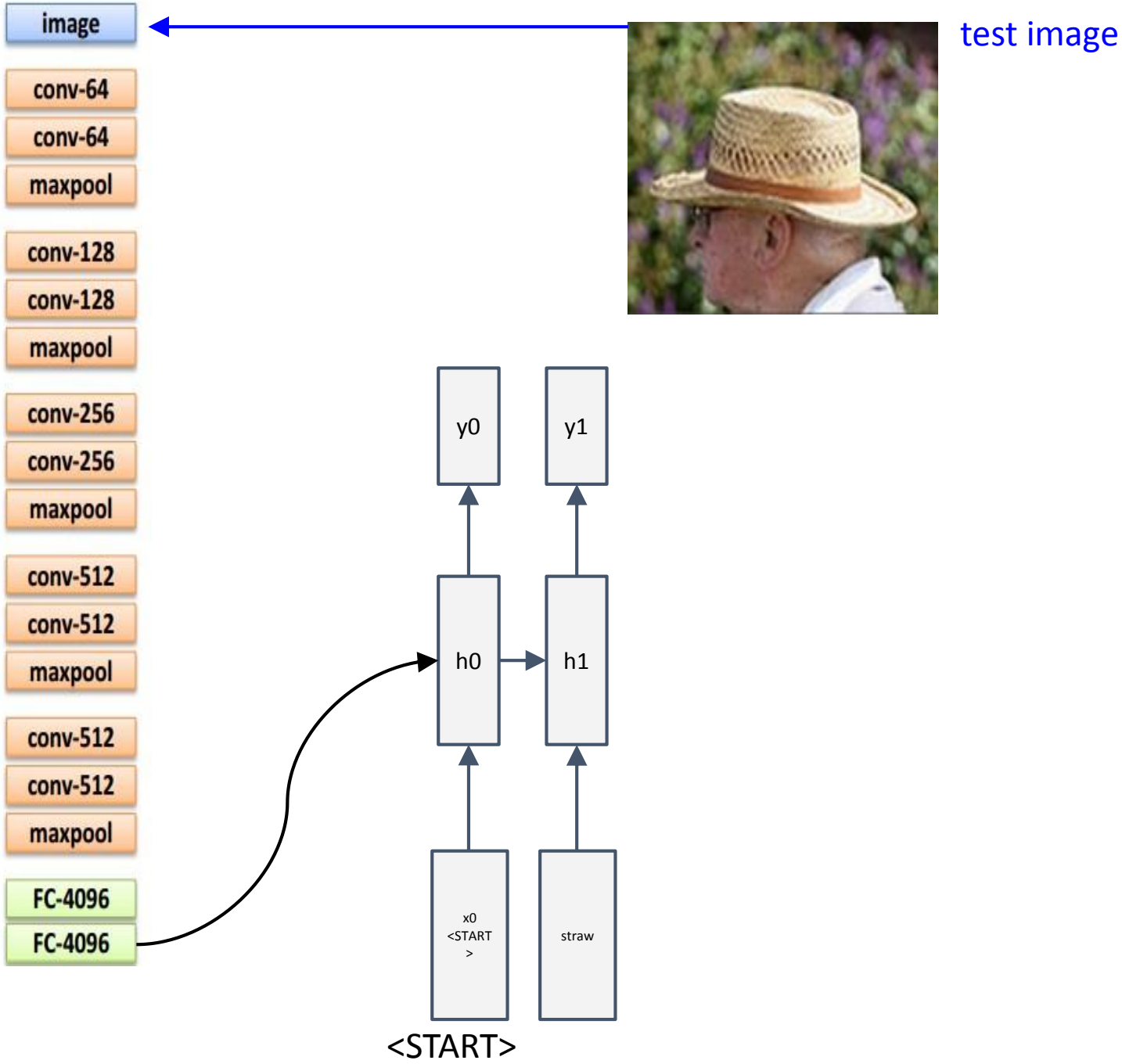
FC-4096
test image
y0
h0
x0
<START
>
straw
<START>
sample!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FC-4096
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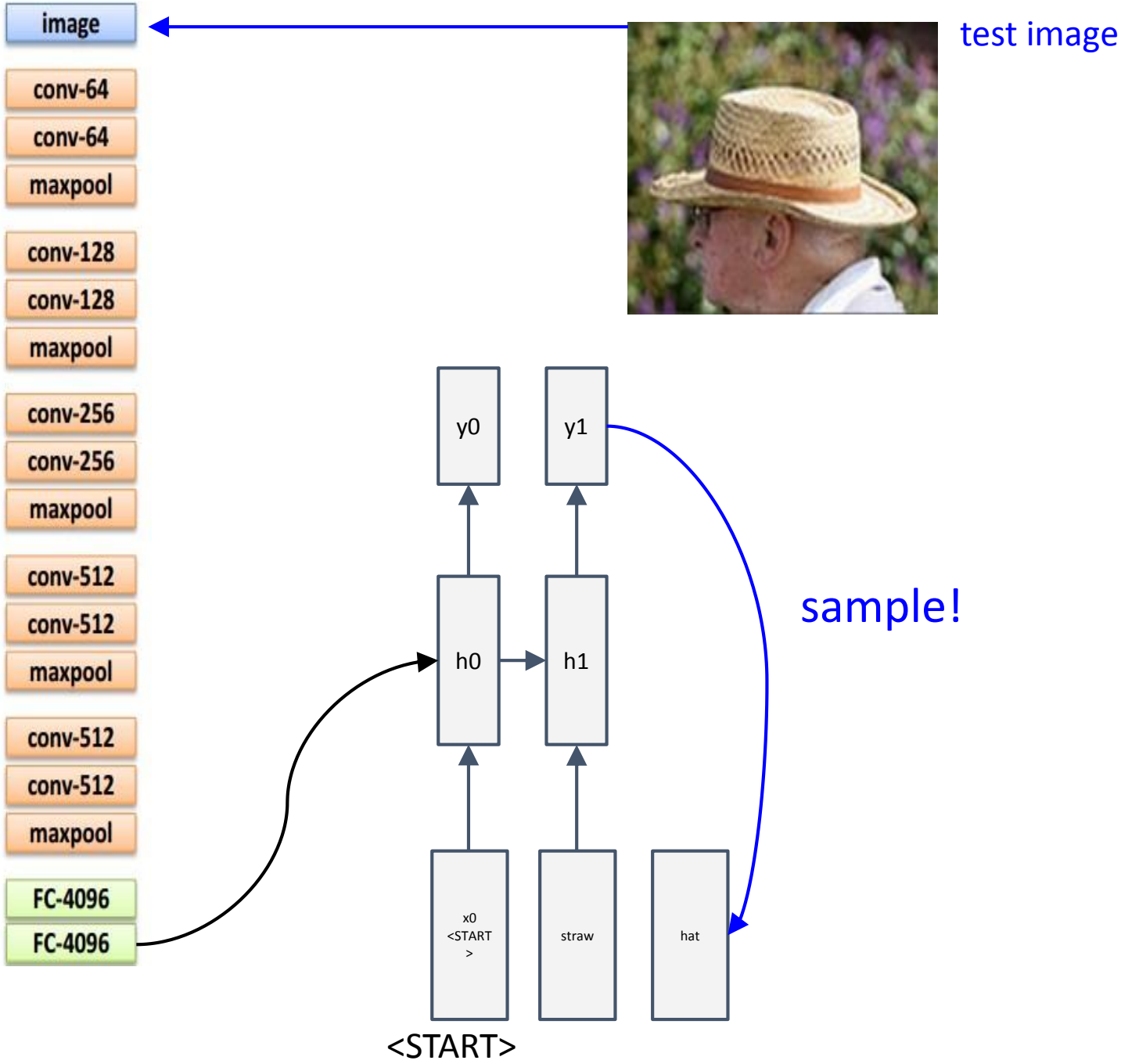
<START>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test image
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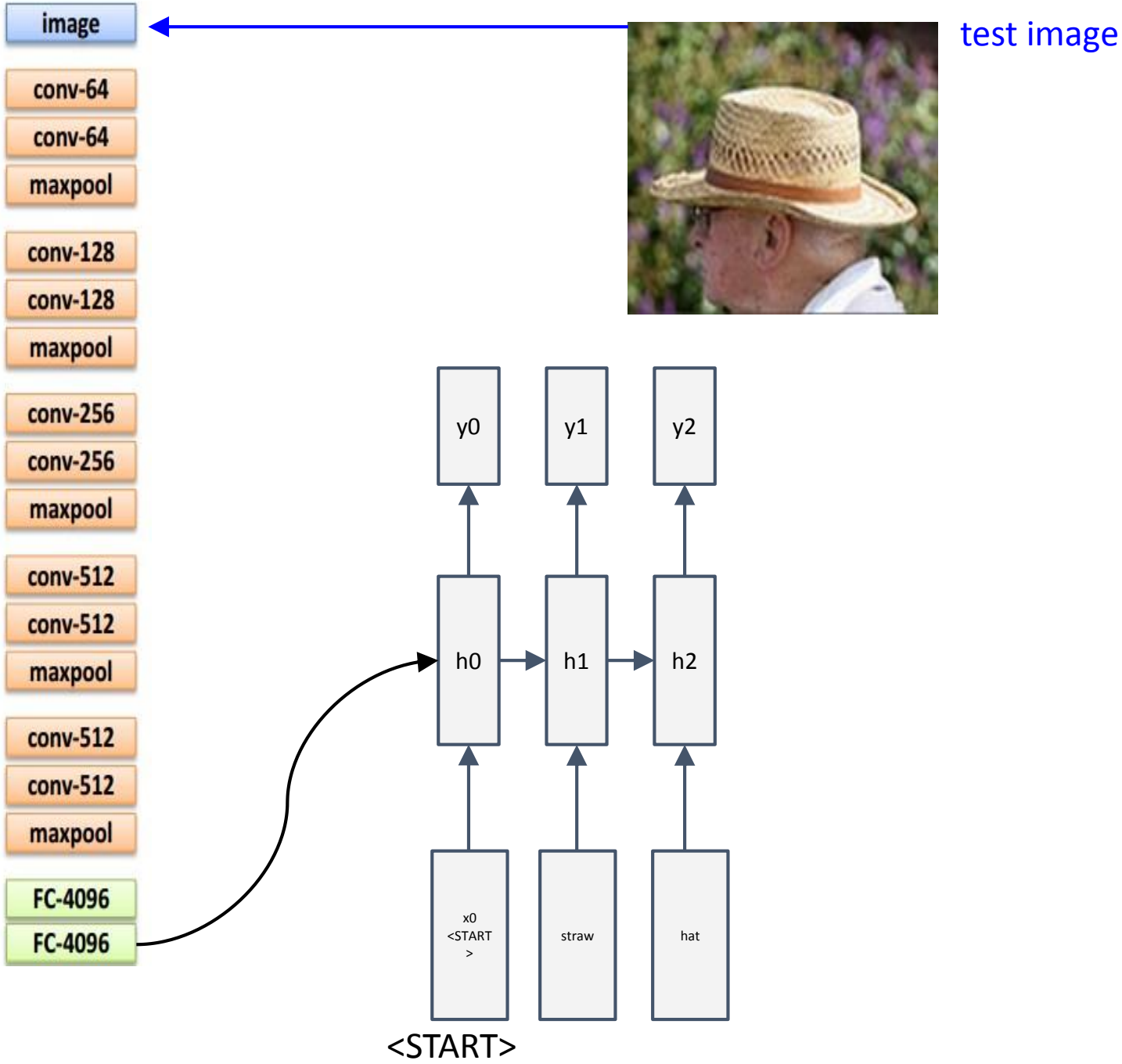
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test image
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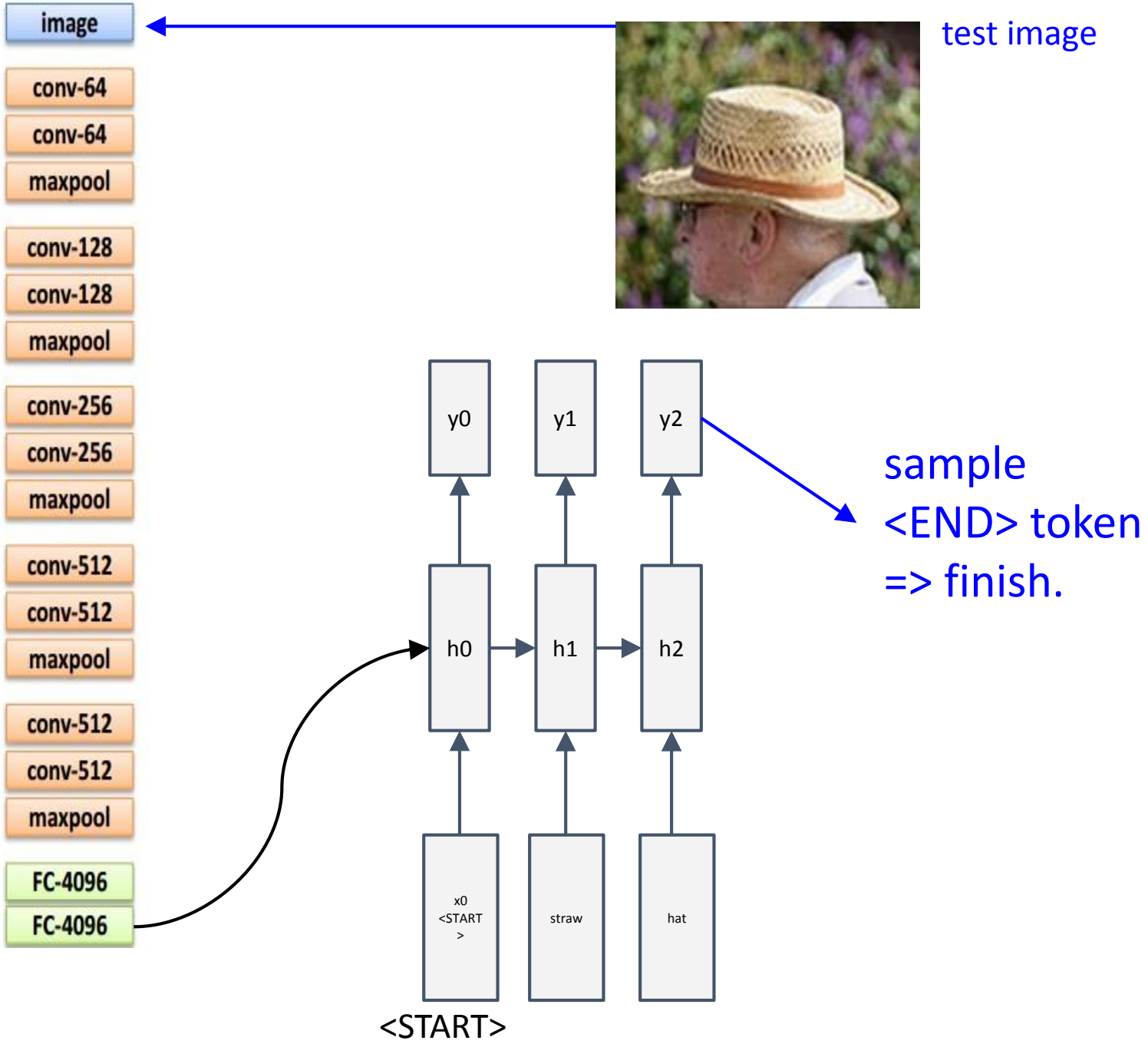
image
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conv-128
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maxpool
conv-512
conv-512
maxpool
FC-4096
FC-4096
test image
y0
y1
y2
h0
h1
h2
x0
<START
>
straw
hat
<START>
sample
<END> token
=> finish.

# Image Sentence Datasets

a man riding a bike on a dirt path through a forest.
bicyclist raises his fist as he rides on desert dirt trail.
this dirt bike rider is smiling and raising his fist in triumph.
a man riding a bicycle while pumping his fist in the air.
a mountain biker pumps his fist in celebration.

Microsoft COCO

*[Tsung-Yi Lin et al. 2014]*

mscoco.org

currently:

~120K images

~5 sentences each

# 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*

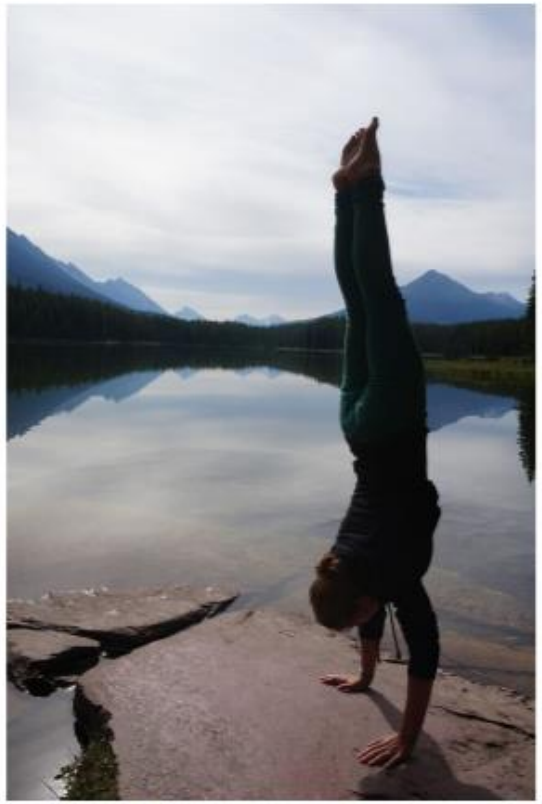
*Two giraffes standing in a grassy field*

*A man riding a dirt bike on a dirt track*

# Image Captioning: Failure Cases

Captions generated using neuraltalk2
All images are CC0 Public domain:
cat suitcase, cat tree, dog, bear,
surfers, tennis, giraffe, motorcycle

*A woman is holding a cat in her hand*



*A woman standing on a beach holding a surfboard*

*A bird is perched on a tree branch*

*A person holding a computer mouse on a desk*

*A man in a baseball uniform throwing a ball*

# RNN: Summary

- RNNs allow a lot of flexibility in architecture design
- Vanilla RNNs are simple but don't work very well
- Backward flow of gradients in RNN can explode or vanish.
  - Exploding is controlled with gradient clipping.
  - Vanishing is controlled with additive interactions (LSTM)
- Common to use LSTM or GRU: their additive interactions improve gradient flow
- Better/simpler architectures are a hot topic of current research
- Better understanding (both theoretical and empirical) is needed.