

Recall from last time ...

Transfer Learning

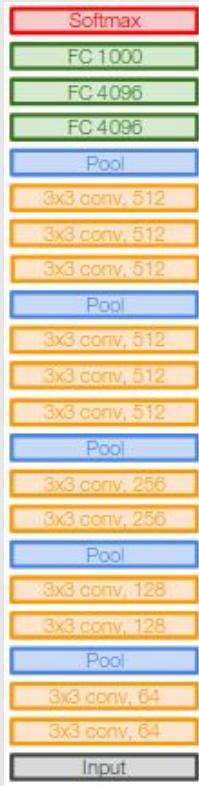
“You need a lot of a data if you want to train/use CNNs”

Transfer Learning

“You need a lot of data if you
want to train these CNNs”



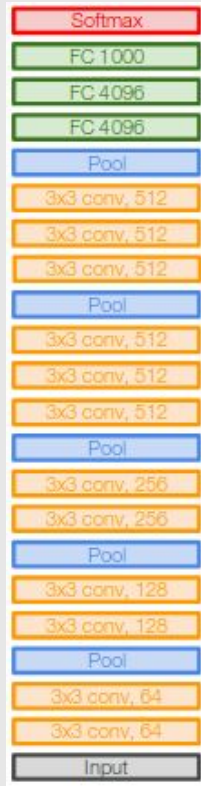
Transfer Learning with CNNs



Feature Extractor

1. Train on ImageNet

Transfer Learning with CNNs



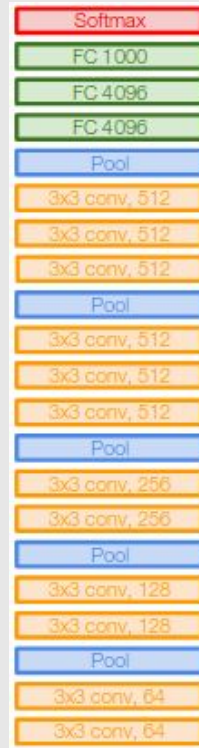
**Feature
Extractor**

1. Train on
ImageNet

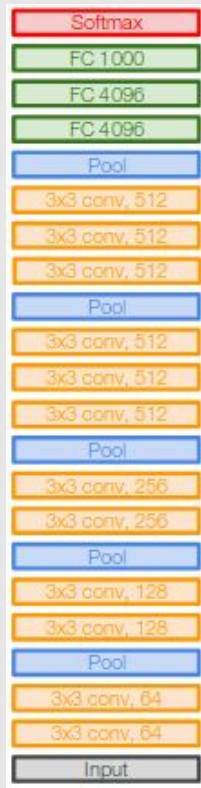
Skin lesion



input



Transfer Learning with CNNs



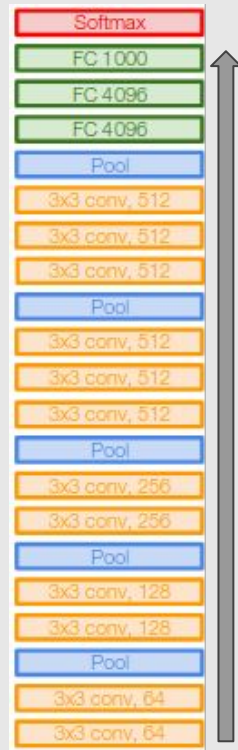
**Feature
Extractor**

1. Train on
ImageNet

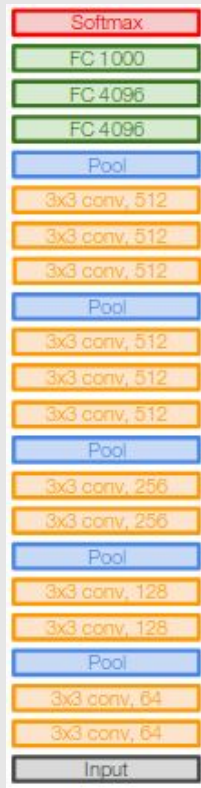
Skin lesion



input



Transfer Learning with CNNs



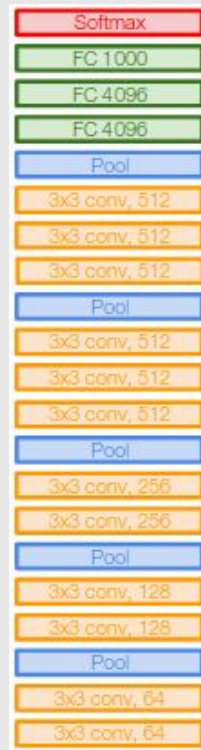
**Feature
Extractor**

1. Train on
ImageNet

Skin lesion

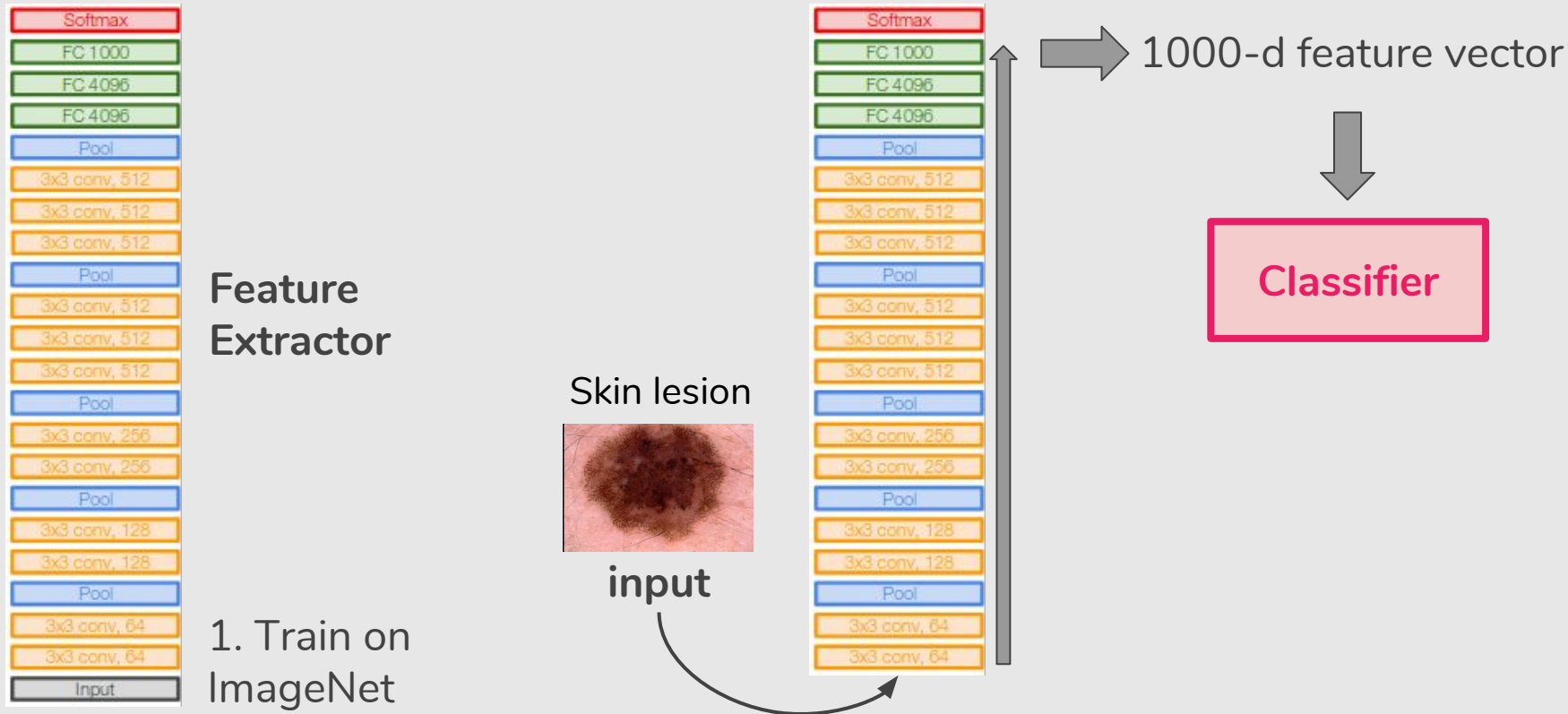


input

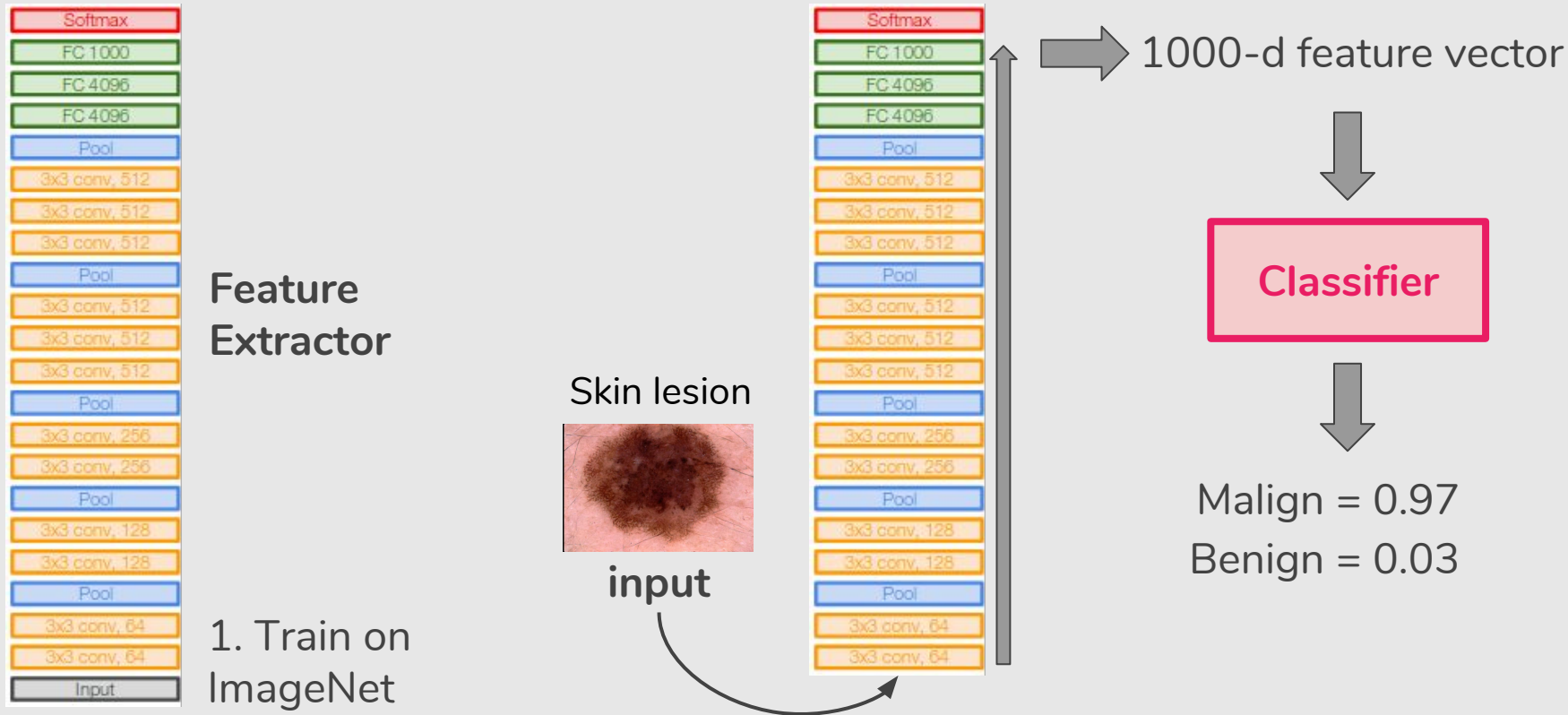


1000-d feature vector

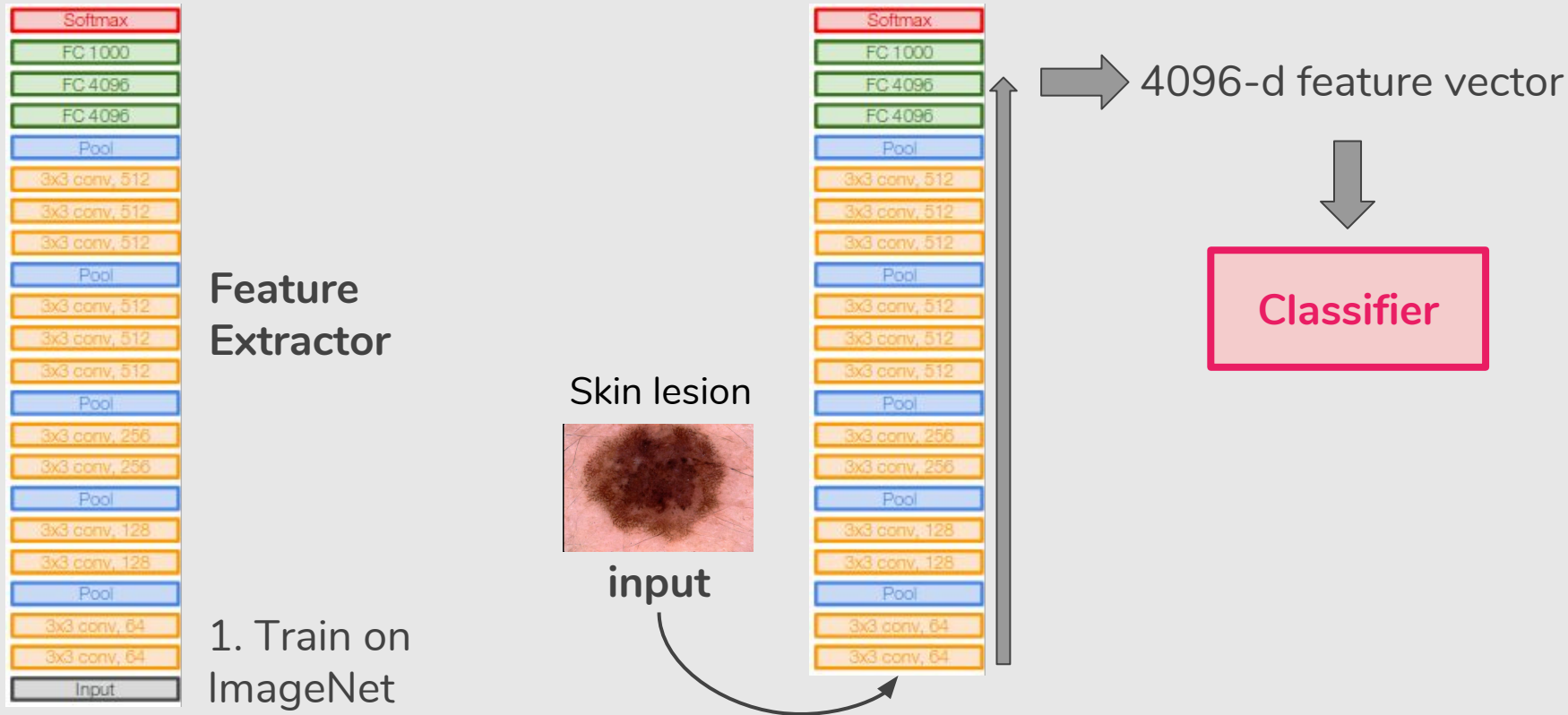
Transfer Learning with CNNs



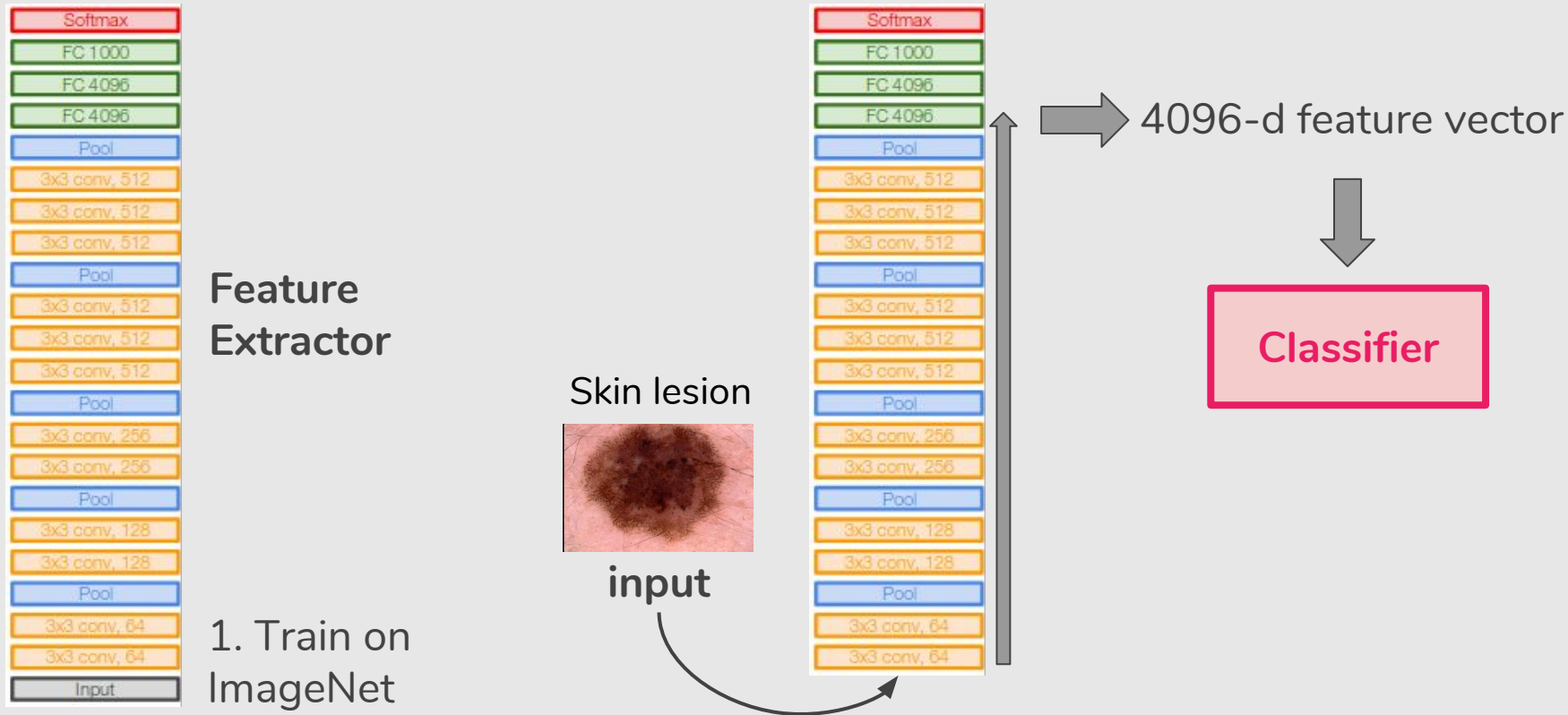
Transfer Learning with CNNs



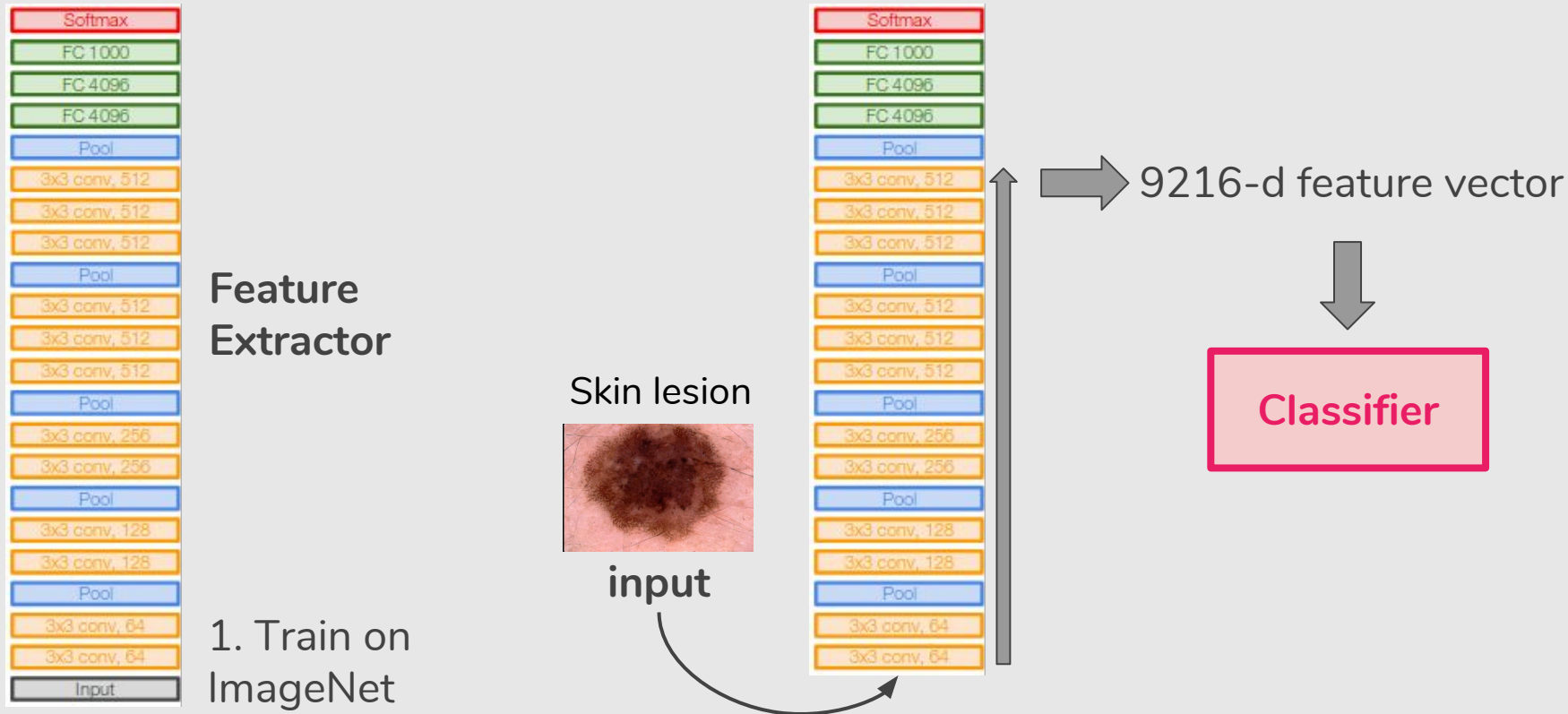
Transfer Learning with CNNs



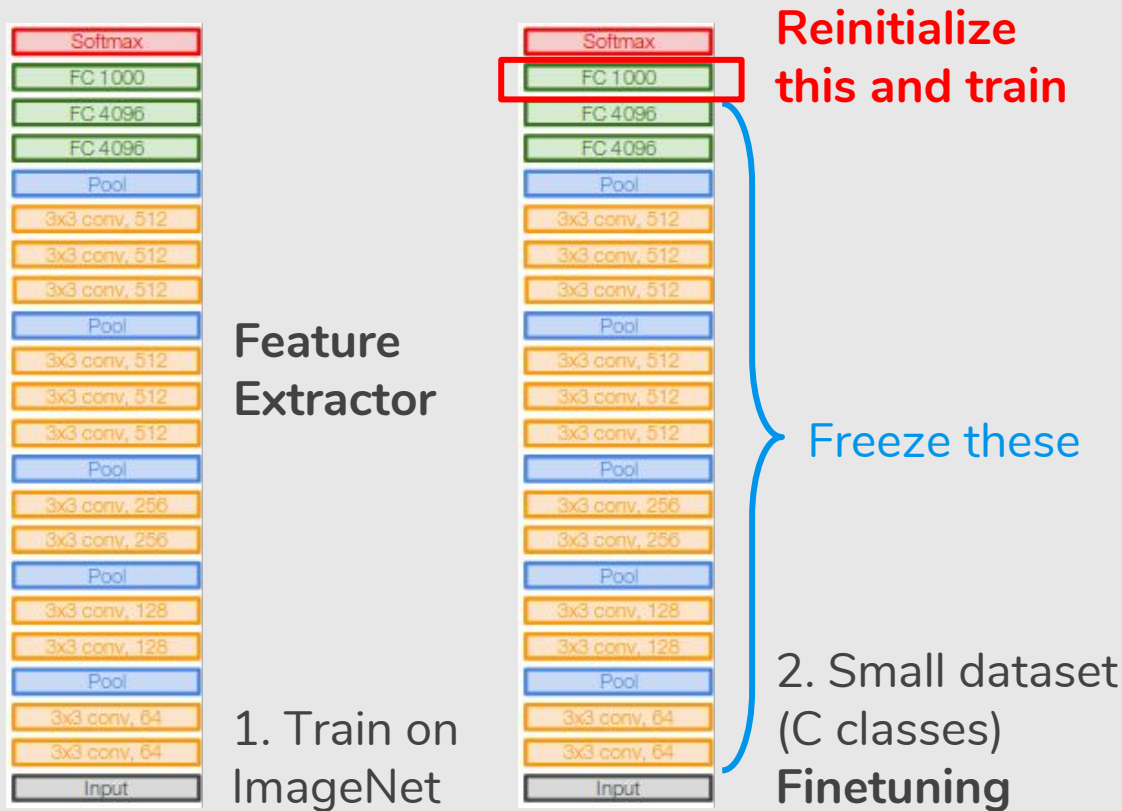
Transfer Learning with CNNs



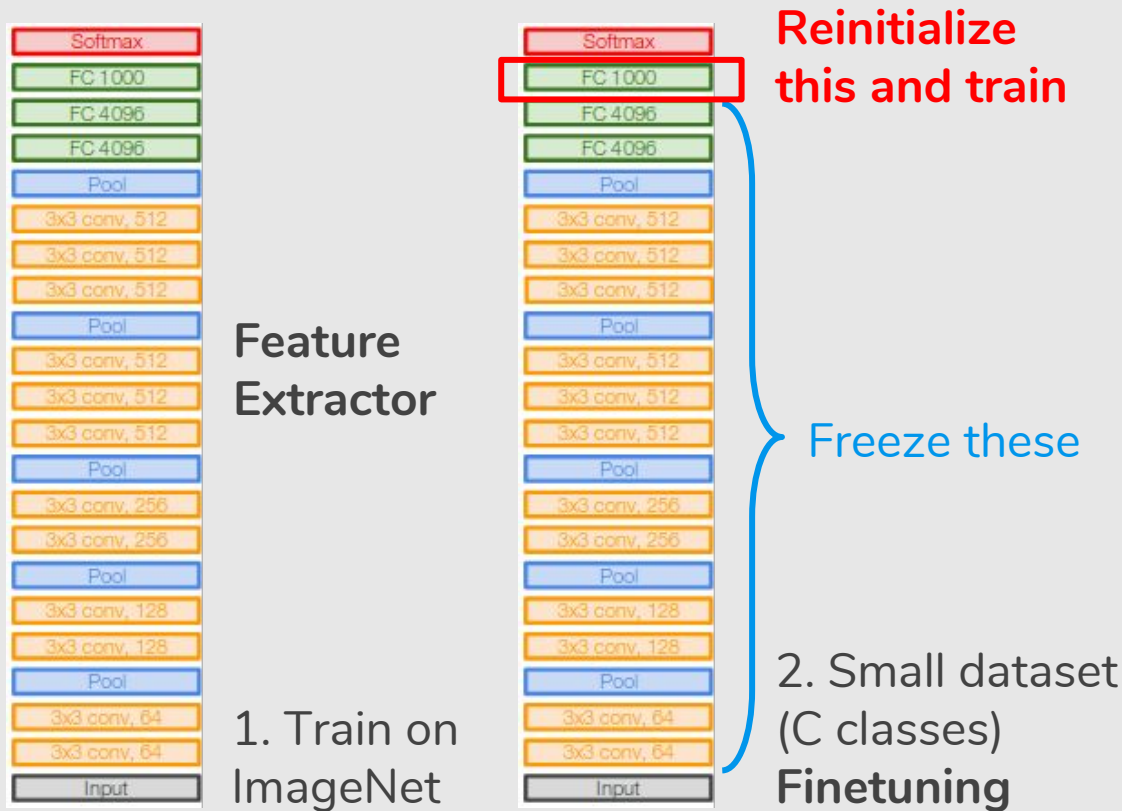
Transfer Learning with CNNs



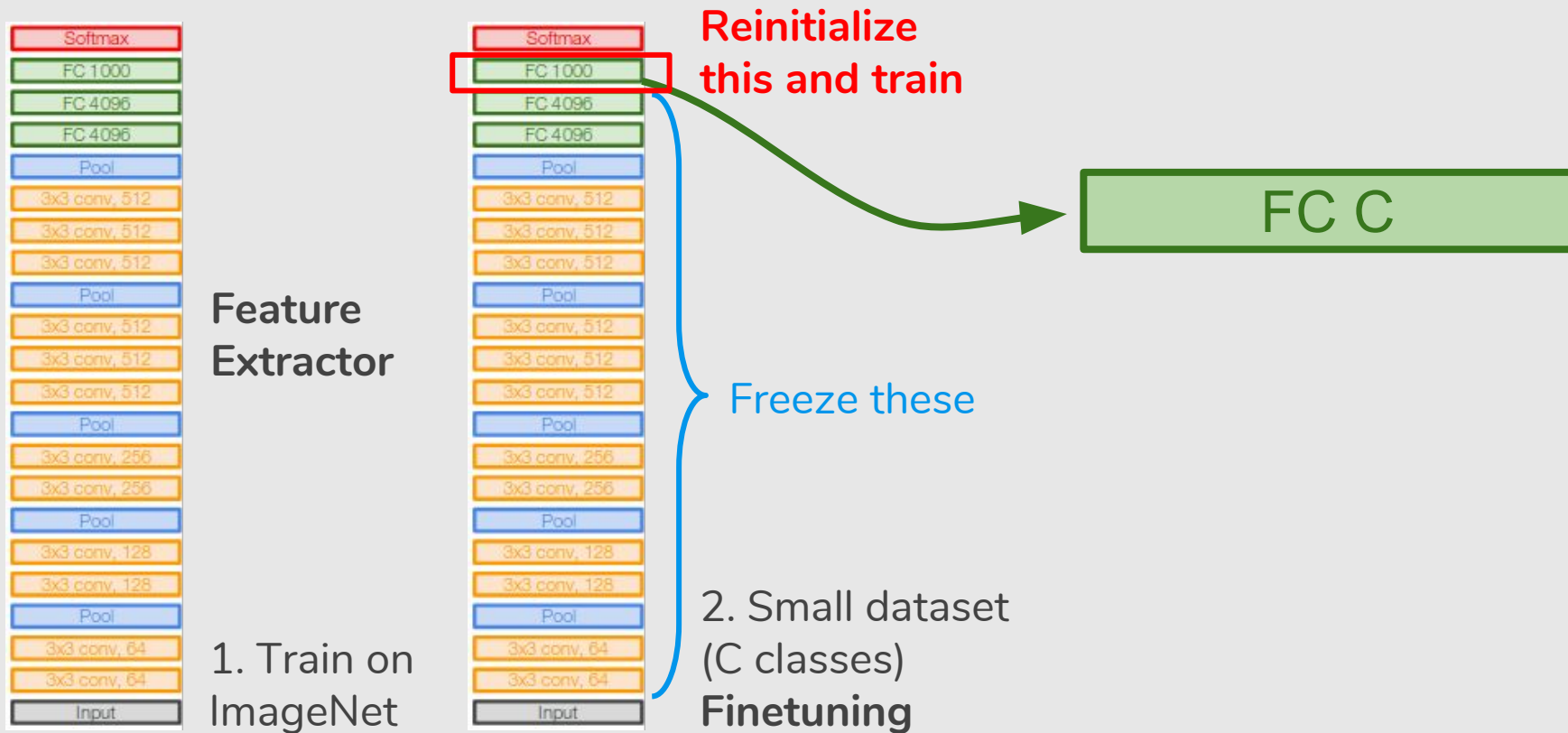
Transfer Learning with CNNs



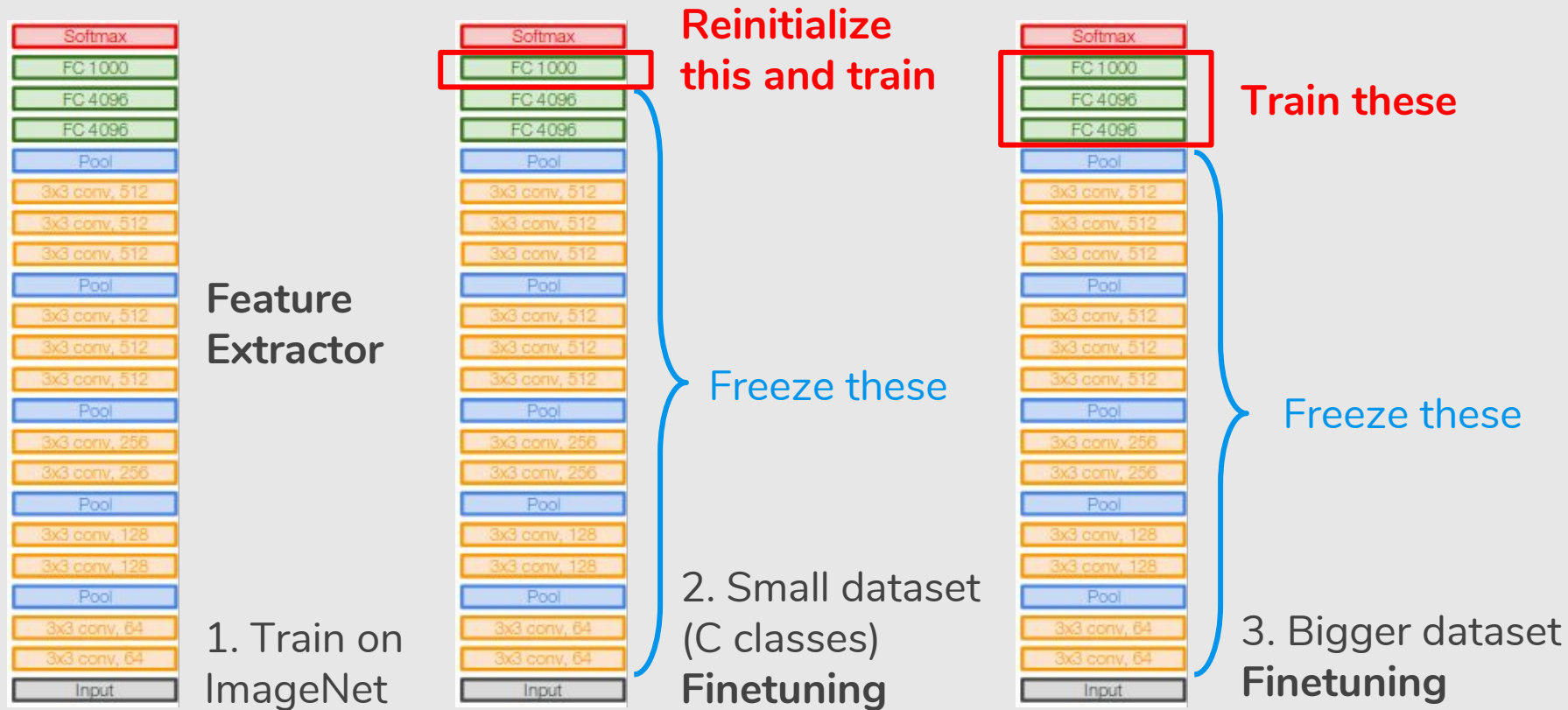
Transfer Learning with CNNs



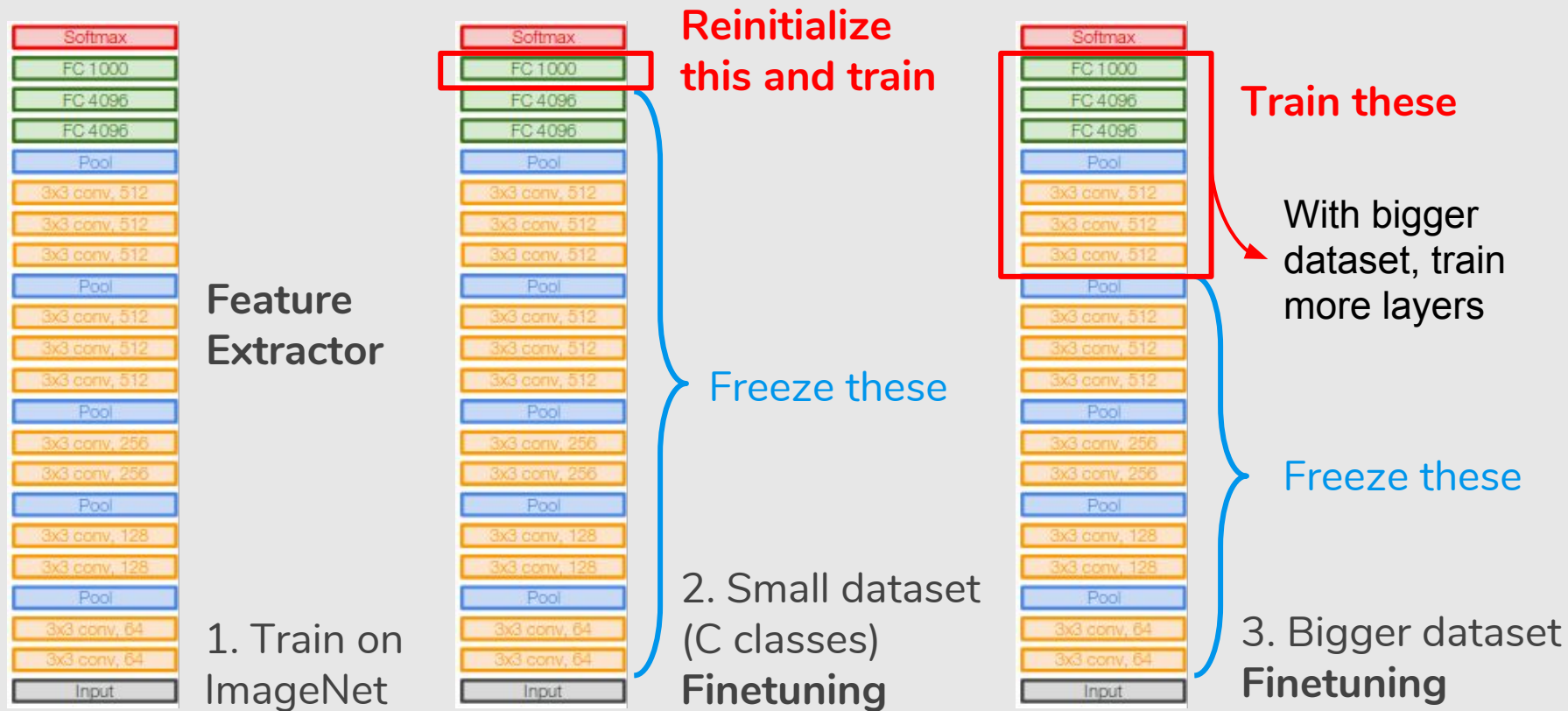
Transfer Learning with CNNs



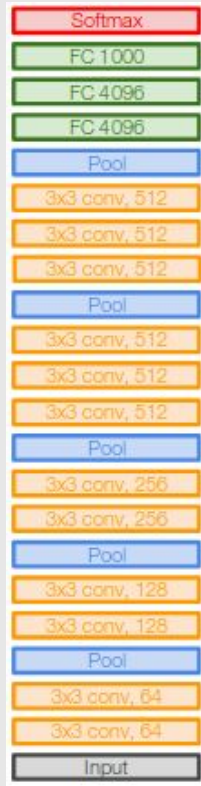
Transfer Learning with CNNs



Transfer Learning with CNNs



Transfer Learning with CNNs

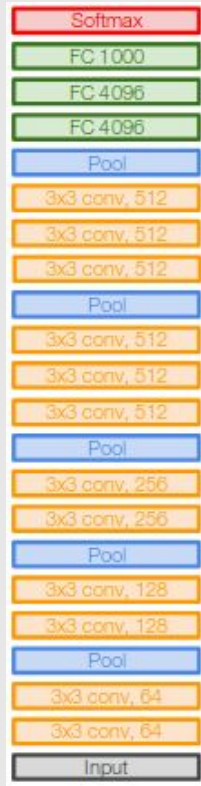


More specific

More generic

	Very similar dataset	Very different dataset
Very little data	?	?
Quite a lot of data	?	?

Transfer Learning with CNNs

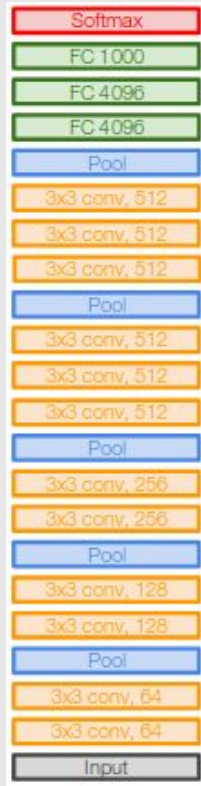


More specific

More generic

	Very similar dataset	Very different dataset
Very little data	Use Linear Classifier on top layer	?
Quite a lot of data	Finetune a few layers	?

Transfer Learning with CNNs

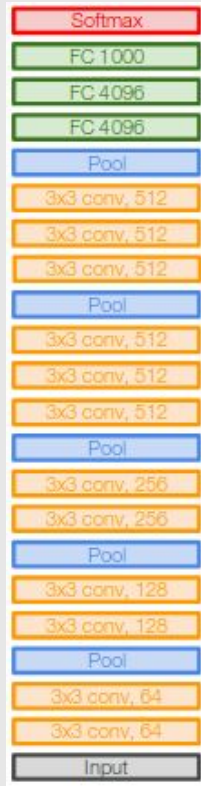


More specific

More generic

	Very similar dataset	Very different dataset
Very little data	Use Linear Classifier on top layer	?
Quite a lot of data	Finetune a few layers	Finetune a larger number of layers

Transfer Learning with CNNs



More specific

More generic

	Very similar dataset	Very different dataset
Very little data	Use Linear Classifier on top layer	You're in trouble ... Try linear classifier from different stages
Quite a lot of data	Finetune a few layers	Finetune a larger number of layers

Take away for your projects and beyond:

Have some dataset of interest but it has $< \sim 1\text{M}$ images?

1. Find a very large dataset that has similar data, train a big CNN there
2. Transfer learn to your dataset

Take away for your projects and beyond:

Have some dataset of interest but it has $< \sim 1\text{M}$ images?

1. Find a very large dataset that has similar data, train a big CNN there
2. Transfer learn to your dataset

Deep learning frameworks provide a “Model Zoo” of pretrained models so you don’t need to train your own.

TensorFlow: <https://github.com/tensorflow/models>

PyTorch: <https://github.com/pytorch/vision>

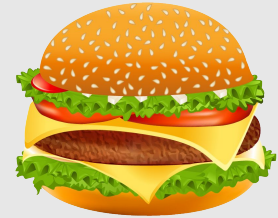
Recurrent Neural Networks (RNNs)



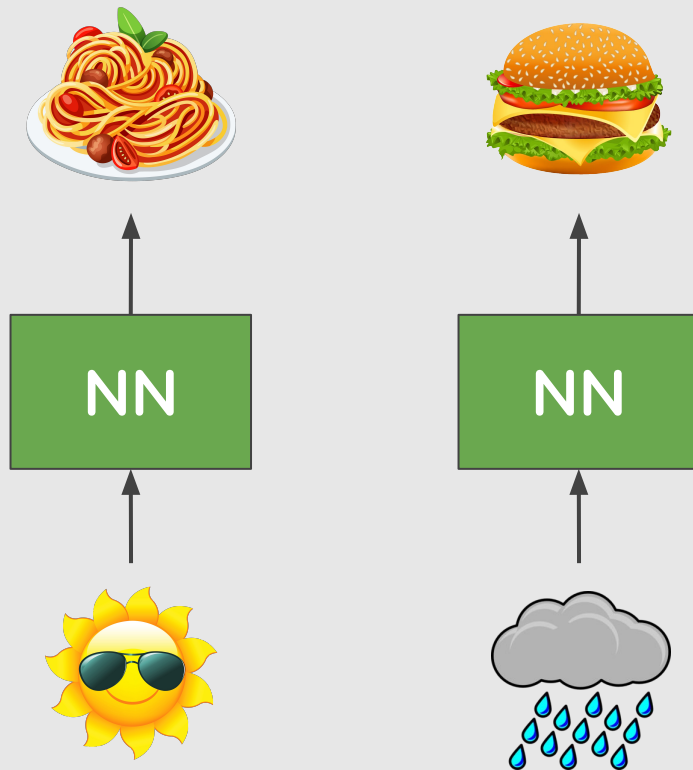
Weather



Perfect Roommate



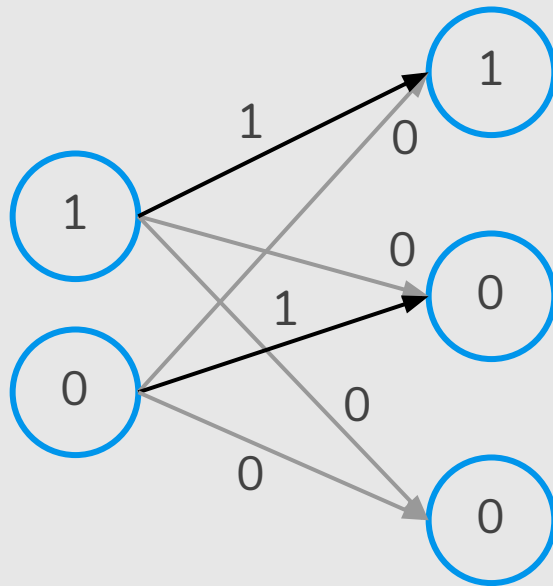
Neural Network



Neural Network

$$\begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{pmatrix}$$

$$\begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

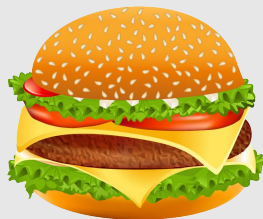


$$\begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$$





Pasta



Burger



Salad



Cooking Schedule

Monday



Tuesday



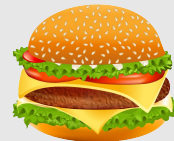
Wednesday



Thursday



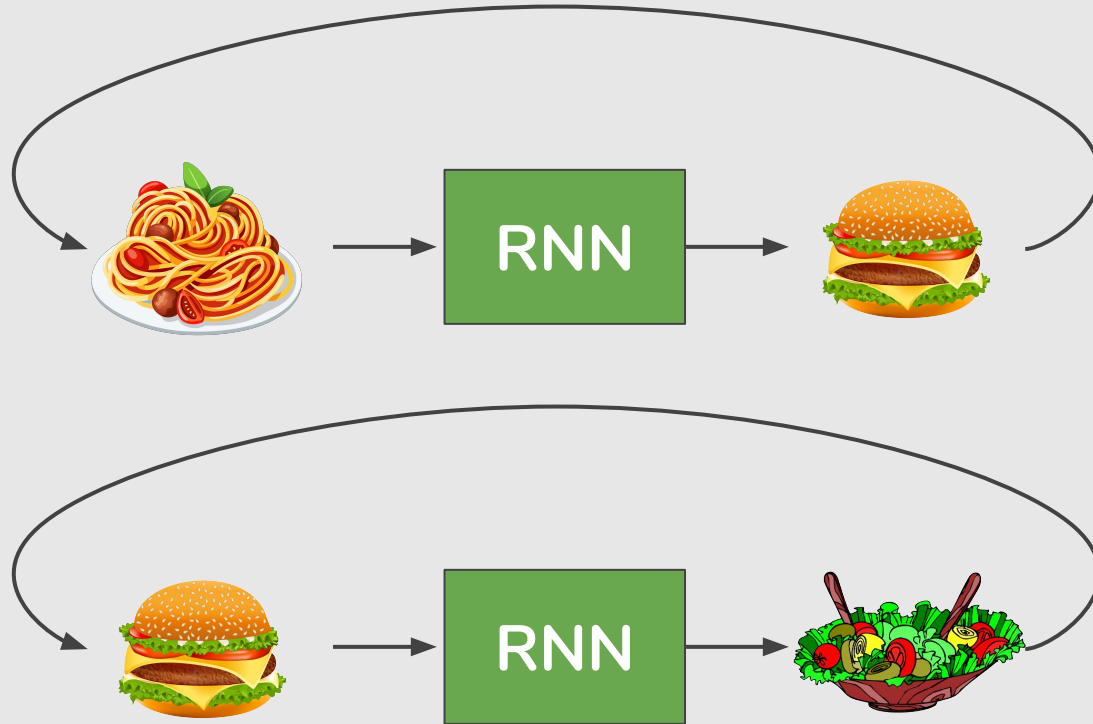
Friday



Saturday

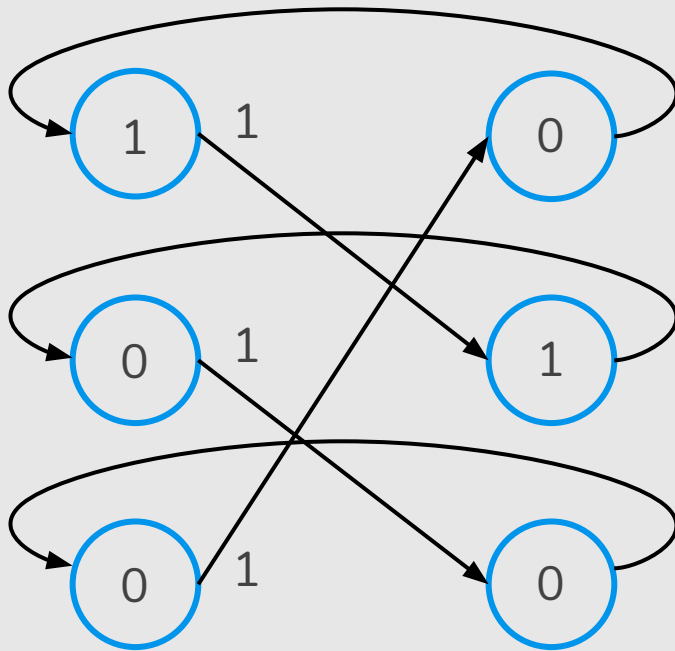


Recurrent Neural Network

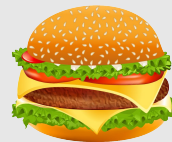


Simple (Recurrent) Neural Network

$$\begin{bmatrix} 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$



$$\begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$





Sunny
Same as yesterday

Weather



Rain
Next dish



Cooking Schedule

Monday



Tuesday



Wednesday



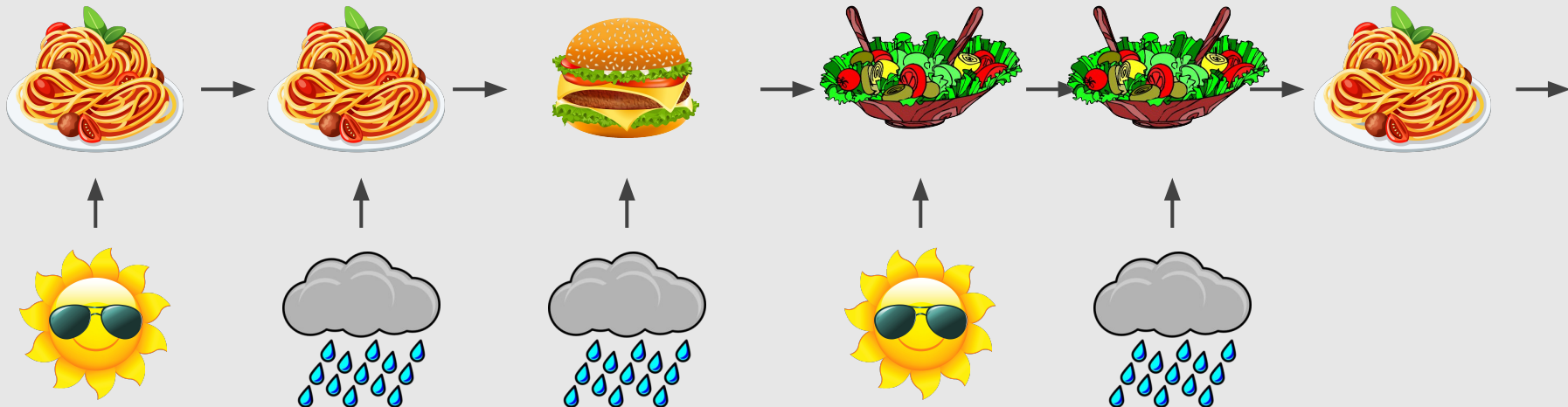
Thursday



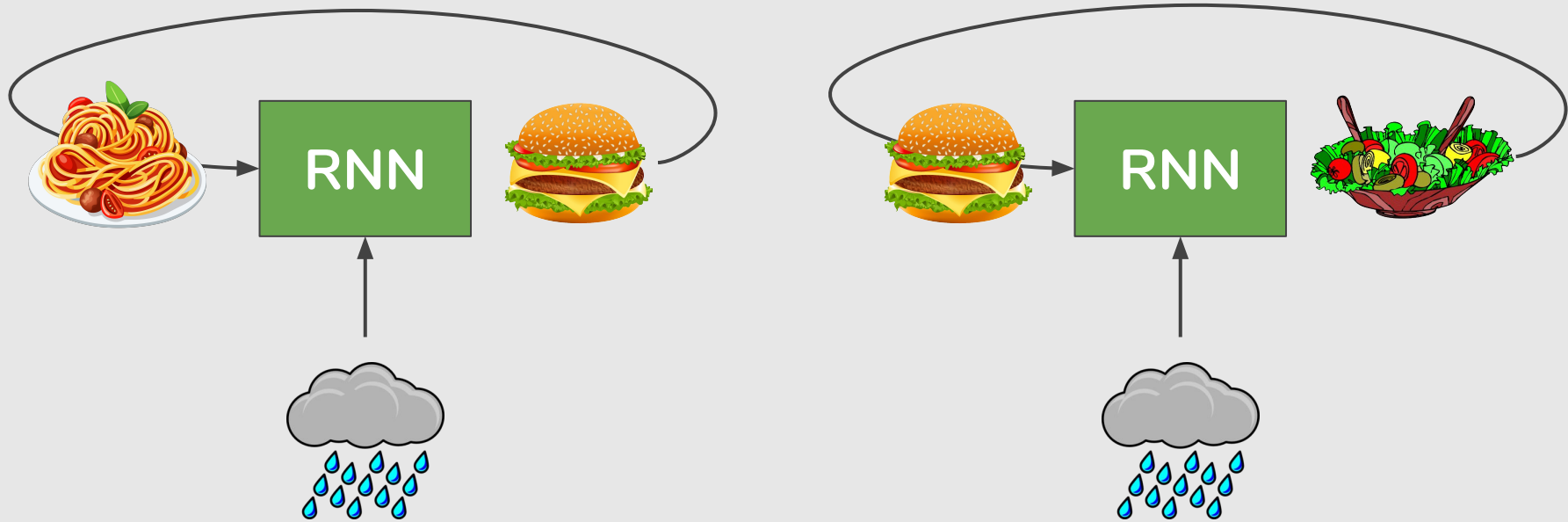
Friday



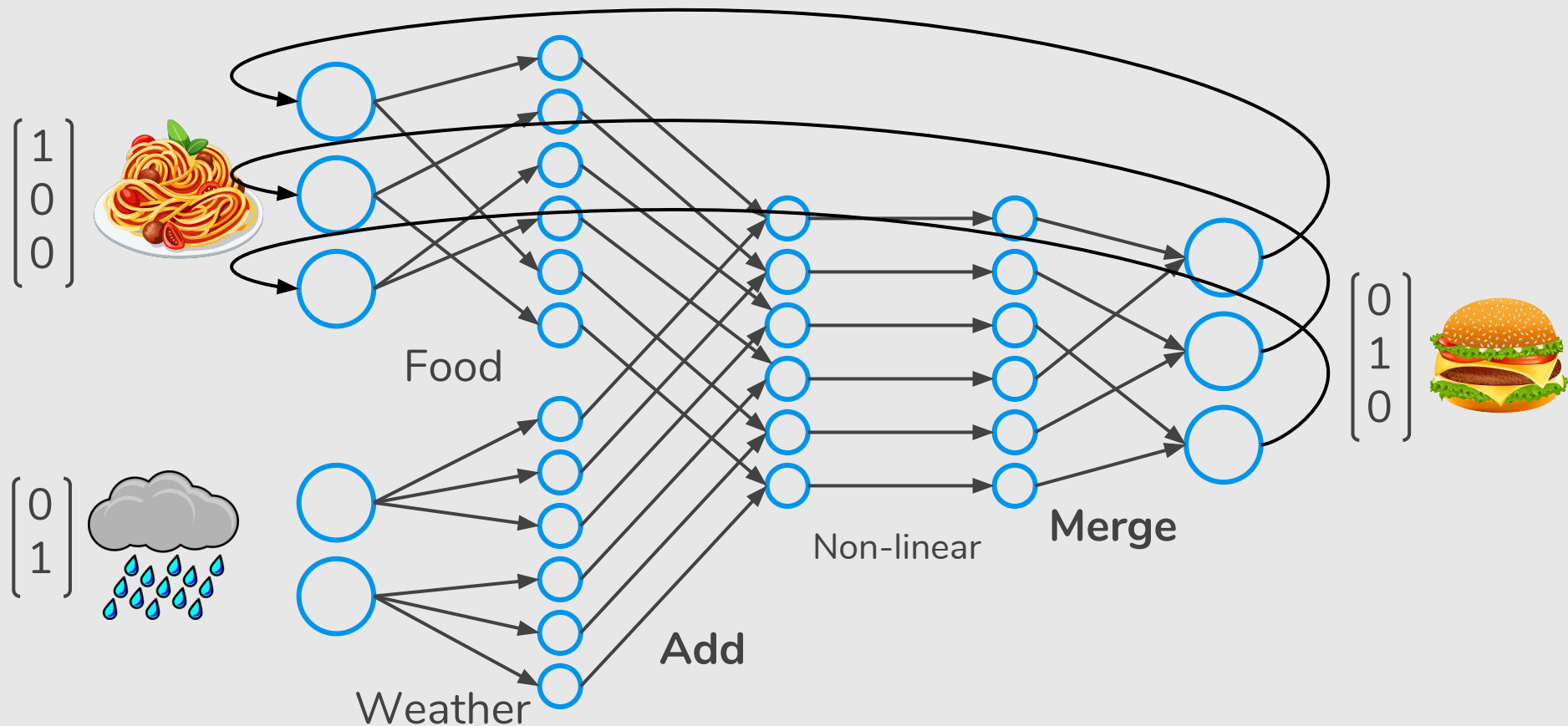
Saturday



Recurrent Neural Network



Recurrent Neural Network



How to train the RNN?

Start with Random Weights

a	b	c
d	e	f
g	h	i
j	k	l
m	n	o
p	q	r

Food



Add

s	t
u	v
w	x
z	A
B	C
D	E

Weather



Merge

F	G	H	I	J	K
L	M	N	O	P	Q
R	S	T	U	V	X

Deep Neural Networks

Machine Learning and Pattern Recognition

(Largely based on slides from Luis Serrano & Fei-Fei Li & Andrej Karpathy & Justin Johnson & Serena Yeung)

Prof. Sandra Avila
Institute of Computing (IC/Unicamp)

MC886/MO444, October 25, 2018

Recurrent Neural Networks: Process Sequences

one to one



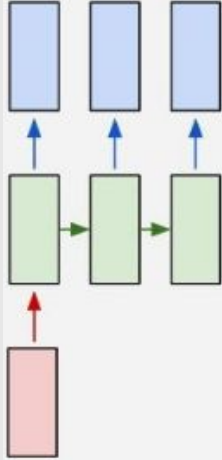
Vanilla Neural
Networks

Recurrent Neural Networks: Process Sequences

one to one



one to many



Vanilla Neural
Networks

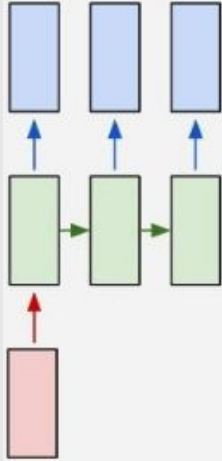
Image Captioning
image \Rightarrow seq. words

Recurrent Neural Networks: Process Sequences

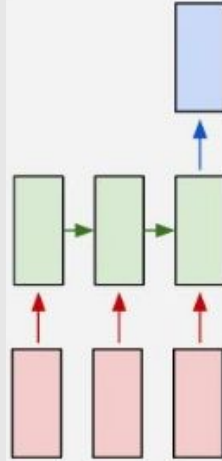
one to one



one to many



many to one



Vanilla Neural
Networks

Sentiment Classification
seq. words \Rightarrow sentiment

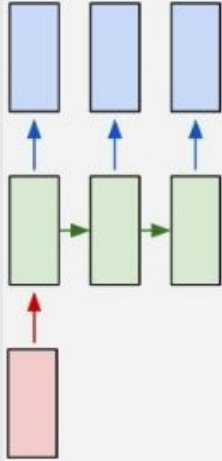
Image Captioning
image \Rightarrow seq. words

Recurrent Neural Networks: Process Sequences

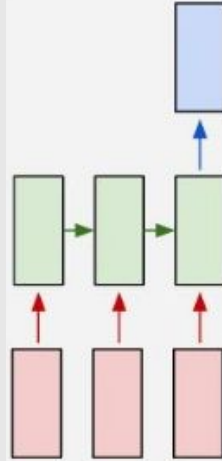
one to one



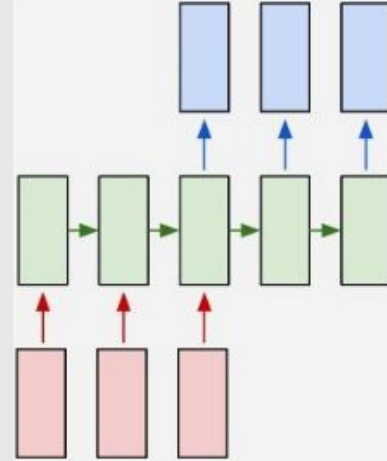
one to many



many to one



many to many



Vanilla Neural
Networks

Sentiment Classification
seq. words \Rightarrow sentiment

Image Captioning
image \Rightarrow seq. words

Machine Translation
seq. words \Rightarrow seq. of words

Recurrent Neural Networks: Process Sequences

one to one



Vanilla Neural
Networks

one to many

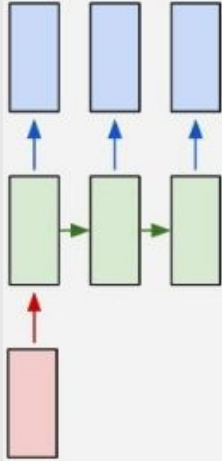
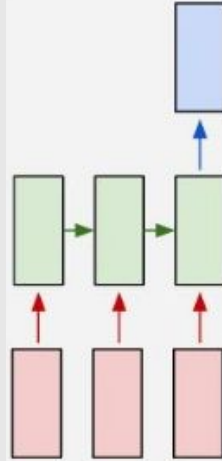


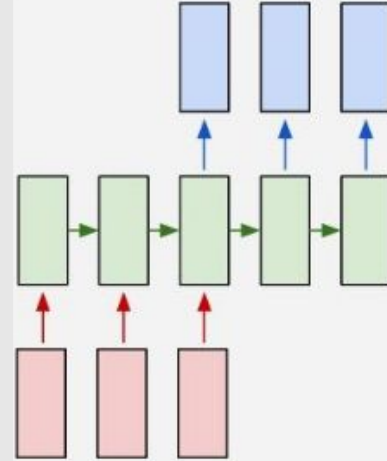
Image Captioning
image \Rightarrow seq. words

many to one



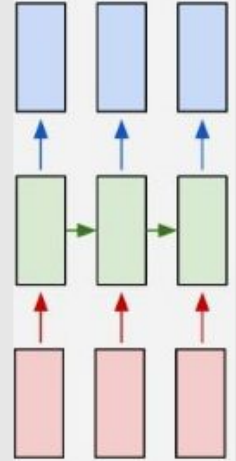
Sentiment Classification
seq. words \Rightarrow sentiment

many to many



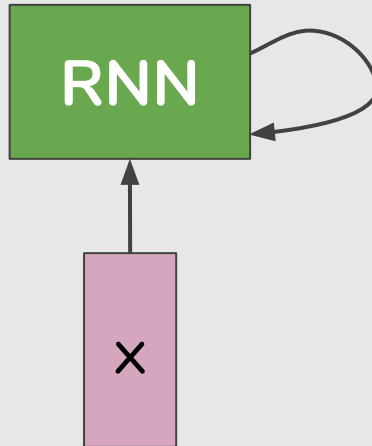
Machine Translation
seq. words \Rightarrow seq. of words

many to many

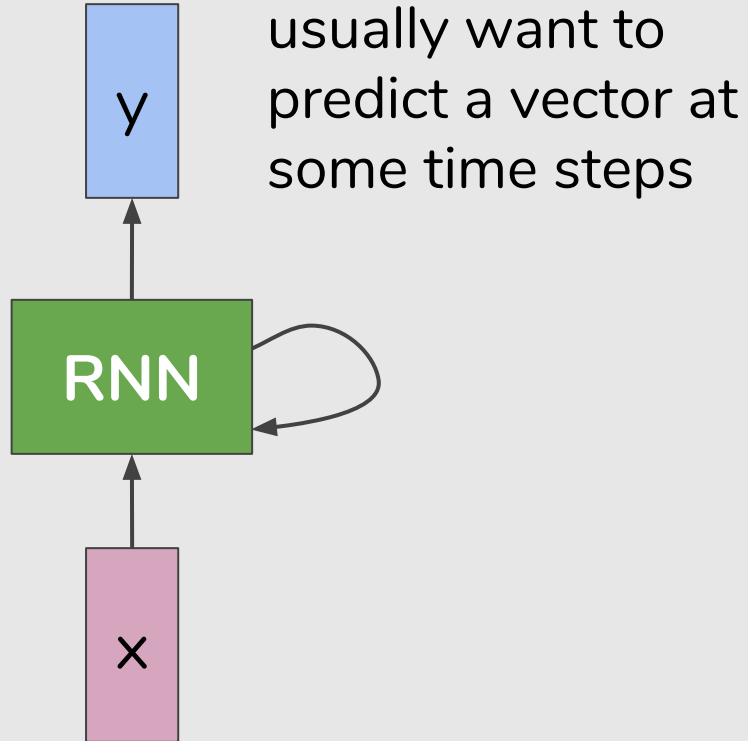


**Video classification
on frame level**

Recurrent Neural Network



Recurrent Neural Network



Recurrent Neural Network

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

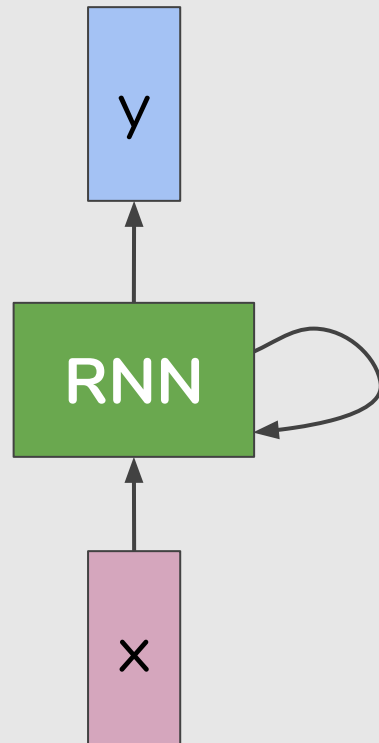
$$h_t = f_W(h_{t-1}, x_t)$$

new state

some function
with parameters W

old state

input vector at
some time step

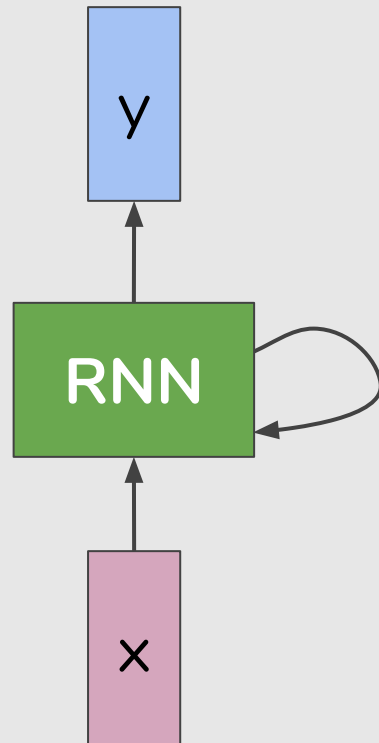


Recurrent Neural Network

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.



Recurrent Neural Network

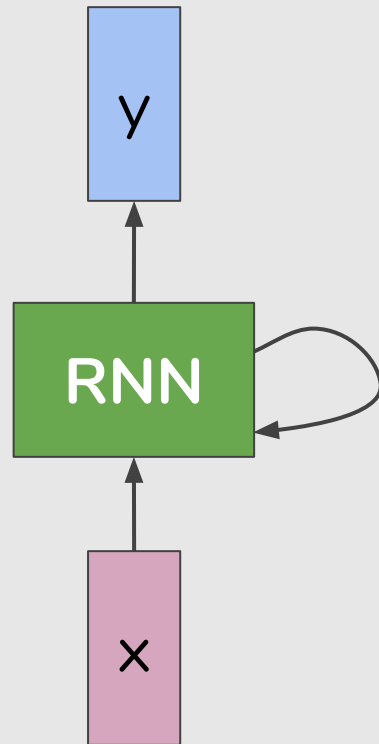
The state consists of a single “hidden” vector \mathbf{h} :

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

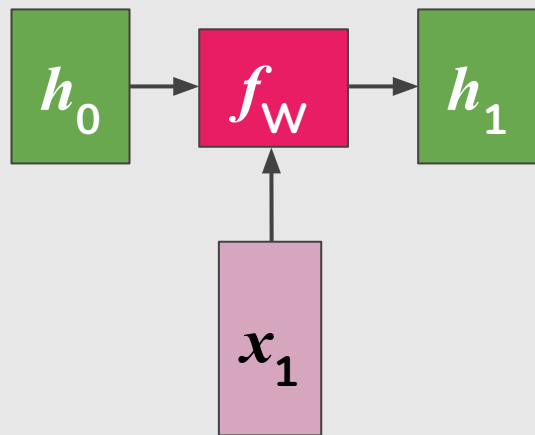


$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

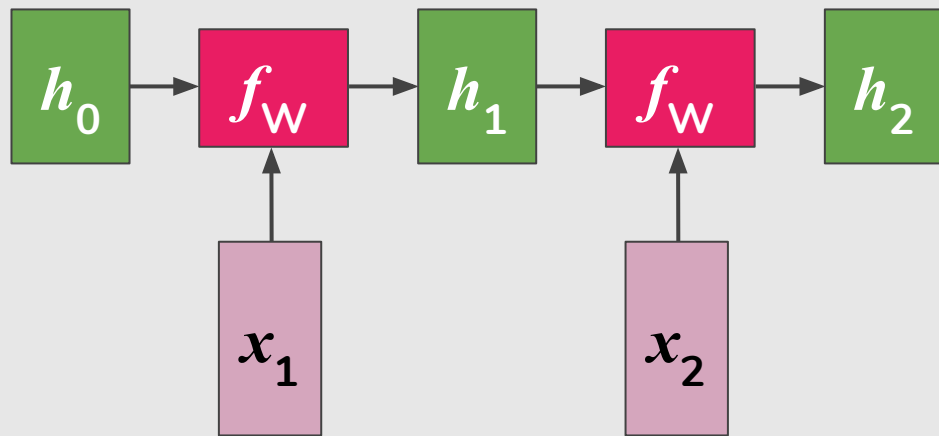
$$y_t = W_{hy}h_t$$



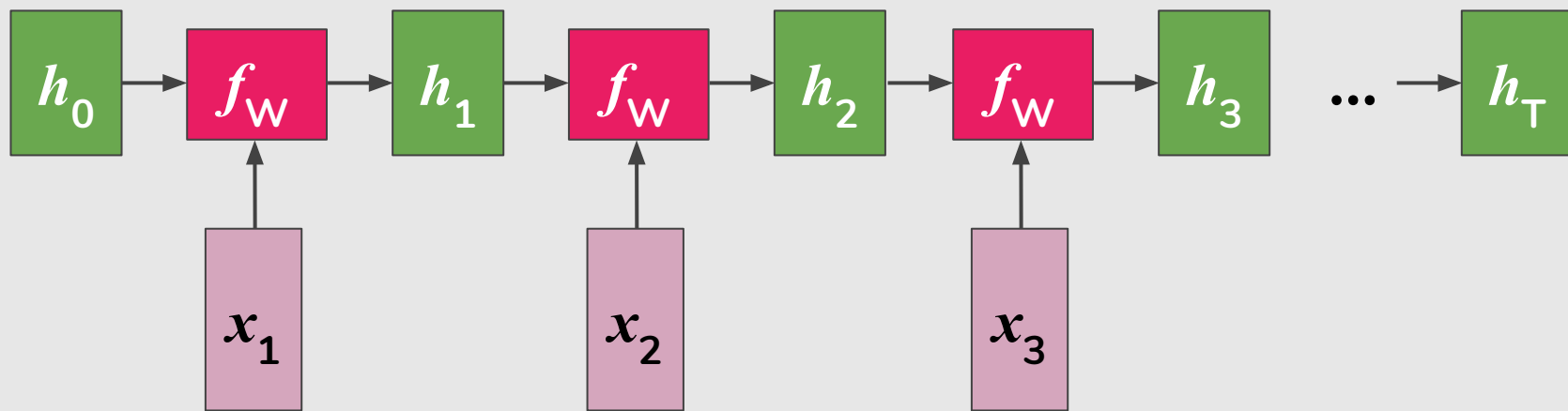
RNN: Computational Graph



RNN: Computational Graph

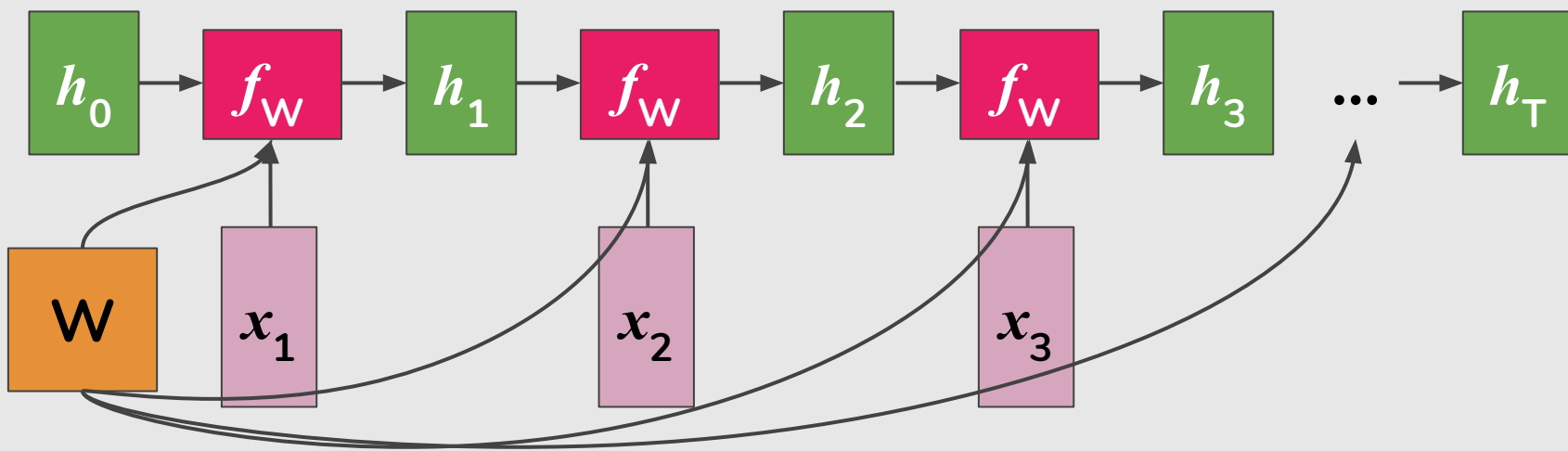


RNN: Computational Graph

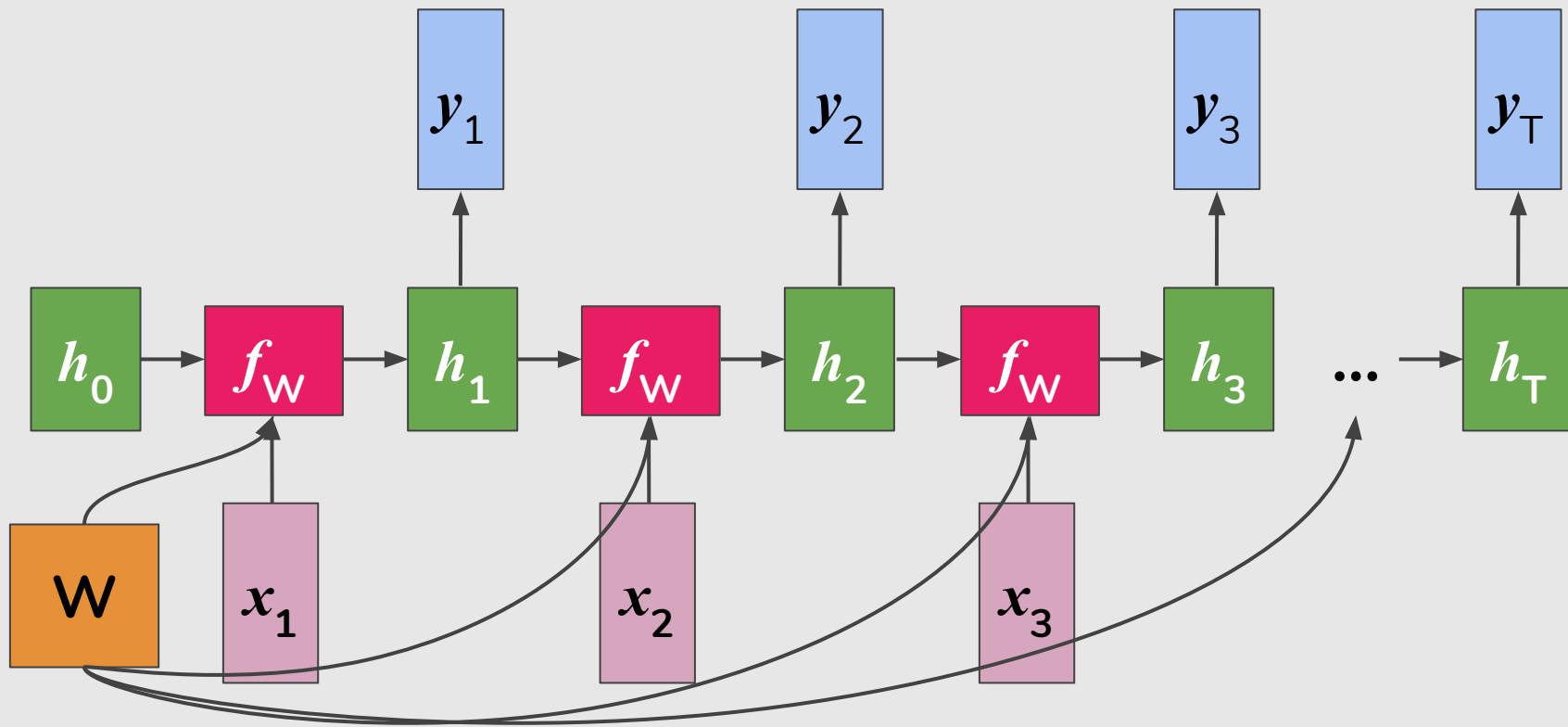


RNN: Computational Graph

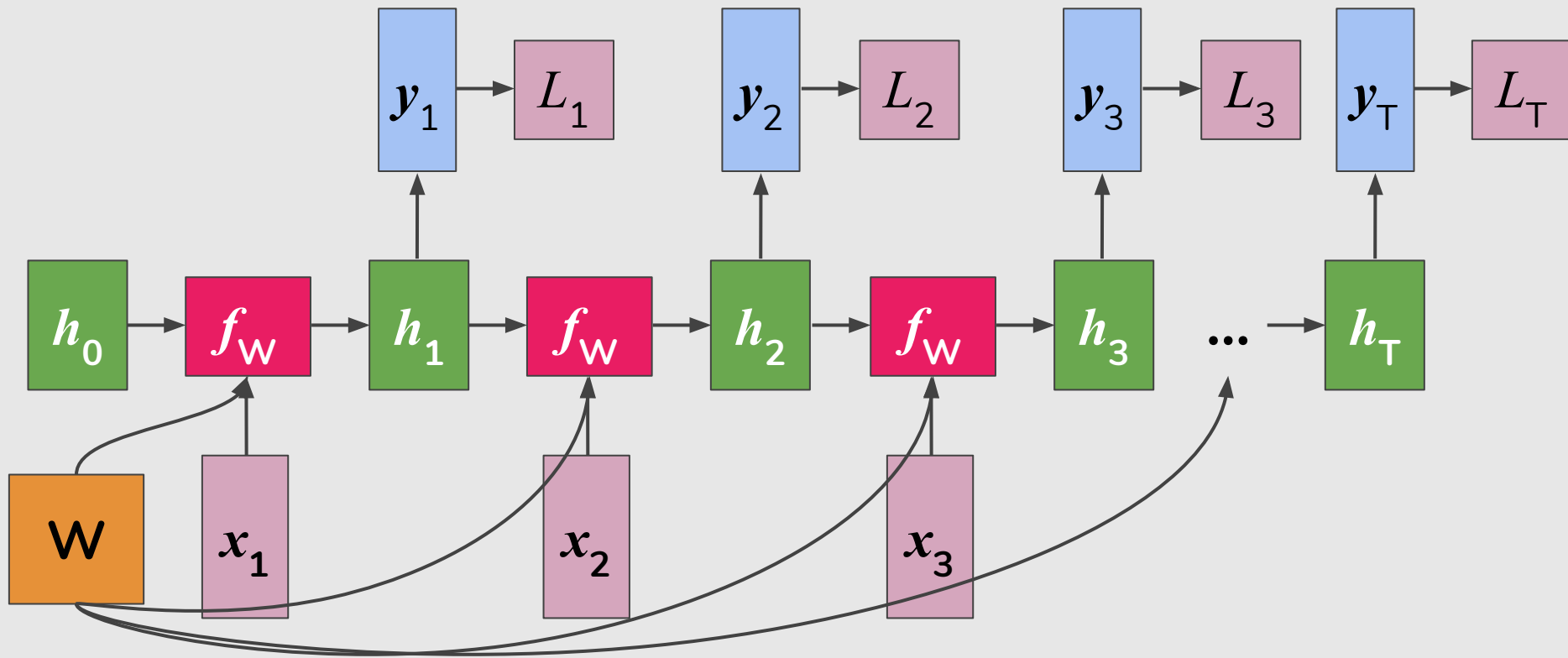
Re-use the same weight matrix at every time-step



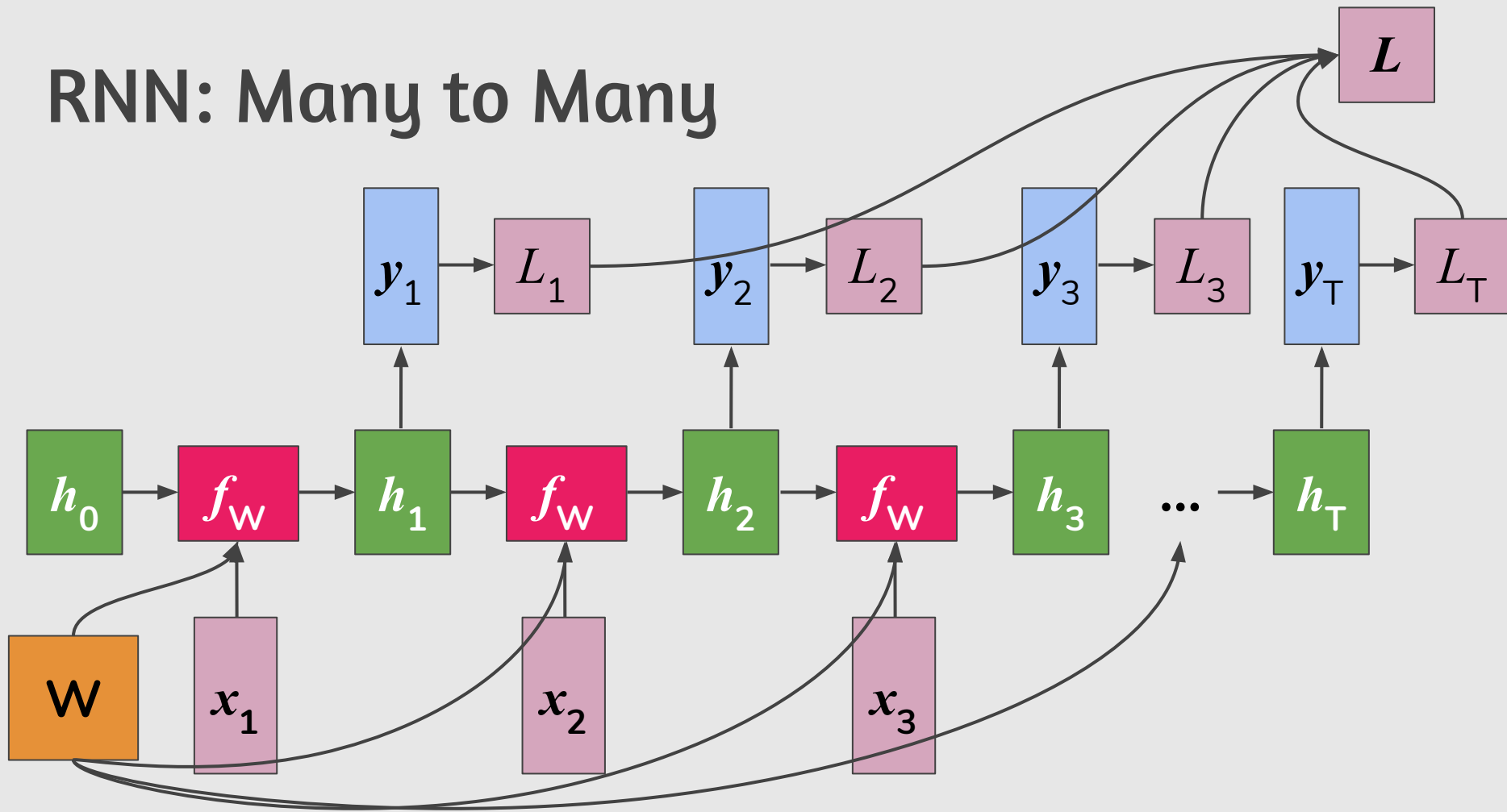
RNN: Computational Graph



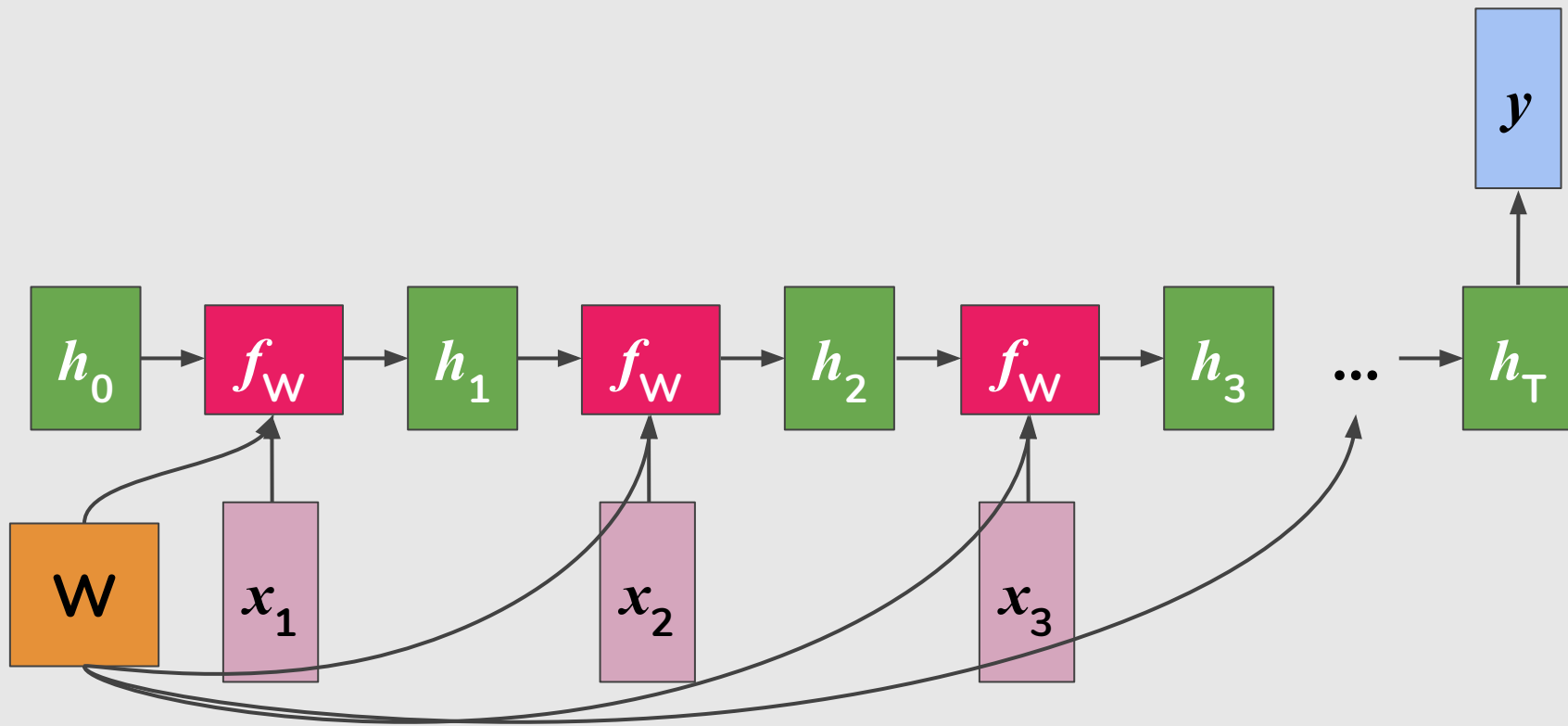
RNN: Many to Many



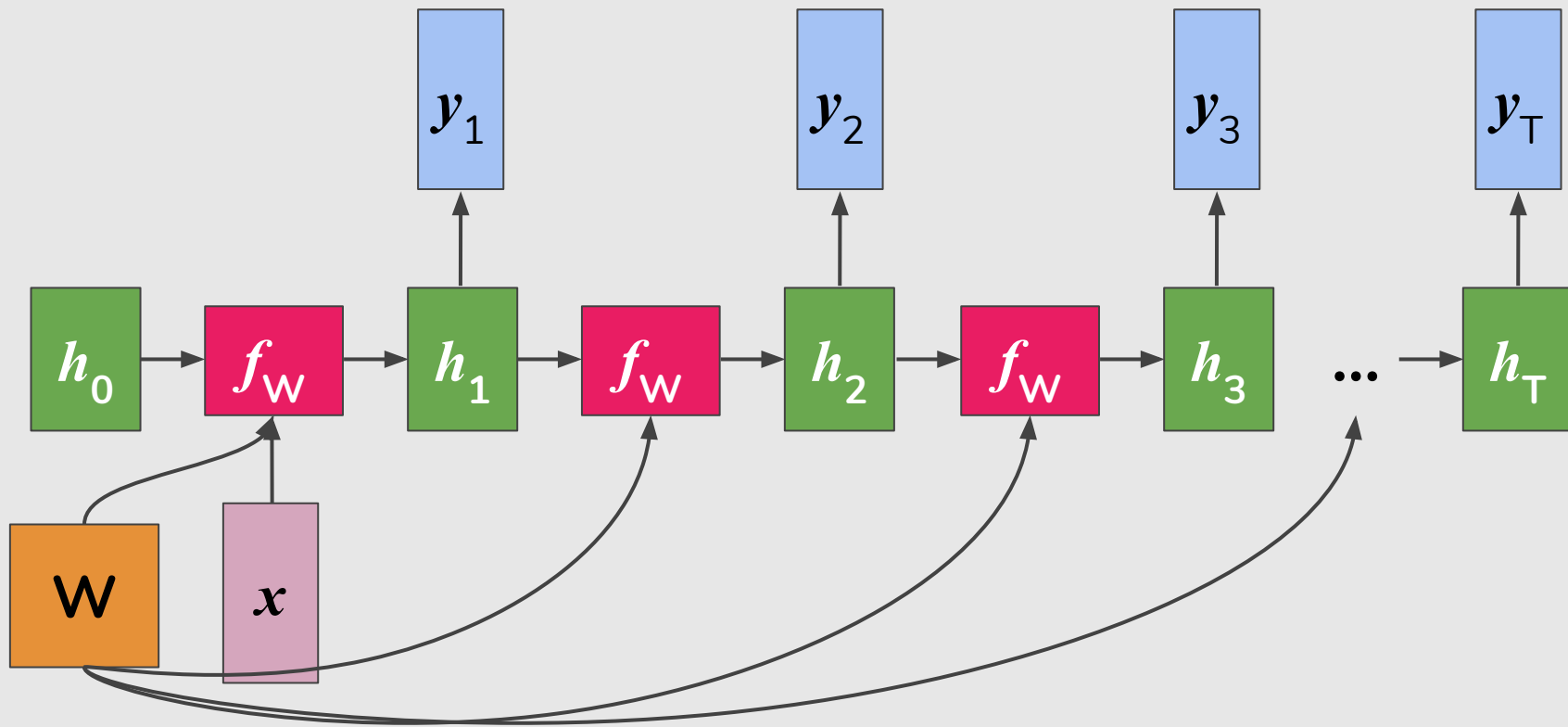
RNN: Many to Many



RNN: Many to One



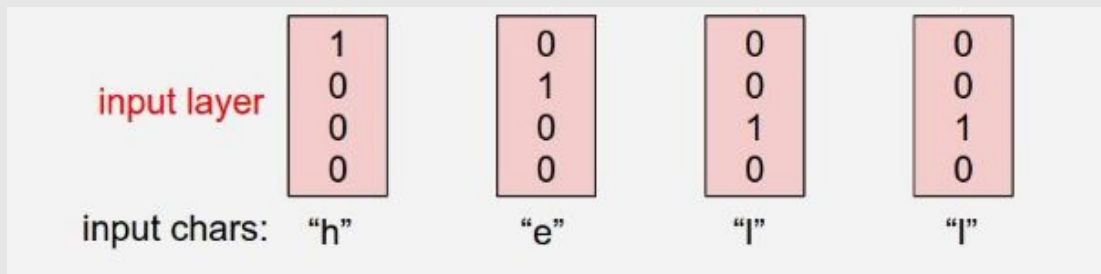
RNN: One to Many



Character-level Language Model

Vocabulary:
[h,e,l,o]

Example training
sequence:
“hello”

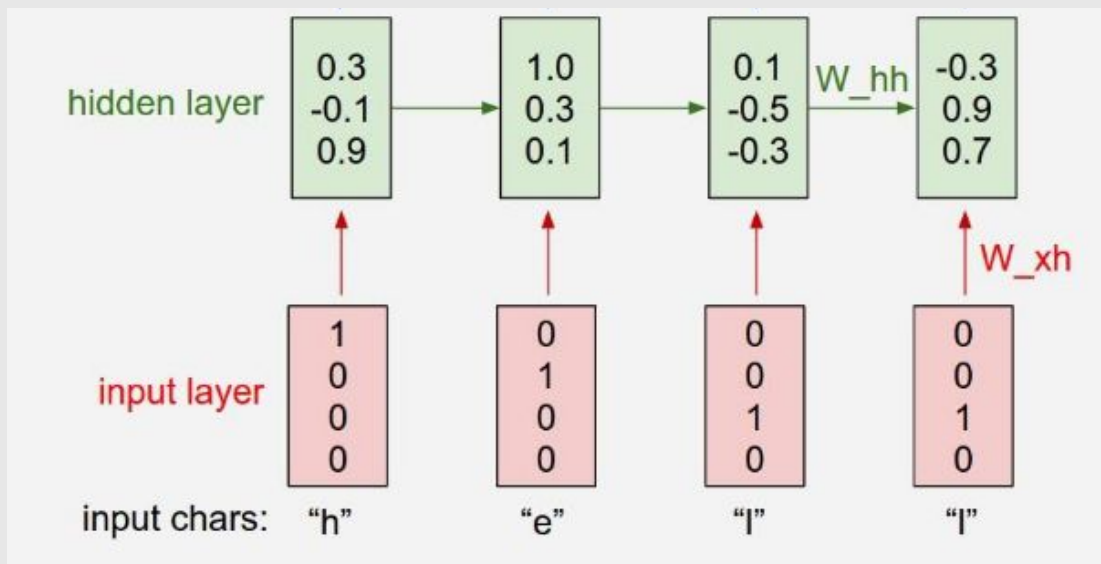


Character-level Language Model

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

Vocabulary:
[h,e,l,o]

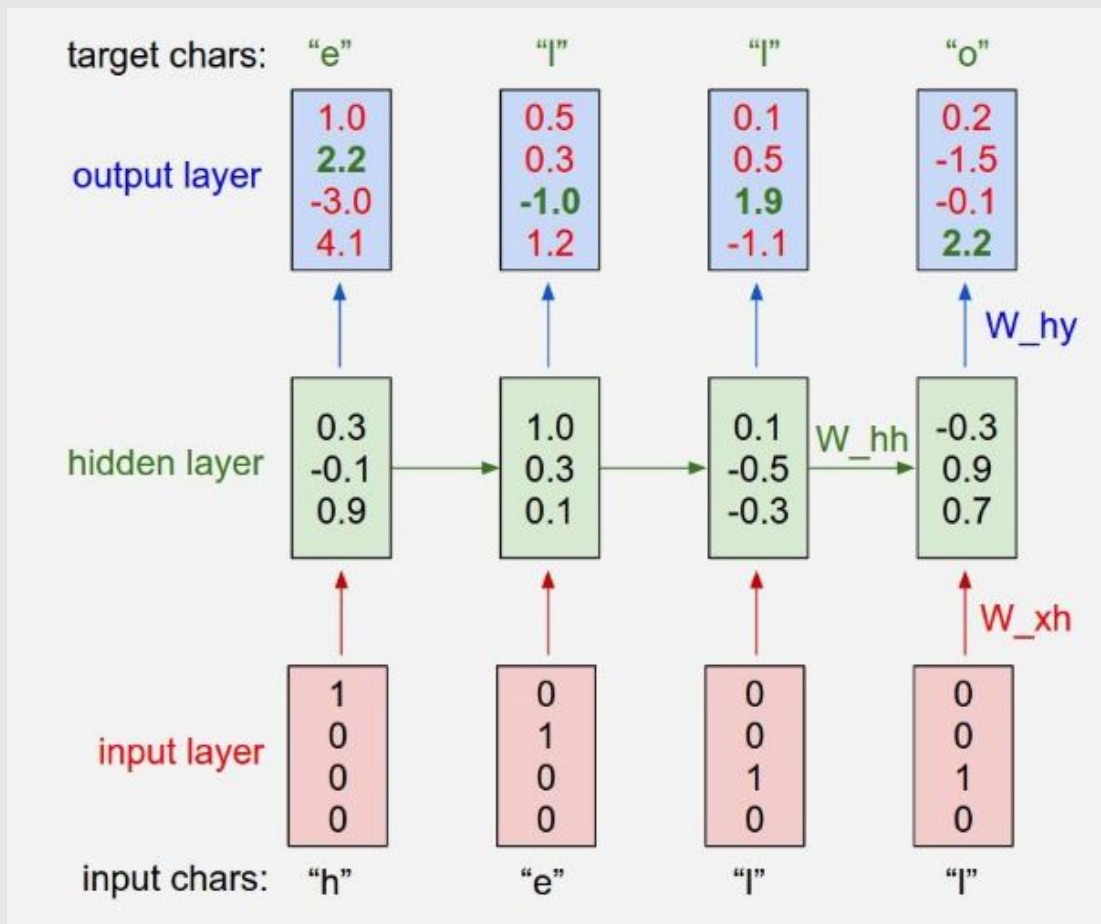
Example training
sequence:
“hello”



Character-level Language Model

Vocabulary:
[h,e,l,o]

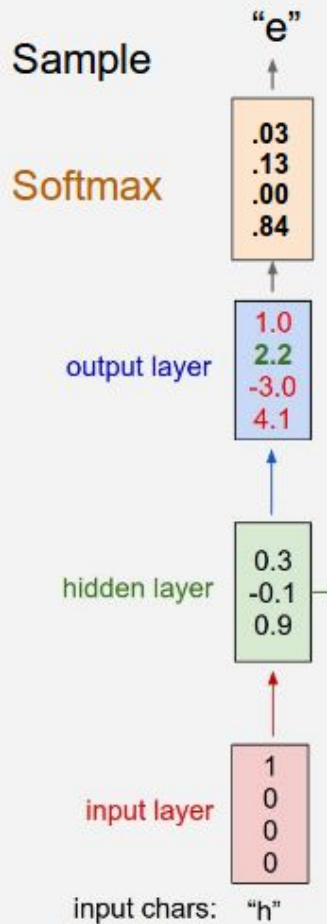
Example training
sequence:
"hello"



Character-level Language Model

Vocabulary:
[h,e,l,o]

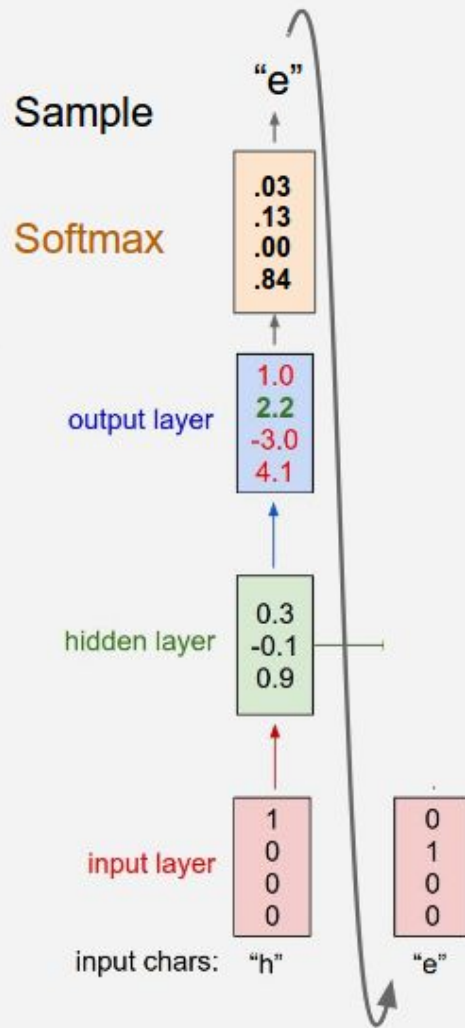
At test-time sample
characters one at a time,
feed back to model



Character-level Language Model

Vocabulary:
[h,e,l,o]

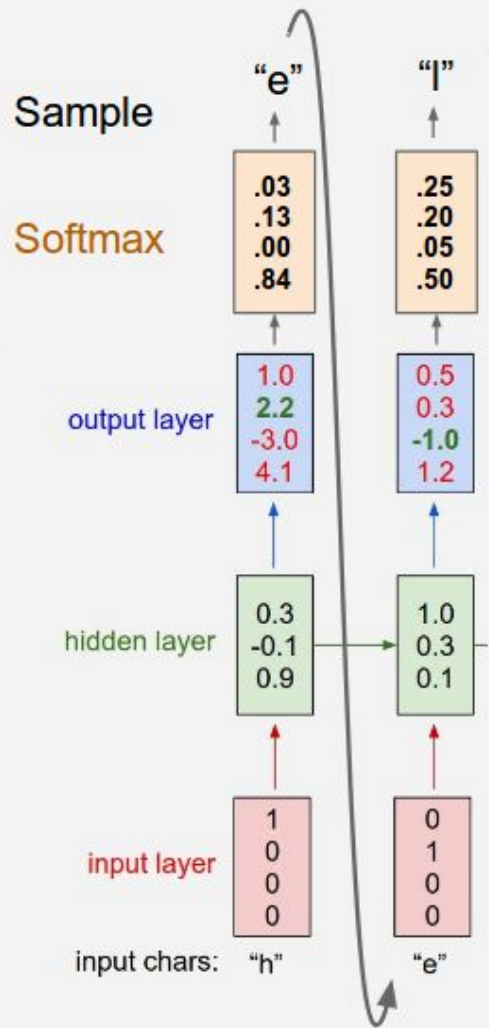
At test-time sample
characters one at a time,
feed back to model



Character-level Language Model

Vocabulary:
[h,e,l,o]

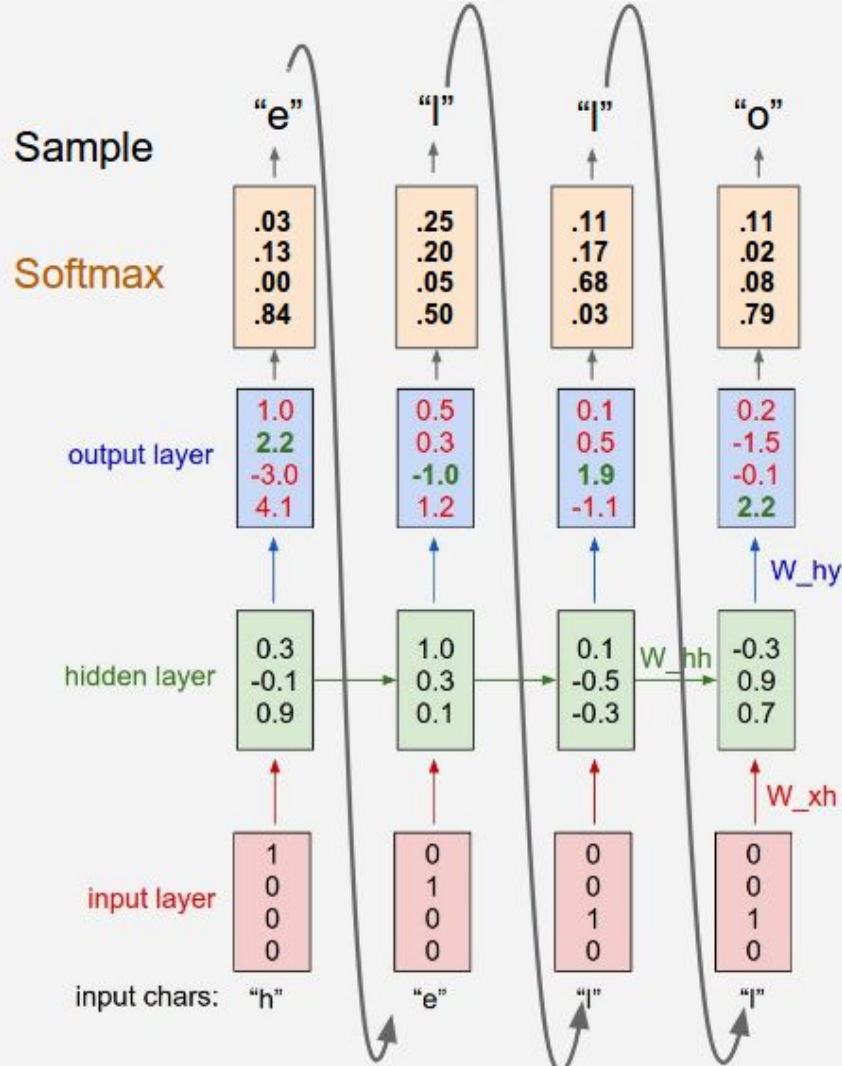
At test-time sample
characters one at a time,
feed back to model

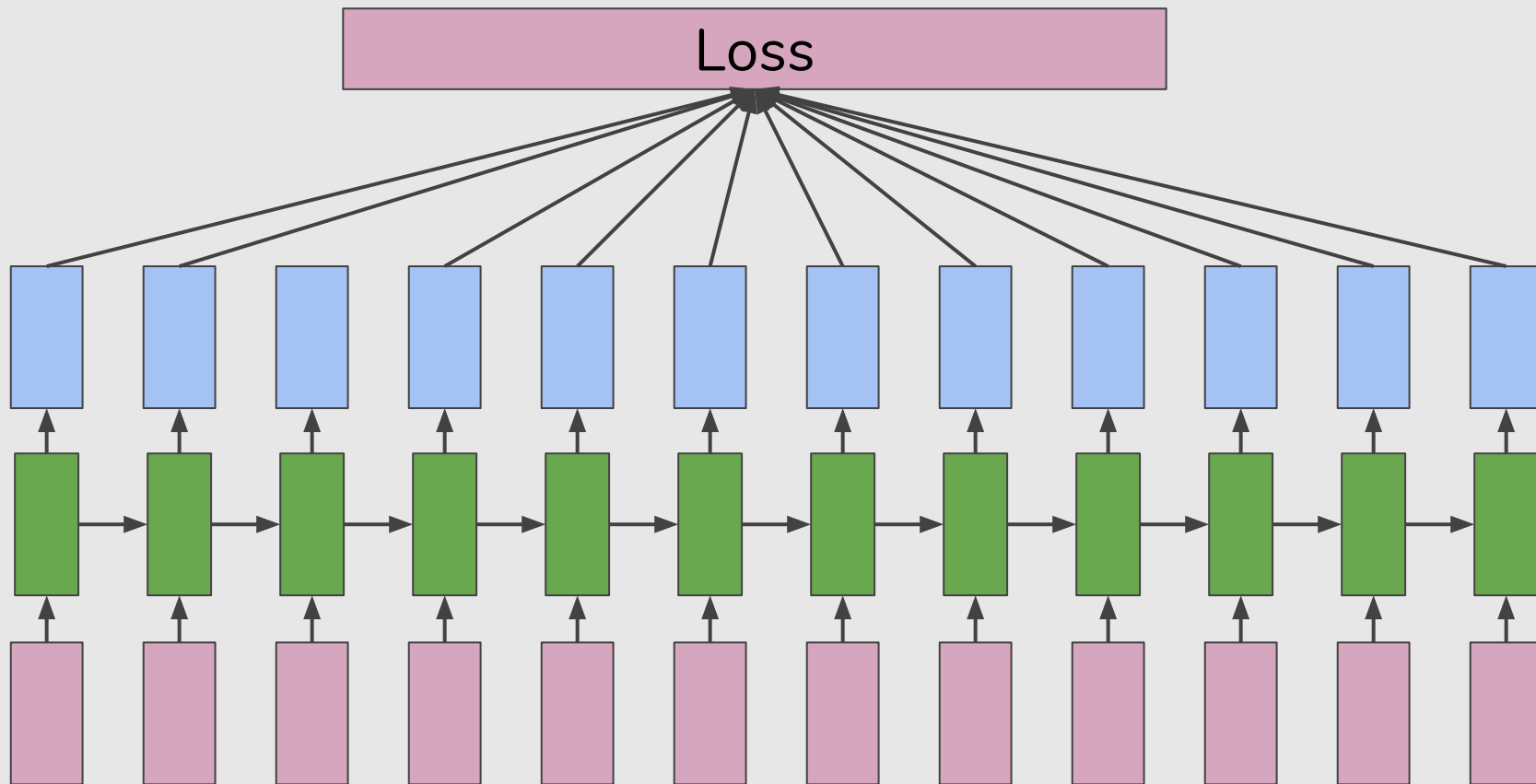


Character-level Language Model

Vocabulary:
[h,e,l,o]

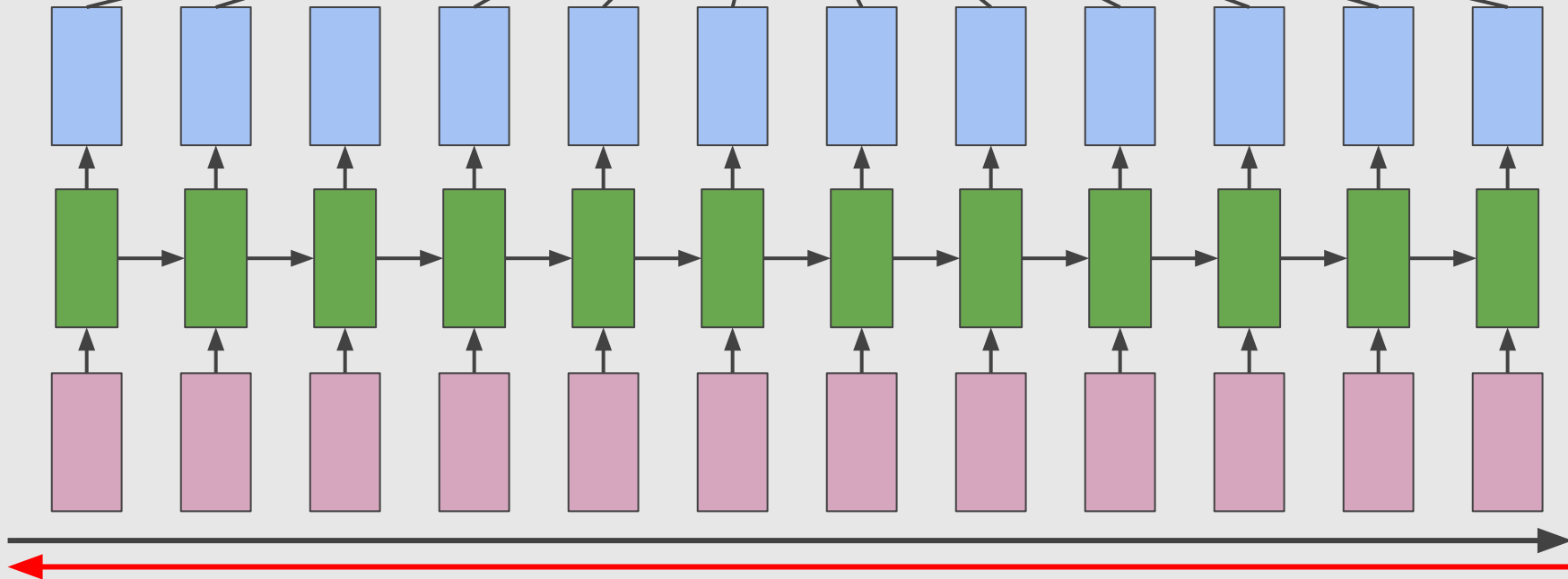
At test-time sample characters one at a time, feed back to model

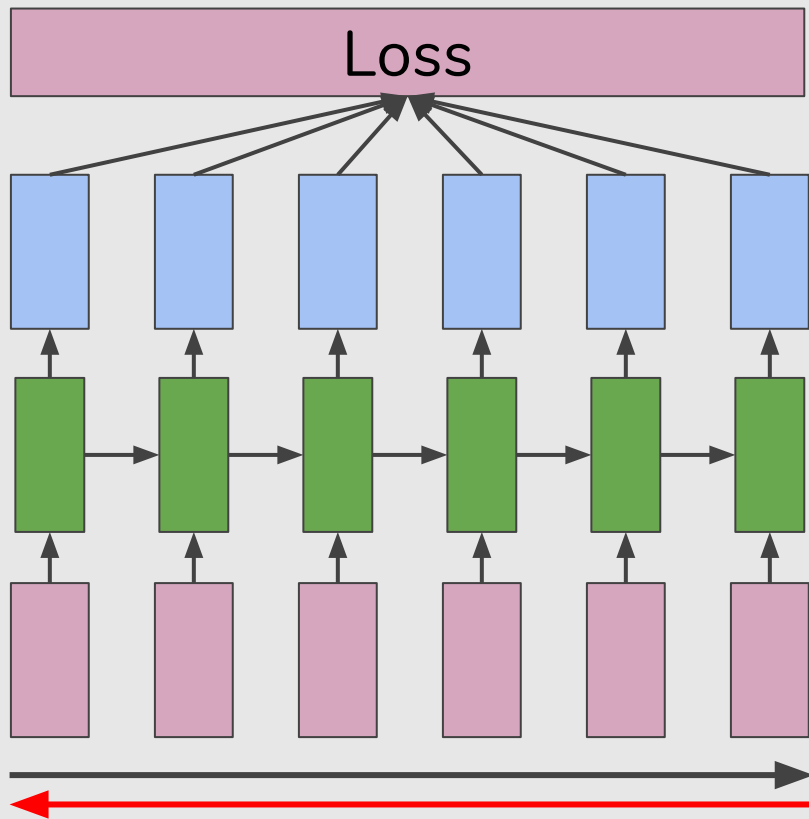




Loss

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

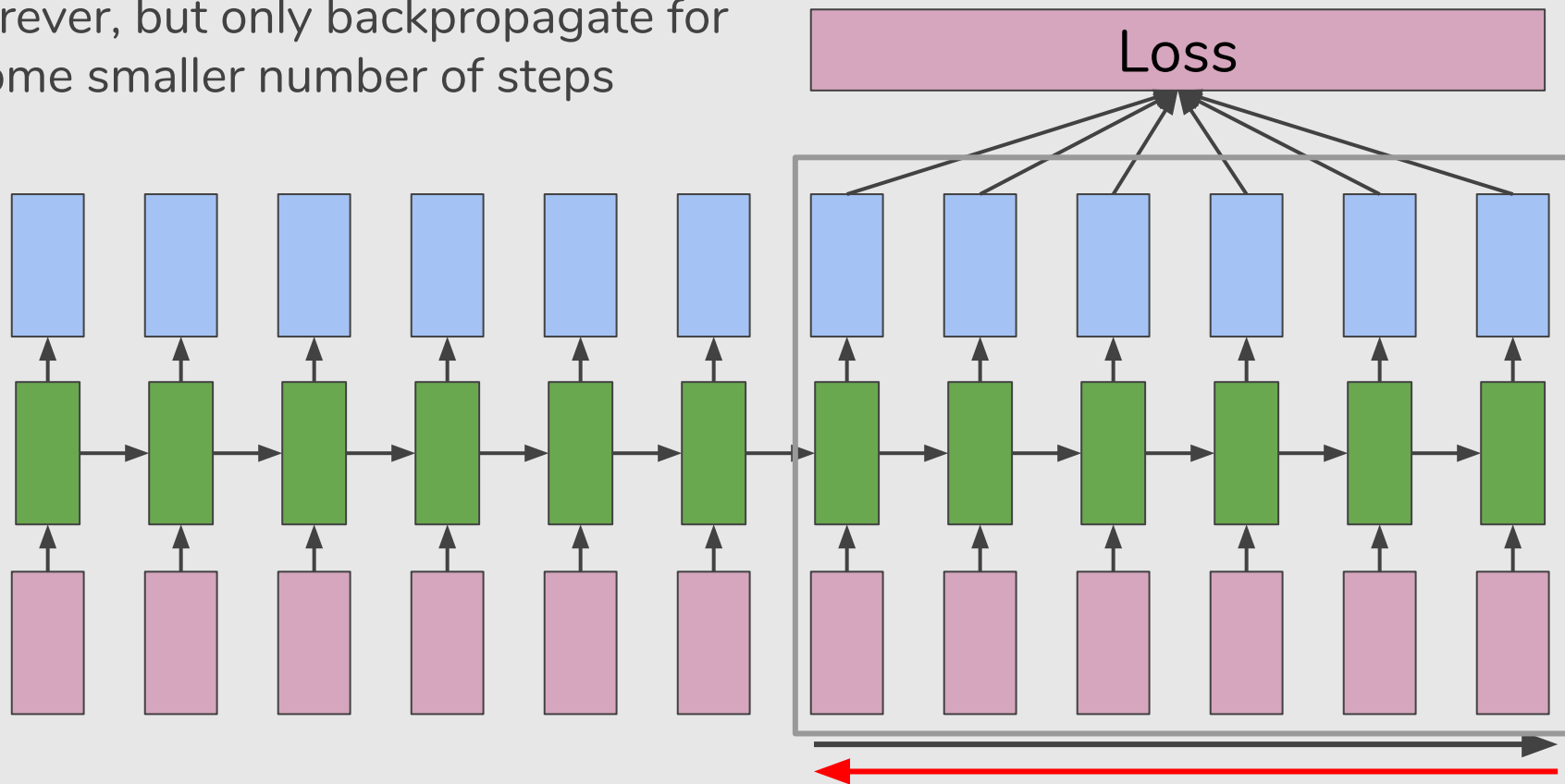




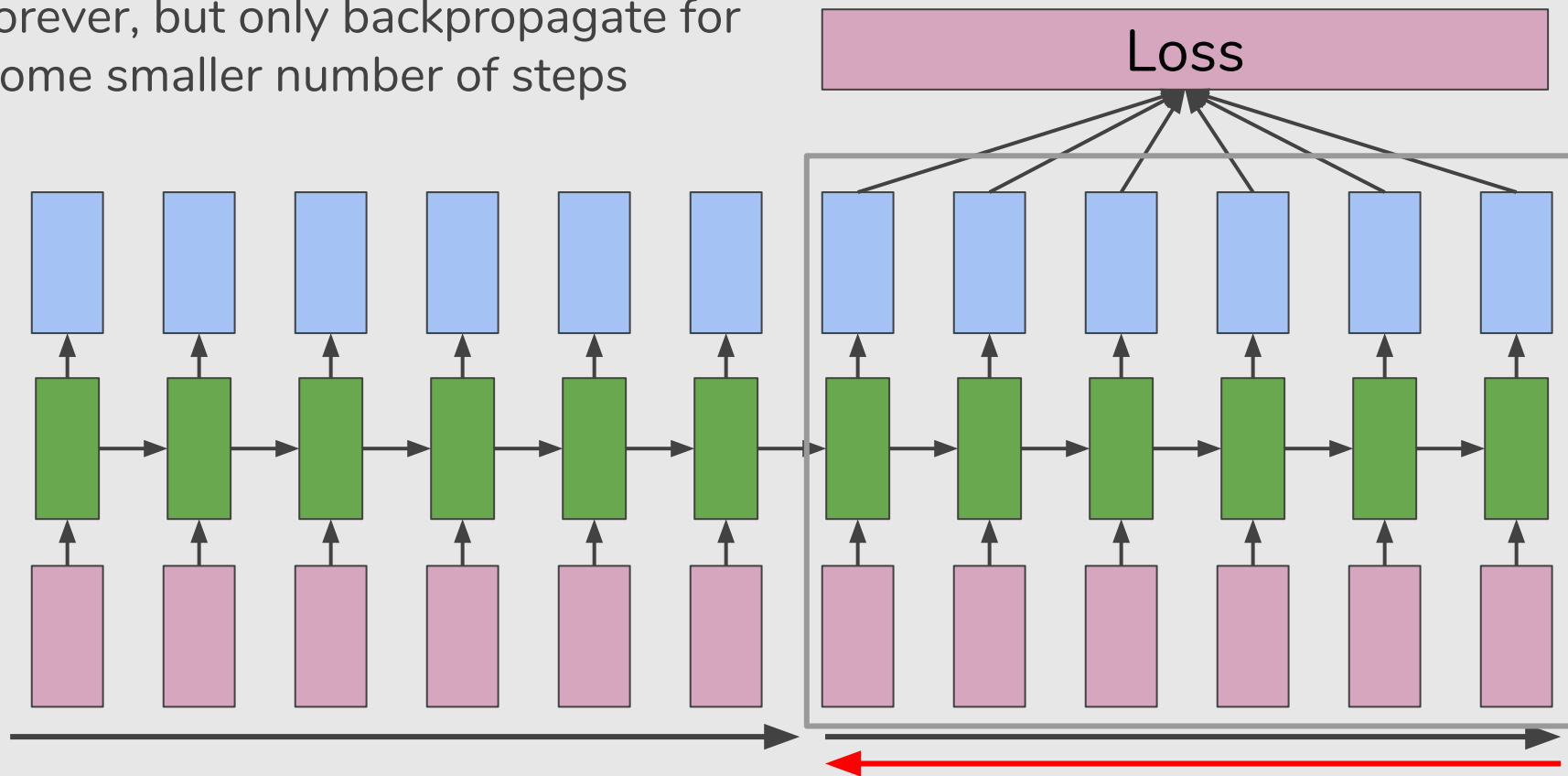
Truncated backpropagation
through time

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

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



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



min-char-rnn.py 112 lines of Python

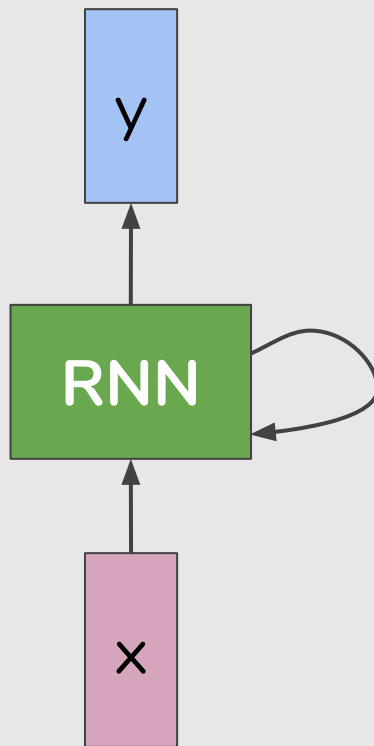
```
1  """
2  Minimal character level vanilla RNN model, written by Andrej Karpathy (@karpathy)
3  """
4
5  import numpy as np
6
7  # data I/O
8
9  data = open('input.txt', 'r').read() # should be simple plain text file
10 chars = list(set(data))
11 data_size, vocab_size = len(data), len(chars)
12 print 'data has %d characters, nd unique: %s' % (data_size, vocab_size)
13 char_to_ix = {c:i for i, c in enumerate(chars)}
14 ix_to_char = {i:c for i, c 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 = 0.001
20
21 # model parameters
22 wih = np.random.randn(hidden_size, vocab_size)*0.1 # input to hidden
23 whh = np.random.randn(hidden_size, hidden_size)*0.1 # hidden to hidden
24 why = np.random.randn(vocab_size, hidden_size)*0.1 # hidden to output
25 bix = np.zeros((vocab_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 an array of initial hidden state
32     returns the loss, gradients on model parameters, and last hidden state
33     """
34     xs, hs, ys, ps = {}, {}, {}, {}
35     htf = 1 # no copy(hprev)
36     loss = 0
37     # forward pass
38     for t in xrange(len(inputs)):
39         xs[t] = np.zeros((vocab_size, 1)) # encode in 1-of-K representation
40         xs[t][inputs[t]] = 1
41         hs[t] = np.tanh(np.dot(wih, xs[t]) + np.dot(whh, htf-1) + bh) # hidden state
42         ys[t] = np.dot(why, hs[t]) + by # unnormalized log probabilities for next chars
43         ps[t] = np.exp(ys[t]) / np.sum(np.exp(ys[t])) # probabilities for next chars
44         loss += -np.log(ps[t][targets[t], 0]) # softmax (cross-entropy) loss
45     # backward pass: compute gradients going backwards
46     dwh, dwhh, dwhy = np.zeros_like(wih), np.zeros_like(whh), np.zeros_like(why)
47     dht, dby = np.zeros_like(hs), np.zeros_like(by)
48     dhtext = np.zeros_like(hs)
49     for t in reversed(range(len(inputs))):
50         dy = np.copy(dht)
51         dy[targets[t]] -= 1 # backprop into y
52         dhty = np.dot(dy, hs[t], T)
53         dht = dy
54         dh = np.dot(why, T, dy) + dhtext # backprop into h
55         dxtw = (1 - hs[t] * hs[t]) * dh # backprop through tanh nonlinearity
56         dht = dxtw
57         dwh += np.dot(dhtw, xs[t], T)
58         dwhh += np.dot(dhtw, hs[t-1], T)
59         dhtext = np.dot(whh, T, dhtw)
60     for dparam in [dwh, dwhh, dwhy, dht, dby, dhtext]:
61         return loss, dwh, dwhh, dwhy, dht, dby, hs[len(inputs)-1]
62
63 def sample(h, seed_ix, n):
64     """
65     sample a sequence of integers from the model
66     h is memory state, seed_ix is seed letter for first time step
67     """
68     x = np.zeros((vocab_size, 1))
69     s[seed_ix] = 1
70     ixes = []
71     for t in xrange(n):
72         h = np.tanh(np.dot(wih, x) + np.dot(whh, h) + bh)
73         y = np.dot(why, h) + by
74         p = np.exp(y) / np.sum(np.exp(y))
75         ix = np.random.choice(range(vocab_size), p=p.ravel())
76         x = np.zeros((vocab_size, 1))
77         x[ix] = 1
78         ixes.append(ix)
79     return ixes
80
81 n, p = 0, 0
82 dwh, dwhh, dwhy = np.zeros_like(wih), np.zeros_like(whh), np.zeros_like(why)
83 dht, dby = np.zeros_like(hs), np.zeros_like(by) # memory variables for Adagrad
84 smooth_loss = -np.log(1.0/vocab_size)*seq_length # loss at iteration 0
85 while True:
86     # prepare inputs (we're sweeping from left to right in steps seq_length long)
87     if p+seq_length > len(data) or s == n:
88         hprev = np.zeros((hidden_size, 1)) # reset RNN memory
89         p = 0 # go from start of data
90         inputs = [char_to_ix[ch] for ch in data[p:seq_length]]
91         targets = [char_to_ix[ch] for ch in data[p+seq_length-1:]]
92
93         # sample from the model and then
94         if n % 100 == 0:
95             sample_ix = sample(hprev, inputs[0], 200)
96             txt = ''.join(ix_to_char[ix] for ix in sample_ix)
97             print '%s\n' % txt, # [fmt, 1]
98
99         # forward seq_length characters through the net and fetch gradients
100         loss, dwh, dwhh, dwhy, dht, dby, hprev = lossfun(inputs, targets, hprev)
101         smooth_loss = smooth_loss * 0.999 + loss * 0.001
102         if n % 100 == 0: print 'iter %d, loss: %f' % (n, smooth_loss) # print progress
103
104     # perform parameter update with Adagrad
105     for dparam, dwh, whh, why, ht, by, dhtext in zip([dwh, dwhh, dwhy, dht, dby, dhtext],
106                                                       [dwh, dwhh, dwhy, dht, dby],
107                                                       [dwh, dwhh, dwhy, dht, dby]):
108         param = dparam + dparam * dparam / np.sqrt(dparam + 1e-4) # Adagrad update
109         param += -learning_rate * dparam
110     p += seq_length # move data pointer
111     n += 1 # iteration counter
```

THE SONNETS

by William Shakespeare

From fairest creatures we desire increase,
That thereby beauty's rose might never die,
But as the ripper should by time decrease,
His tender heir might bear his memory;
But thou, contracted to thine own bright eyes,
Feed'st thy light's flame with self-substantial fuel,
Making a famine where abundance lies,
Thyself thy foe, to thy sweet self too cruel:
Thou that art now the world's fresh ornament,
And only herald to the gaudy spring,
Within thine own buduriest thy content,
And tender churl mak'st waste in niggarding:
Pity the world, or else this glutton be,
To eat the world's due, by the grave and thee.

When forty winters shall besiege thy brow,
And dig deep trenches in thy beauty's field,
Thy youth's proud livery so gazed on now,
Will be a tatter'd weed of small worth held:
Then being asked, where all thy beauty lies,
Where all the treasure of thy lusty days;
To say, within thine own deep sunken eyes,
Were an all-eating shame, and thriftless praise.
How much more praise deserv'd thy beauty's use,
If thou couldst answer 'This fair child of mine
Shall sum my count, and make my old excuse,'
Proving his beauty by succession thine!
This were to be new made when thou art old,
And see thy blood warm when thou feel'st it cold.



At first:

tyntd-iafhatawiaoighrdemot lytdws e ,tfti, astai f ogoh eoase rrranbyne 'nhthnee e
plia tklrqd 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 shuw y 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 nudes 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 apt, 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.

The Stacks Project

[home](#) [about](#) [tags explained](#) [tag lookup](#) [browse](#) [search](#) [bibliography](#) [recent comments](#) [blog](#) [add slogans](#)

Browse chapters

Part	Chapter	online	TeX source	view pdf
Preliminaries				
	1. Introduction	online	tex 	pdf 
	2. Conventions	online	tex 	pdf 
	3. Set Theory	online	tex 	pdf 
	4. Categories	online	tex 	pdf 
	5. Topology	online	tex 	pdf 
	6. Sheaves on Spaces	online	tex 	pdf 
	7. Sites and Sheaves	online	tex 	pdf 
	8. Stacks	online	tex 	pdf 
	9. Fields	online	tex 	pdf 
	10. Commutative Algebra	online	tex 	pdf 

Parts

1. [Preliminaries](#)
2. [Schemes](#)
3. [Topics in Scheme Theory](#)
4. [Algebraic Spaces](#)
5. [Topics in Geometry](#)
6. [Deformation Theory](#)
7. [Algebraic Stacks](#)
8. [Miscellany](#)

Statistics

The Stacks project now consists of

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

Latex source



For $\bigoplus_{n=1, \dots, m} \mathcal{L}_{m_n} = 0$, 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 comparico 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

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

and

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

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 $X_{spaces, \acute{e}tale}$ 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 $\mathcal{F}_{x_0} = \mathcal{F}_{x_0} = \mathcal{F}_{X, \dots, 0}$.

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 $\mathcal{J}_{n,0} \circ \bar{A}_2$ 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 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. □

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 $\mathcal{F} \rightarrow \mathcal{F}$ 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

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

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. □

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

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

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.

□

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 . □

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

$$\mathcal{O}_{X,x} \longrightarrow \mathcal{F}_x \rightarrow \mathcal{O}_{X_{\acute{e}tale}}^{-1} \longrightarrow \mathcal{O}_{X_{\acute{e}tale}}^{-1} \mathcal{O}_{X_{\acute{e}tale}}(\mathcal{O}_{X_{\acute{e}tale}}^{\overline{\eta}})$$

is an isomorphism of covering of $\mathcal{O}_{X_{\acute{e}tale}}$. 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.

Proof. Omitted. □

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

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

Proof. This is an algebraic space. 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. □

Lemma 0.2. This is an integer \mathbb{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

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

be a morphism of algebraic spaces over S and Y .

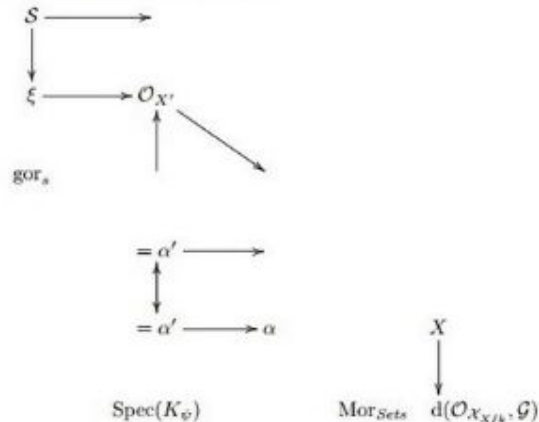
Proof. Let X be a nonzero scheme of X . Let X be an algebraic space. Let \mathcal{F} be a quasi-coherent sheaf of \mathcal{O}_X -modules. The following are equivalent

- (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. □

Proof. Omitted.

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 $X = \text{Spec}(R)$ 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 . □

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"

$$\mathcal{O}_{X,x} \longrightarrow \mathcal{F}_x \longrightarrow \mathcal{O}_{X,x}^{-1} \mathcal{O}_{X,x}(\mathcal{O}_{X,x}^\vee)$$

is an isomorphism of covering of $\mathcal{O}_{X,x}$. 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_λ} is a closed immersion, see Lemma ??.

```

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) & 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 code

Training: “Maior dúvida da aula” 27/october/2017

https://github.com/II Sourcell/recurrent_neural_network

GoogLeNet, Inception Module

Não entendi muito bem sobre as inception layers na GoogLeNet. Entendi a ideia de fazer a mesma coisa de um filtro grande com vários filtros menores. Com vários filtros menores temos menos parâmetros que um filtro grande?

Quando fazemos inception e concatenamos os resultados, podemos comparar isso à criação de vetor de características? Porque estamos retirando tipos diferentes de informações de uma mesma camada de input e juntando elas pra formar um output.

Acho que não consegui entender muito bem o inception module da arquitetura GoogLeNet. Para que ele serve exatamente? Obrigada.

no modelo de inception v4, usa a paralelizacao para obter menos parametros, entao isso quer dizer que enquanto menos parametros e mais profundo da melhores resultados?

Não entendi exatamente que fator possibilitou a remoção das camadas fully connected na GoogLeNet. Pelo que eu entendi, as redes mais modernas voltaram com a camada fully connected. Então quando usá-la ou não usá-la?

Números de parâmetros

Em relação a arquitetura proposta na rede GoogLeNet, não ficou muito claro para mim as camadas internas, principalmente na parte em que aplicar vários filtros menores, equilibra a aplicar um filtro maior (embora o resultado não seja o mesmo).

Não ficou claro para mim qual a vantagem de se utilizar, por exemplo, 3 pequenos filtros 3x3 ao invés de um 7x7. Na aula você comentou que é para evitar diminuir drasticamente a imagem, mas qual a desvantagem disso?

Eu não entendi aquelas contas dos filtros que reduziam o número de parâmetros

ResNet Filtro 1x1

Achei um pouco confuso as dimensões do filtro 1x1. Achei confuso a parte da convolução de tal filtro.

Training: “Maior dúvida da aula” 27/october/2017

```
iter 0, loss: 107.601633
```

```
----
```

```
'ōqIE:ō:3(é
```

```
0 Q.L" cÉhíL' uàfM0)êoâz. àãâéláč- )D(iéêdàF( lLFLrRcFA0nC(Pô( á#HM5éI?#ázHrtGTRF)5wlGaúa2éj?pd7,u  
xp5LQ"r24F7é1efL"CabvêúhyLdã 7àã2à0bm xv?qnAodí'P)mTg4(u4F7ú13ómrQnmeFNbãoúvâ3i?sx suRăjáécó.-  
záy-
```

```
----
```

Training: “Maior dúvida da aula” 27/october/2017

```
iter 0, loss: 107.601633
```

```
----
```

```
'õqIE:õ:3(é  
0 Q.L"cÉhíL'uàfM0)êoâz.ããâéláč-)D(iéêdàF(1LF LRcFA0nC(Pô(á#HM5éI?#ázHrtGTRF)5wlGaúa2éj?pd7,u  
xp5LQ"r24F7é1efL"CabvêúhyLdã 7ãã2à0bm xv?qnAodí'P)mTg4(u4F7ú13ómrQnmeFNbãóúvâ3i?sx suRãjáécó.-  
záy
```

```
--- iter 46000, loss: 23.238596
```

```
-----  
és GoogLeNet. E a rede aprende?
```

0 Daras dúvrvilg. (ende no pré-tro "rar outlara destidas? Com uttres dessar algo us filtros parte novados aplicar au mula.

e narepteno Retênne camada entros lemos e m

Training: “Maior dúvida da aula” 27/october/2017

```
iter 0, loss: 107.601633
```

```
----
```

```
'õqIE:õ:3(é  
0 Q.L"çÉhíL'uàfM0)êoâz.ããâélac-)D(iéêdàF(1LFLrRcFA0nC(Pô(á#HM5éI?#ázHrtGTRF)5wlGaúa2éj?pd7,u  
xp5LQ"r24F7élefl"CabvêúhyLdã 7ãã2à0bm xv?qnAodí'P)mTg4(u4F7ú13ómrQnmeFNbãoúvâ3i?sx suRãjáécó.-  
Záy
```

```
--- iter 46000, loss: 23.238596
```

```
-----  
és GoogLeNet. E a rede aprende?
```

```
0 Daras dúvrvilg. ( ende no pré-tro "rar outlara destinadas? Com uttres dessar algo us filtros  
parte novados aplicar au mula.
```

```
e nar iter 204000, loss: 10.733449
```

```
-----  
to, ina utir alpal asvelum motrio tarada mexexexterna mai reviso de enter meiss grandas
```

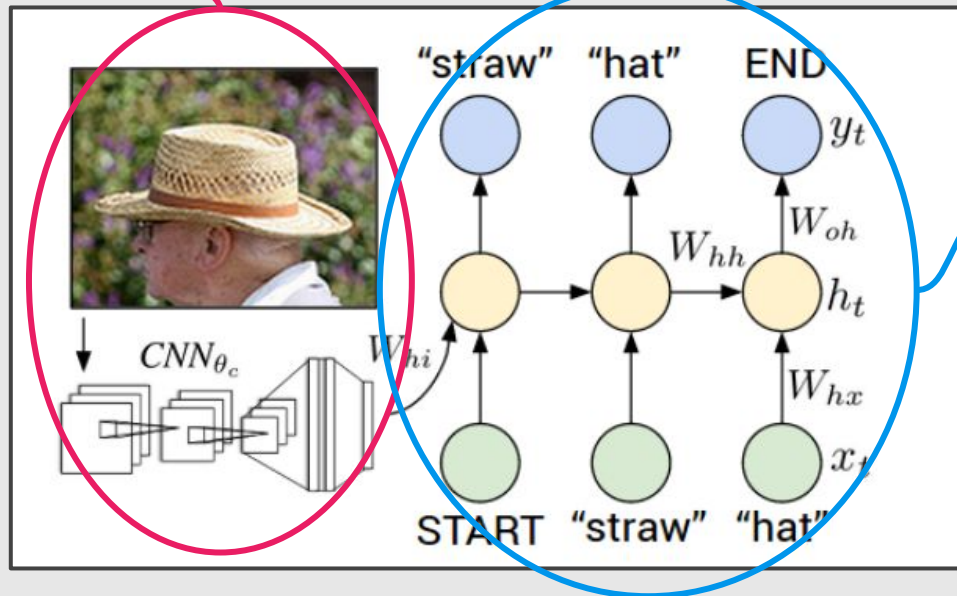
```
##### ResNet Filtro 1x1? Alheing?
```

```
Não entendi exatamente que fia, confenhalo deset desecta..
```

```
##### Como as
```

Image Captioning

Convolutional
Neural Network



Recurrent
Neural
Network

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

Deep Visual-Semantic Alignments for Generating Image Descriptions, Karpathy and Fei-Fei, CVPR 2015

Show and Tell: A Neural Image Caption Generator, Vinyals et al., CVPR 2015

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



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

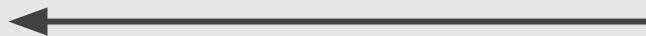
softmax



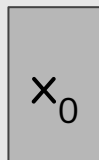
test image



test image



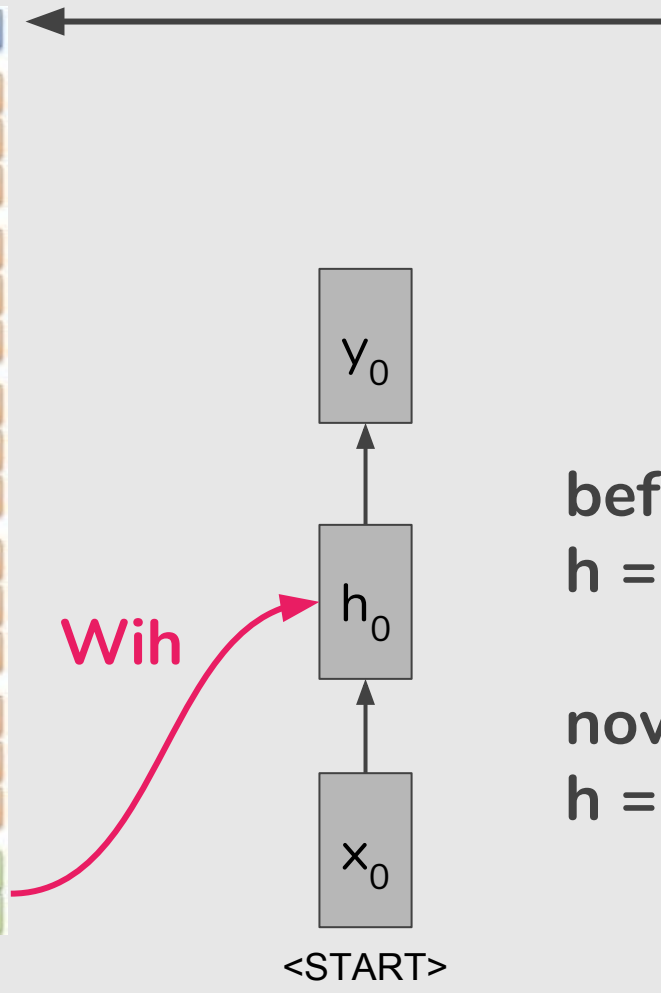
test image



<START>



v



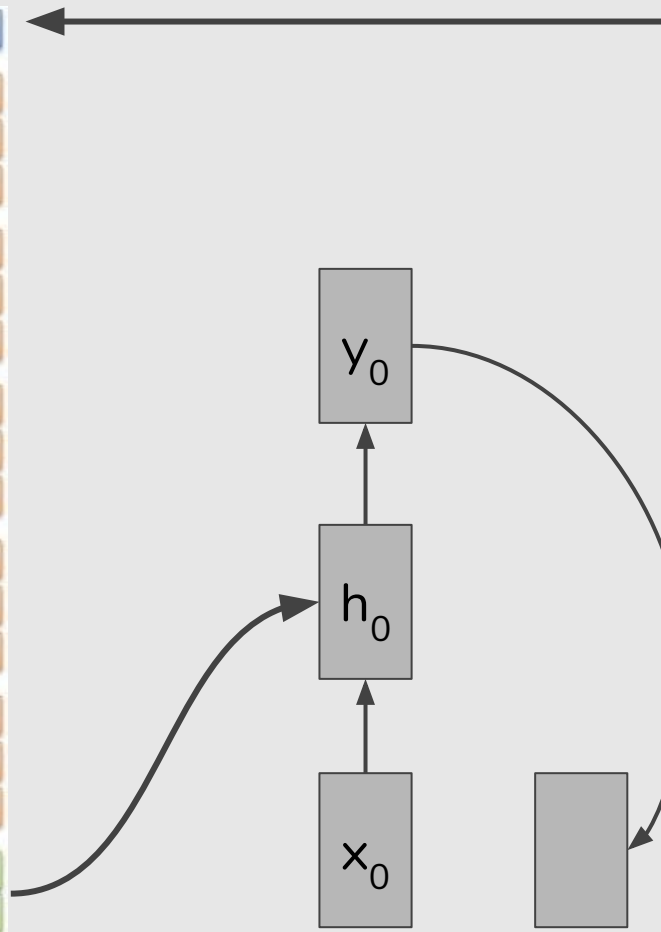
test image

before:

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

now:

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



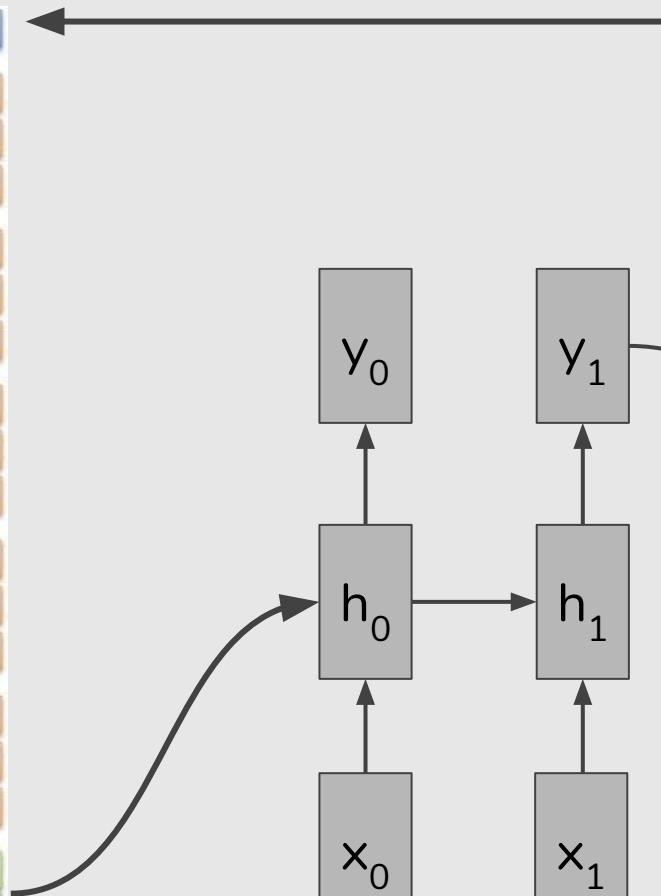
<START>

teddy



test image

sample



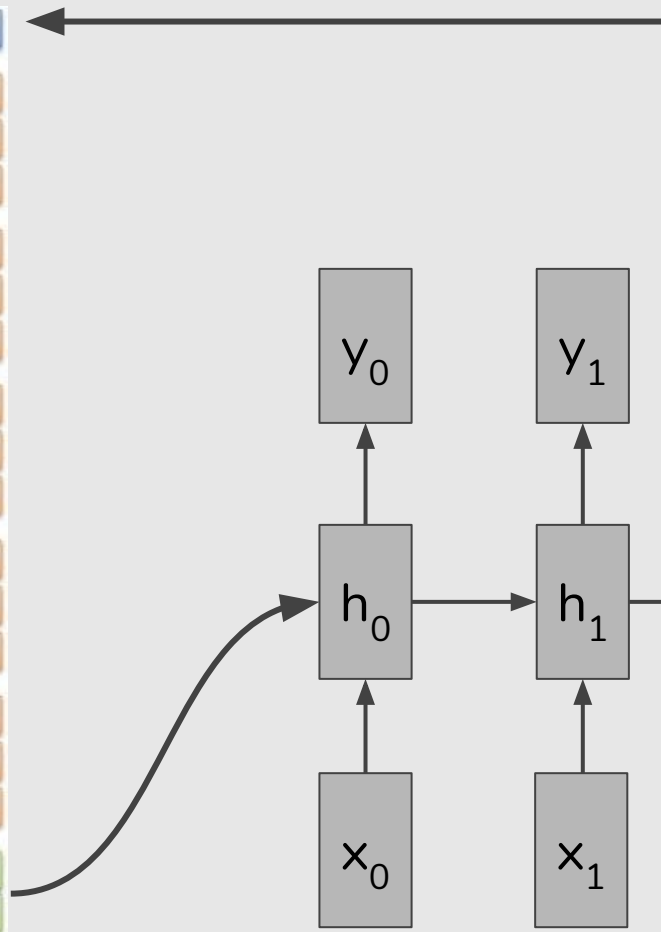
test image

sample

<START>

teddy

bear



<START>

teddy

bear



test image

sample
<END> token
=> finish

Image Captioning

No errors



A white teddy bear sitting in the grass

Minor errors



A man in baseball uniform throwing a ball

Somewhat related



A woman is holding a cat in her hand



A man riding a wave on top of a surfboard



A cat sitting on a suitcase on the floor



A woman standing on a beach holding a surfboard

References

— — —

Machine Learning Books

- Deep Learning, <http://www.deeplearningbook.org/contents/rnn.html>

Machine Learning Courses

- <http://cs231n.stanford.edu/2017/syllabus>
- “The 3 popular courses on Deep Learning”:
<https://medium.com/towards-data-science/the-3-popular-courses-for-deeplearning-ai-ac37d4433bd>