EN.601.482/682 Deep Learning

Basic RNNs

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Reminder

ConvNets

- One-time setup
  - Architecture (Sequential application of convolution, activation, pooling)
  - Activation functions (sigmoid, ReLU, …)
  - Regularization (batch norm, dropout)

- Training
  - Data collection: Preprocessing, Augmentation
  - Training via SGD (update rules)

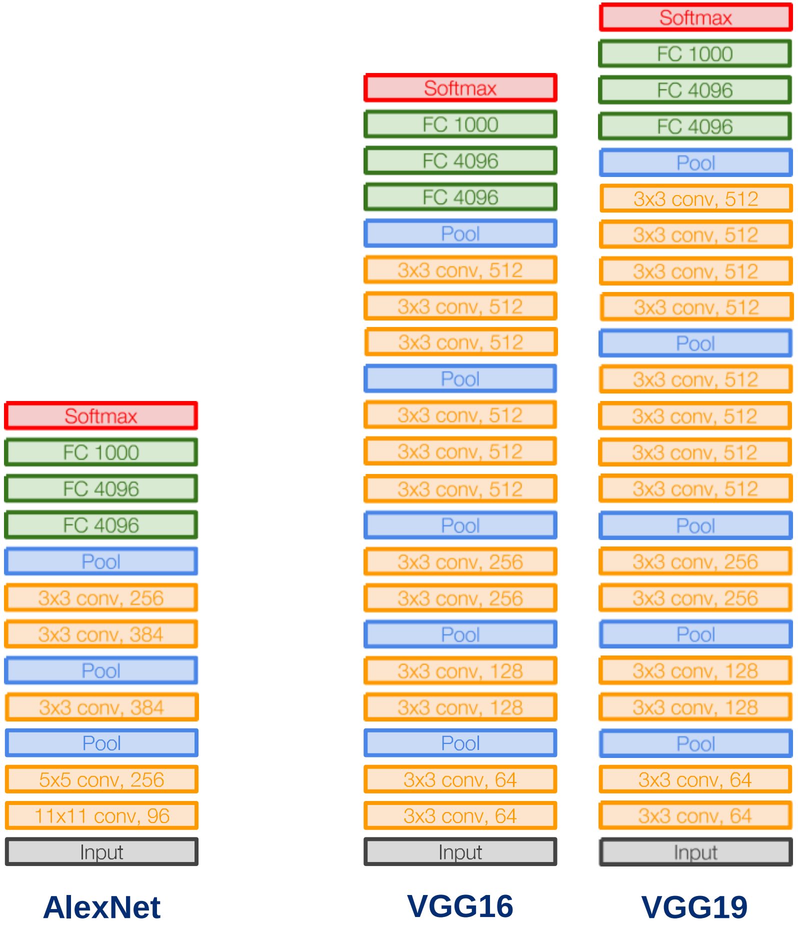
- Transfer learning

Reminder

AlexNet: 8 layers – 11x11 – 5x5 – 3x3

VGG: 16 – 19 layers – 3 times 3x3 conv

→ **Smaller filters, deeper networks!**



Reminder

AlexNet: 8 layers – 11x11 – 5x5 – 3x3

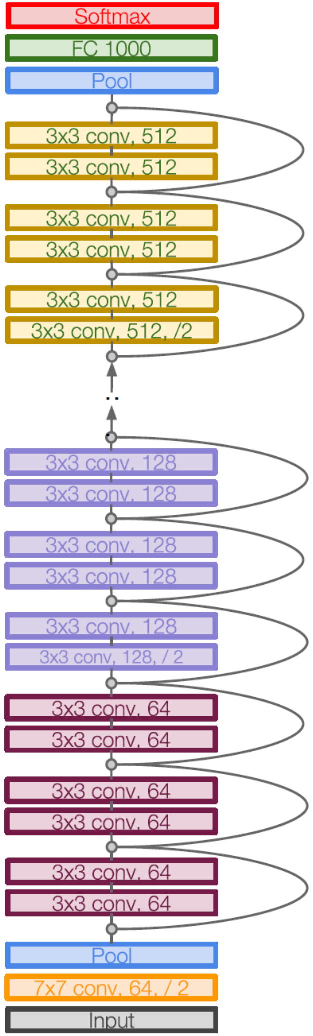
VGG: 16 – 19 layers – 3 times 3x3 conv

→ **Smaller filters, deeper networks!**

ResNet: Even deeper networks → 152 layers

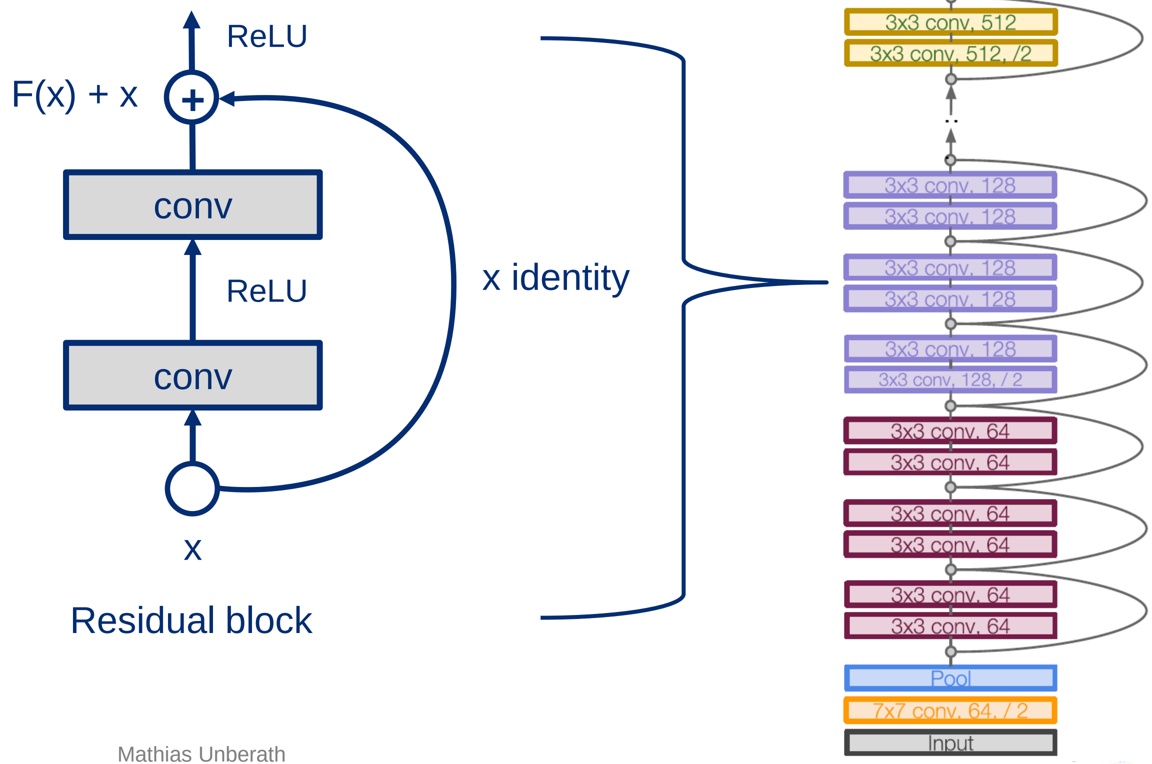
- Deeper models **should** perform better
- When implemented naively, they do not
- Hypothesis: This is an optimization problem!

→ **Learn residual rather than direct mapping**



Reminder

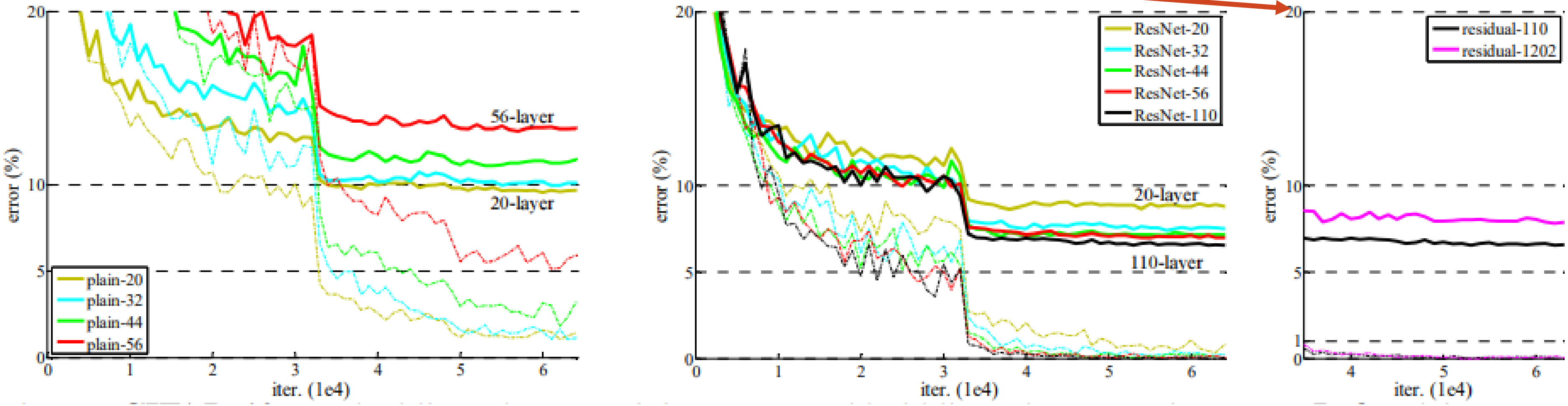
→ **Learn residual rather than direct mapping**



Reminder

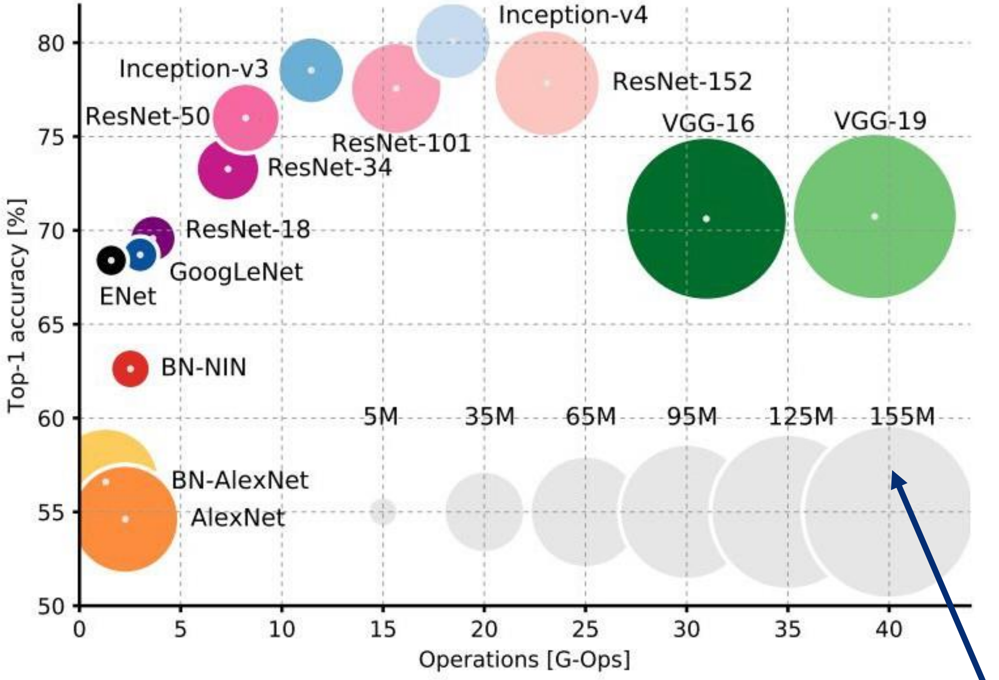
With residual blocks, deeper networks outperform shallower ones!

And we see overfitting when e.g. 1202 layers are used.



Reminder

Convolutional and Fully Connected Layers



Most parameters are in FC layers!

Consider **AlexNet:**

FC6: 256x6x6 → 4096: 38M parameters

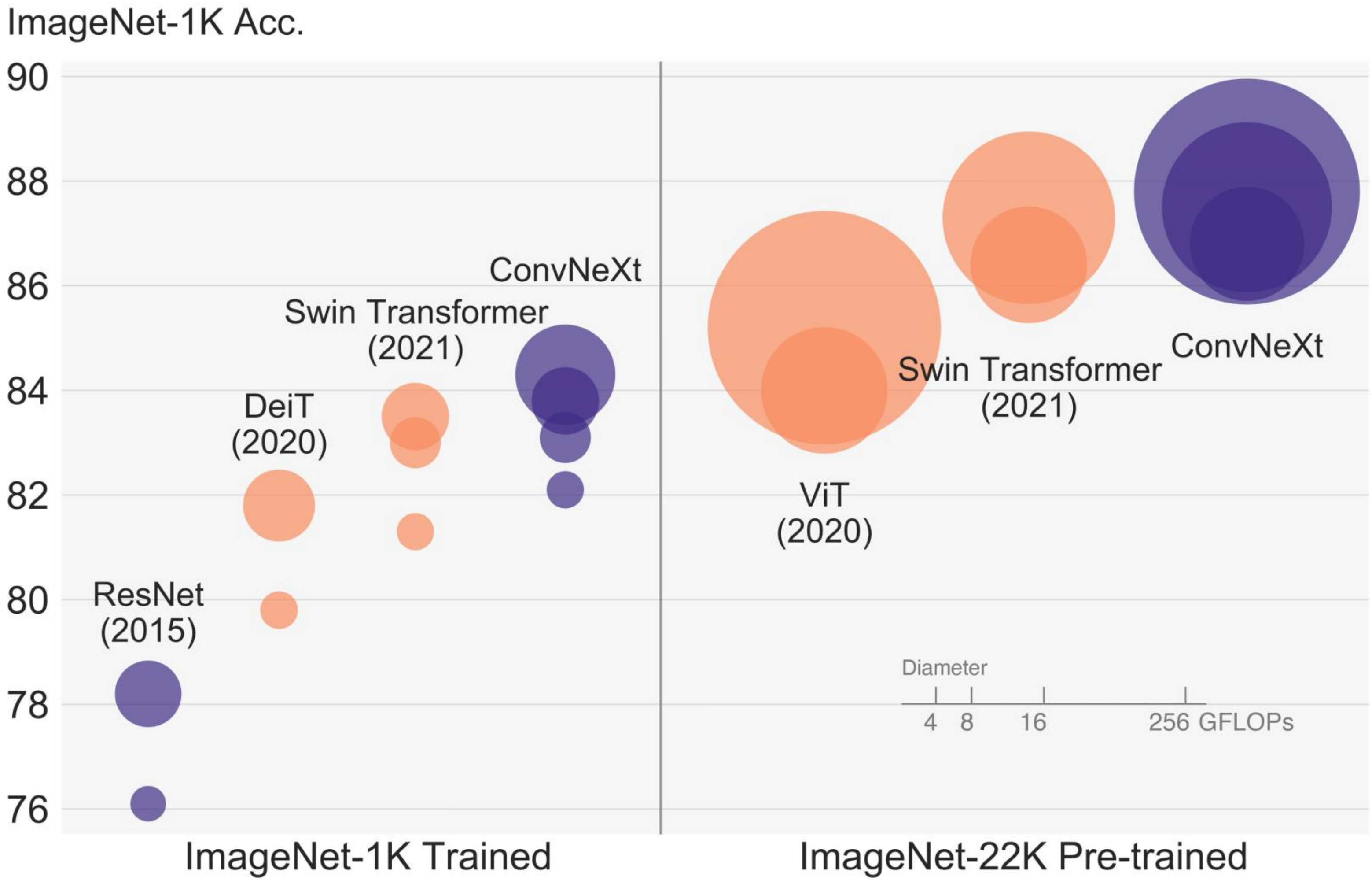
FC7: 4096 → 4096: 17M parameters

FC8: 4096 → 1000: 4M parameters

→ ~59M (out of ~62M) parameters are in FC!

“Nicer” architectures → Fewer parameters

Size of circle indicates number of parameters


ImageNet-1K Acc.
90
88
86
84
82
80
78
76
ConvNeXt
Swin Transformer
(2021)
DeiT
(2020)
ResNet
(2015)
ViT
(2020)
Swin Transformer
(2021)
ConvNeXt
Diameter
4
8
16
256 GFLOPs
ImageNet-1K Trained
ImageNet-22K Pre-trained

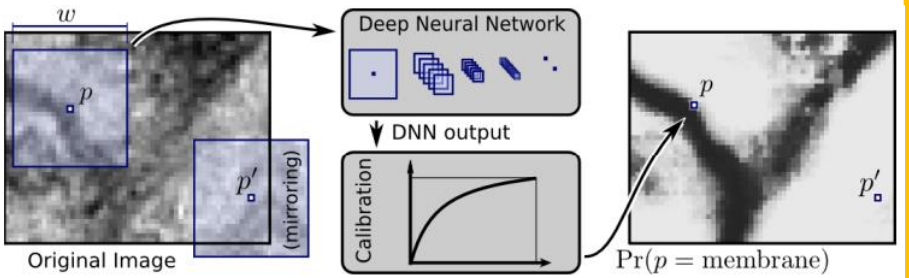
Reminder

“Inherent tension between semantics and location”

→ Global information: Resolves what

→ Local information: Resolves where

This is particularly important for instance segmentation!



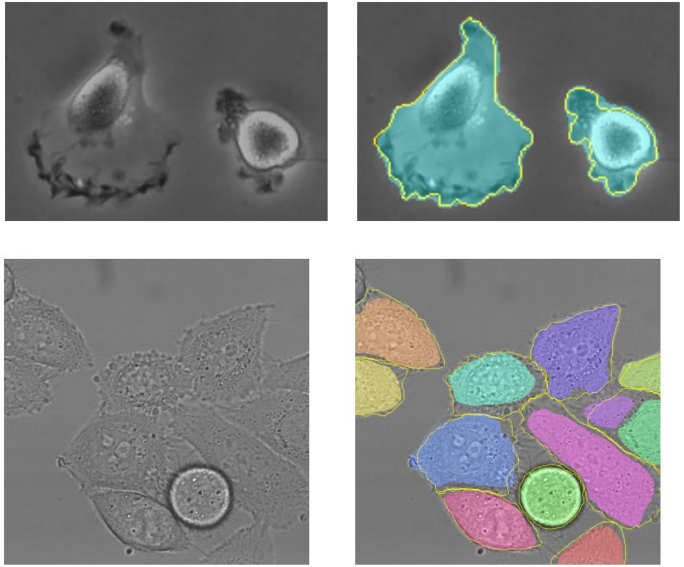
Sliding-window

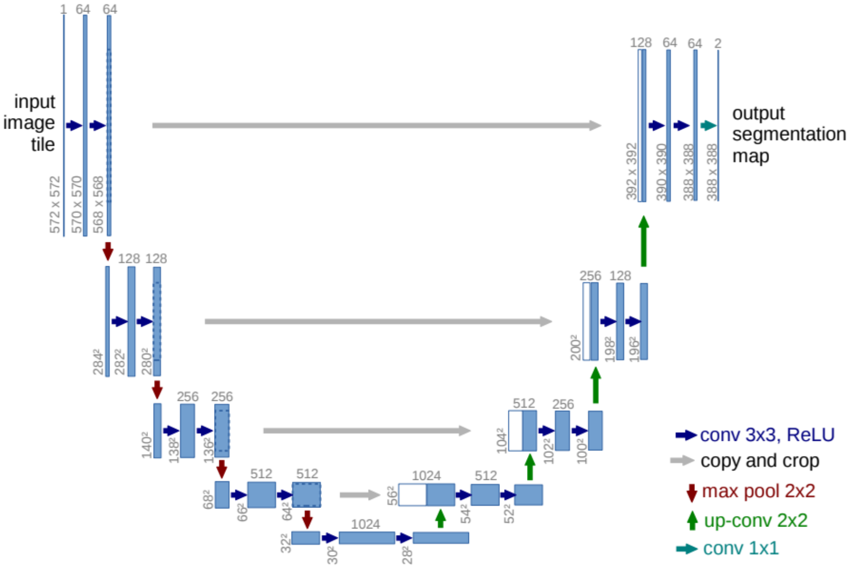
- Small models restricting capacity and receptive fields
- Application to every patch → Slow
- Pooling somewhat prevents “fast change” in output signal → Blurry edges

Reminder

Fully Convolutional Neural Networks

- Fully connected layers are no different from conv layers
- Convolutionize FC layers → Kernels that cover entire input region

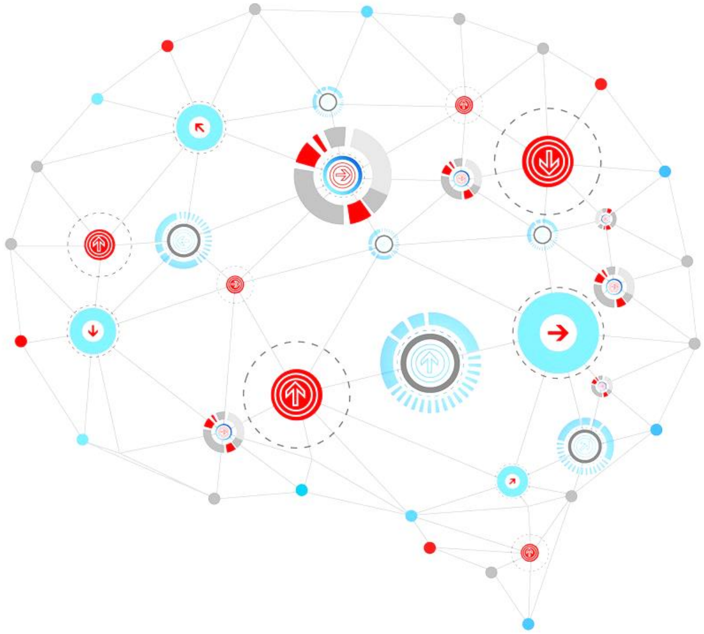




Today's Lecture

Recap: Gradient Flow

Recurrent Neural Networks and LSTM



Basic RNNs

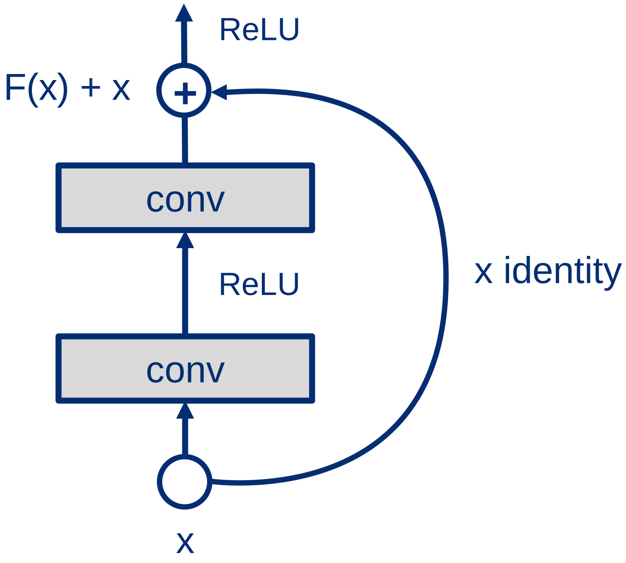
Gradient Flow

Gradient Flow: ResNet

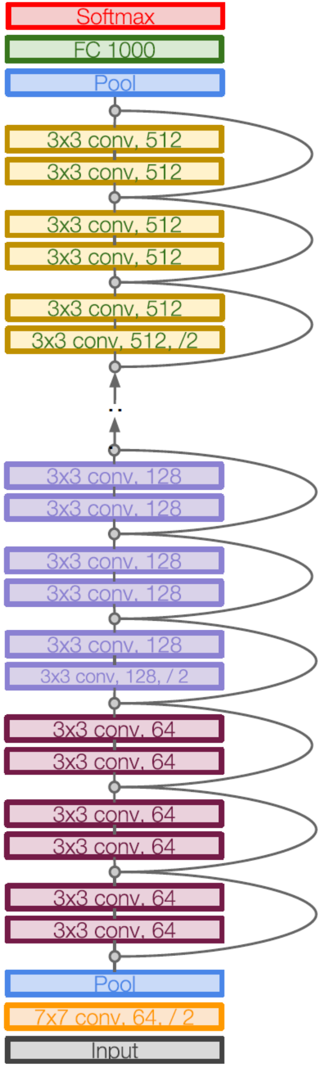
Improve gradient flow by additional connections

- Addition nodes: Distribute gradient
- Creates “highway” for gradient updates!

→ More effective training due to **improved gradient flow**



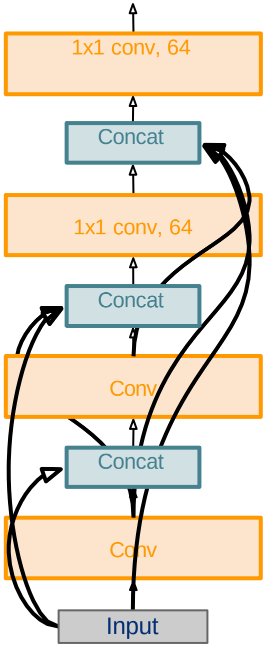
Residual block



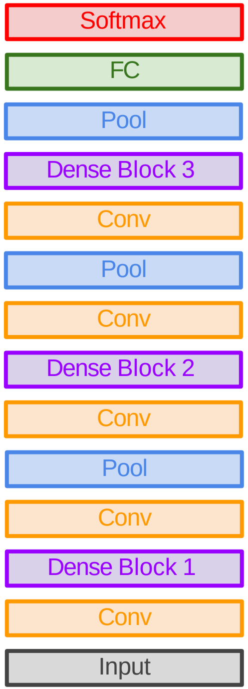
He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition IEEE CVPR (pp. 770-778).

Gradient Flow: DenseNet

Improve gradient flow by additional connections



Dense block

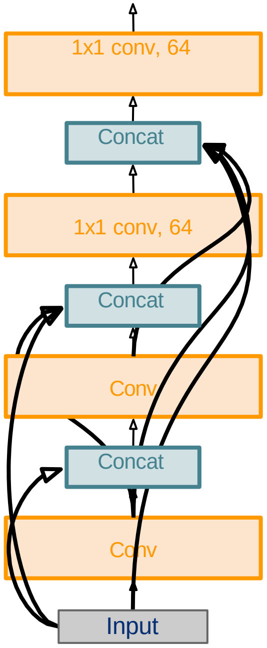


Jégou, S., et al. (2017). The one hundred layers tiramisu: Fully convolutional DenseNets for semantic segmentation. CVPR Workshop (pp. 11-19).

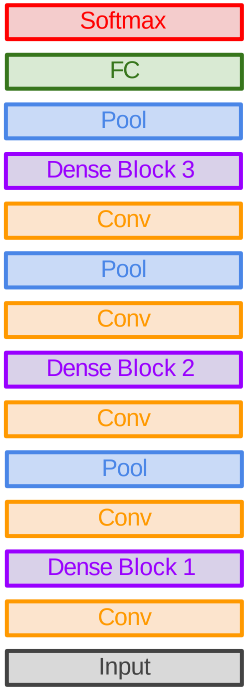
Gradient Flow: DenseNet

Improve gradient flow by additional connections

This is going to be even more important as we move from models that are deep in "space" to models that are deep in "space and time"
→ Sequences!



Dense block



Jégou, S., et al. (2017). The one hundred layers tiramisu: Fully convolutional DenseNets for semantic segmentation. CVPR Workshop (pp. 11-19).

Goal for Today

So far

Image in → Classification out

Every image is self-sufficient

There is only spatial context, and this context is constant

There is no temporal context

Now

Many problems are sequential

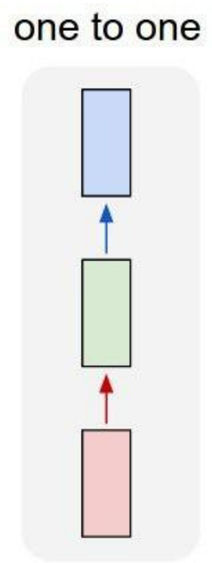
The current state and next state is dependent on the previous one

How can we model something like this with ConvNets?

Basic RNNs

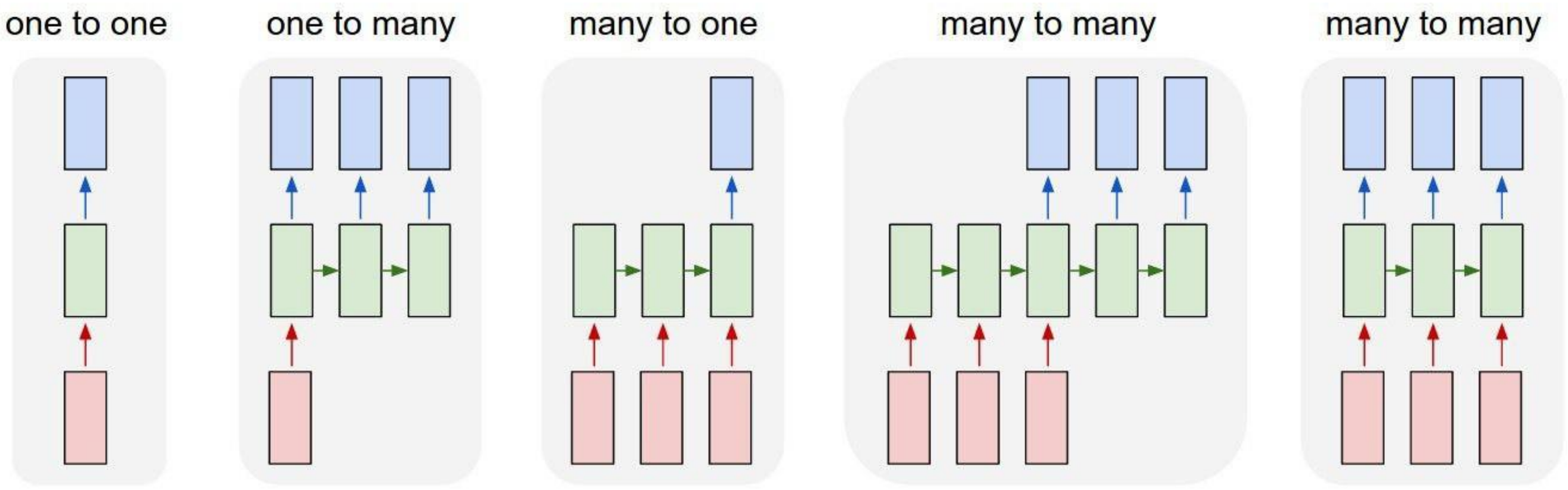
Recurrent Neural Networks and LSTM

“Vanilla” Neural Network



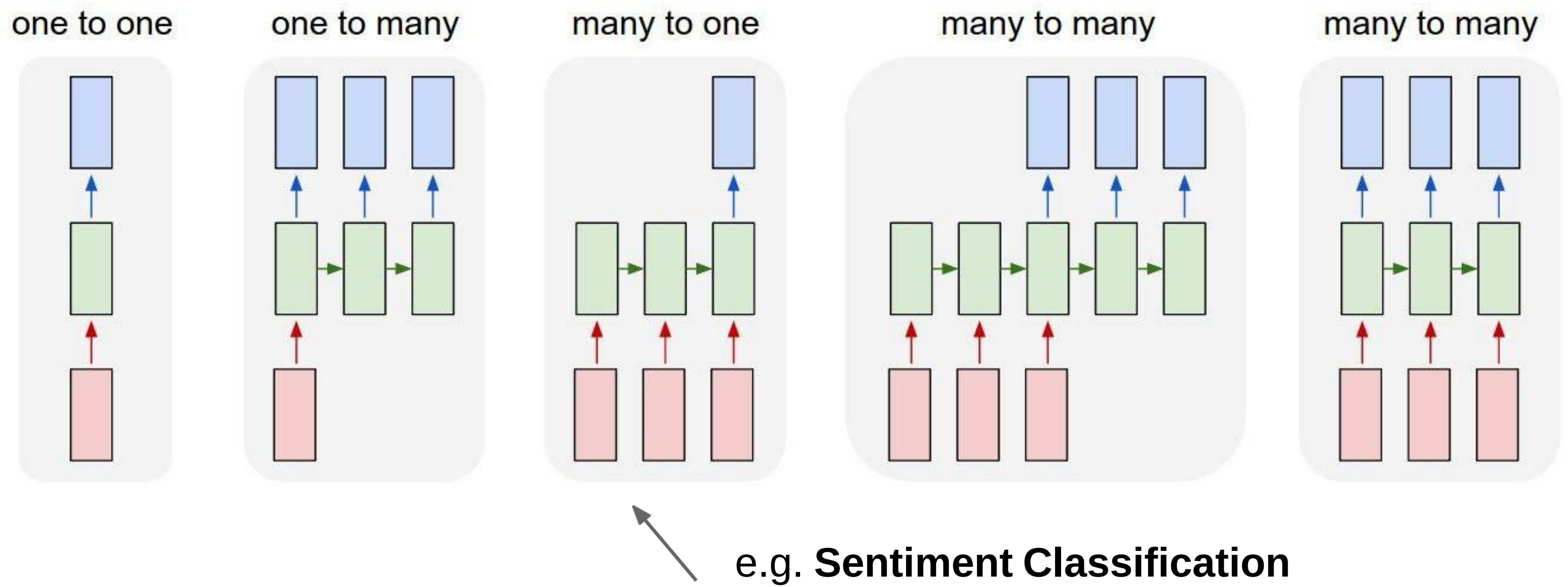
Vanilla Neural Networks

Recurrent Neural Networks: Process Sequences



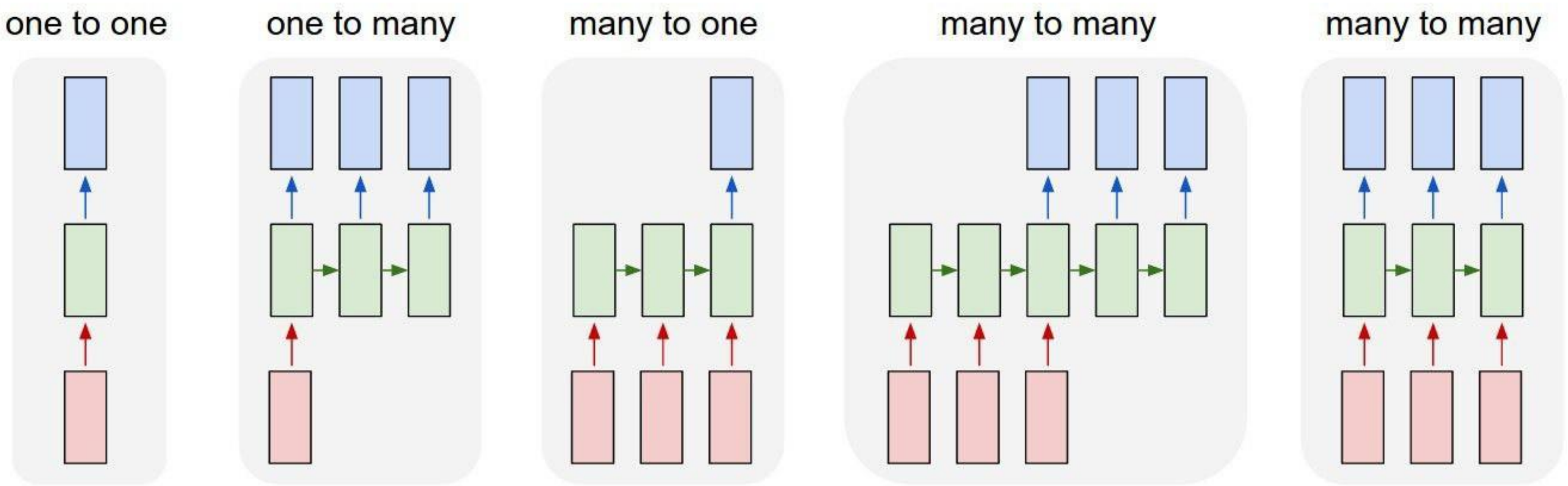
e.g. **Image Captioning**
image -> sequence of words

Recurrent Neural Networks: Process Sequences



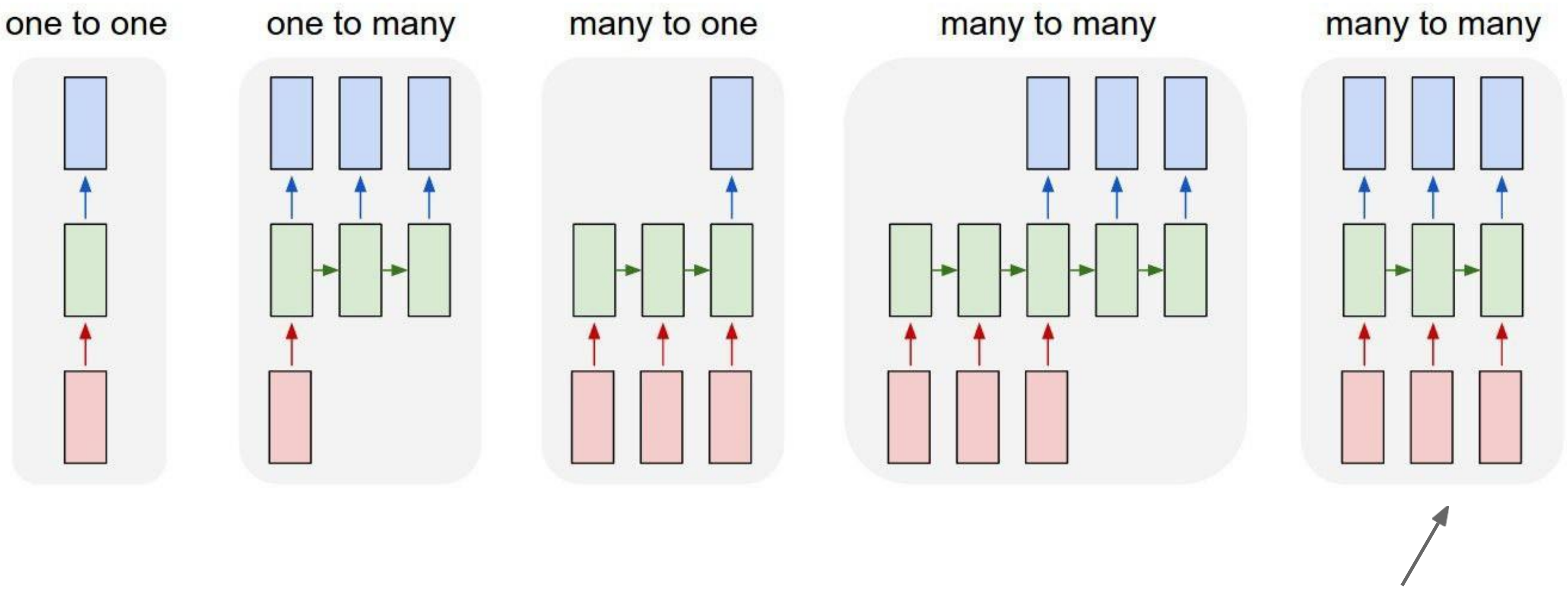
e.g. **Sentiment Classification**
sequence of words -> sentiment

Recurrent Neural Networks: Process Sequences



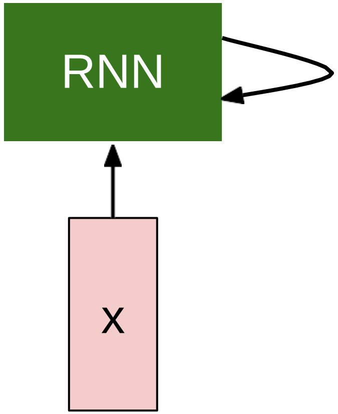
e.g. **Machine Translation**
seq of words -> seq of words

Recurrent Neural Networks: Process Sequences

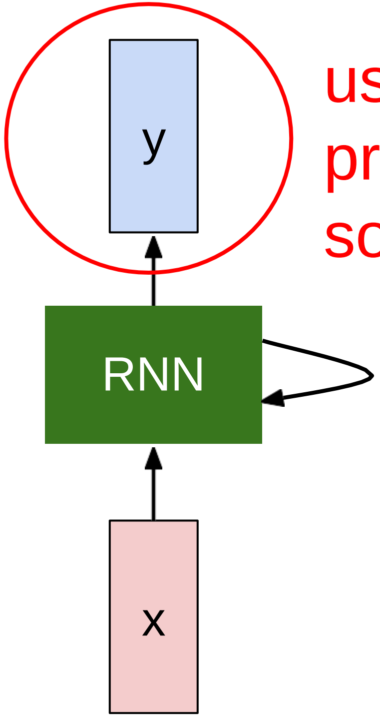


e.g. **Video classification on frame level**

Recurrent Neural Network



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:

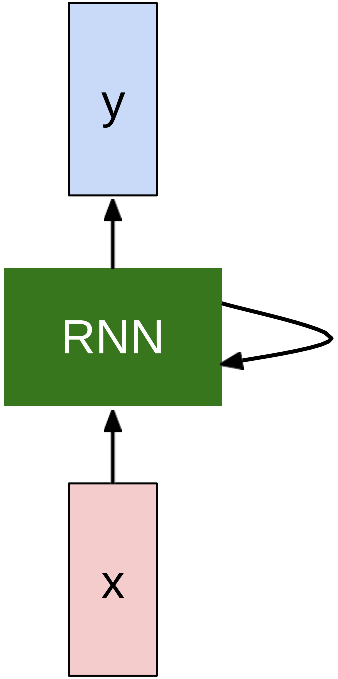
$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state

some function
with parameters W

old state

input vector at
some time step

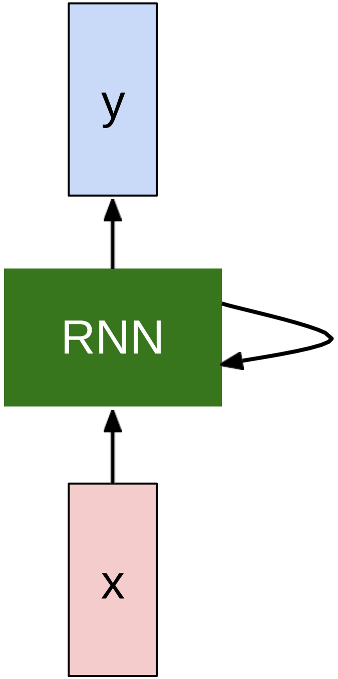


Recurrent Neural Network

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

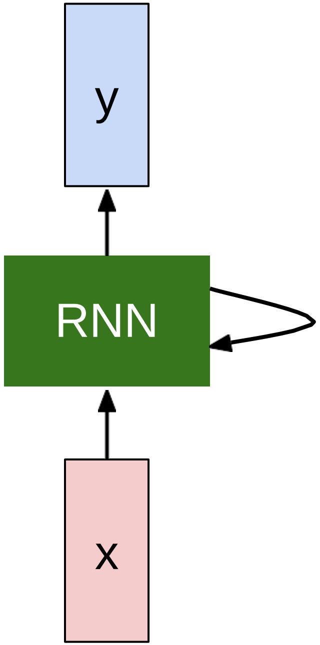
$$h_t = f_W(h_{t-1}, x_t)$$

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



(Vanilla) Recurrent Neural Network

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

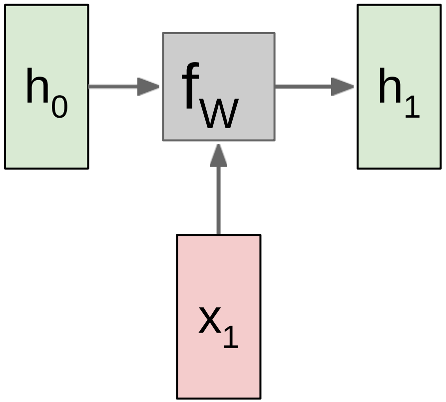


$$h_t = f_W(h_{t-1}, x_t)$$

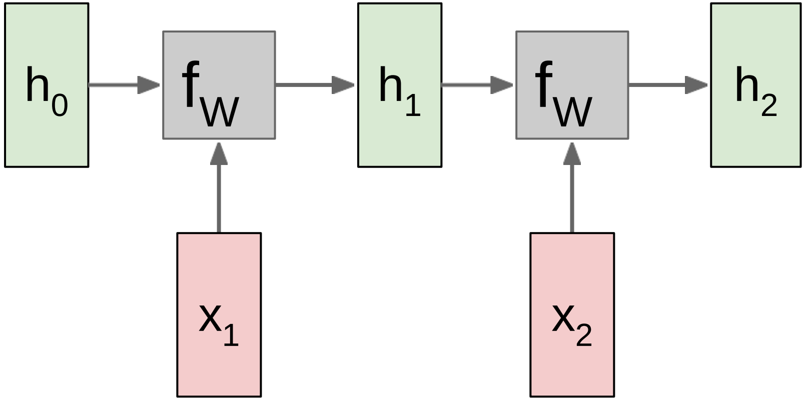
$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

$$y_t = W_{hy}h_t$$

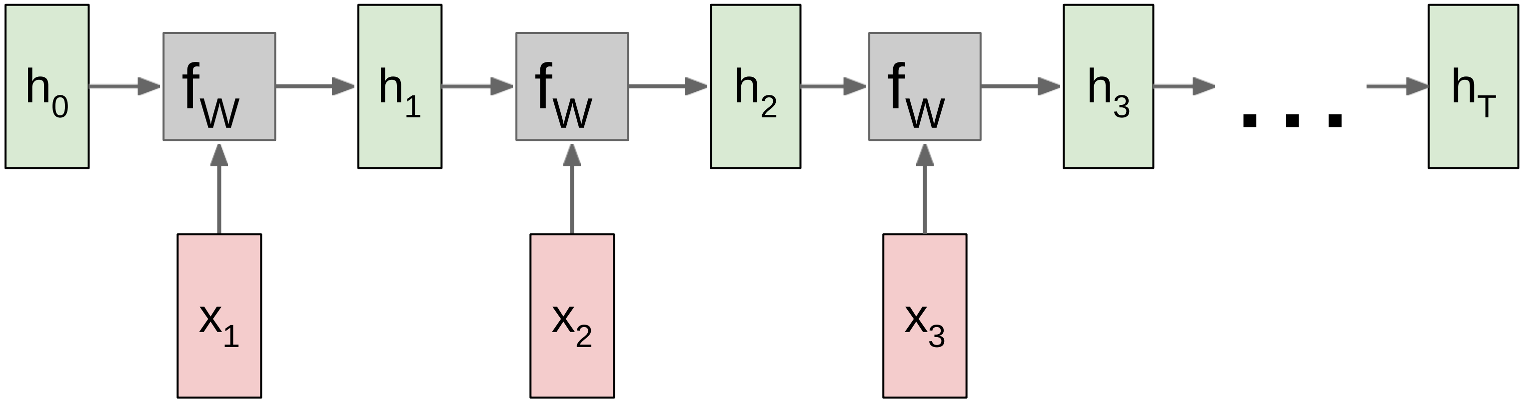
RNN: Computational Graph



RNN: Computational Graph

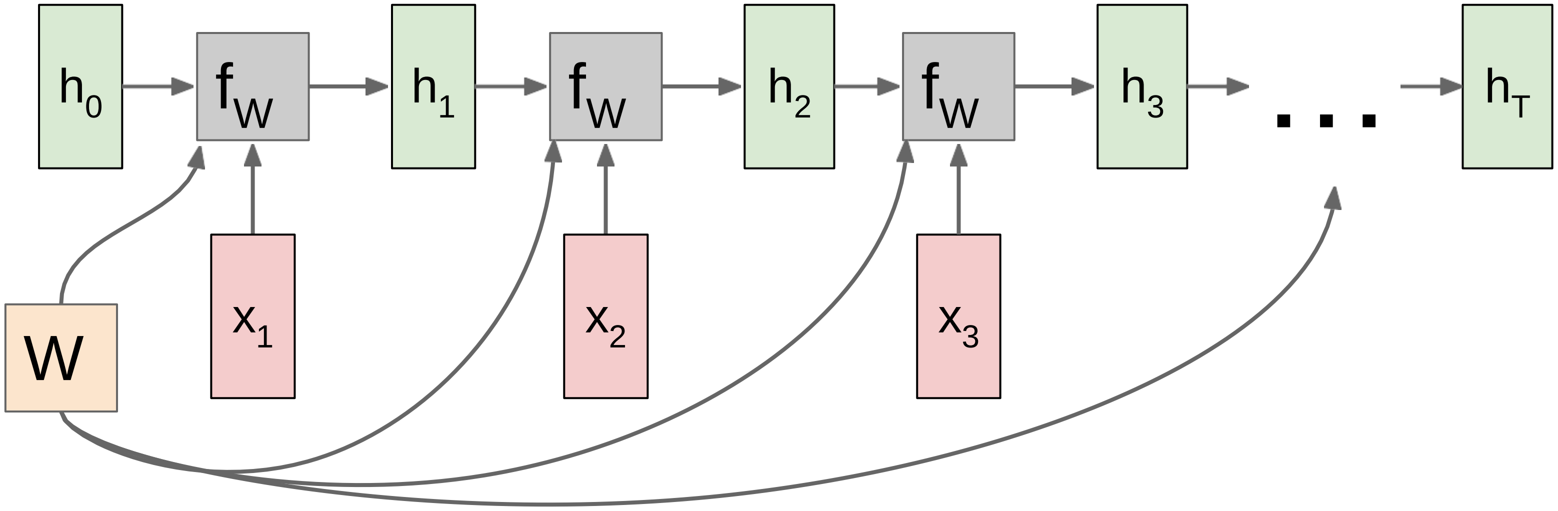


RNN: Computational Graph

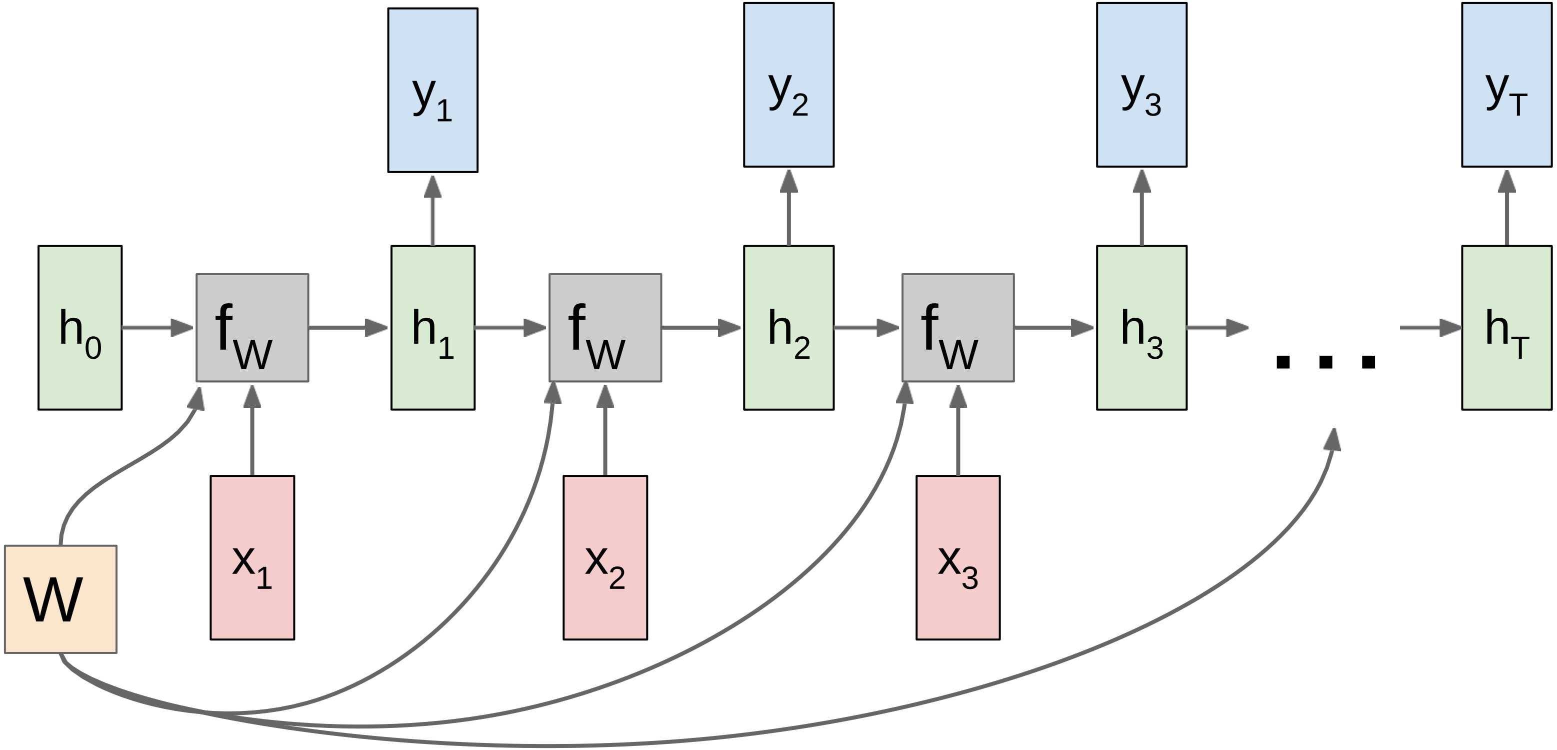


RNN: Computational Graph

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



RNN: Computational Graph: Many to Many



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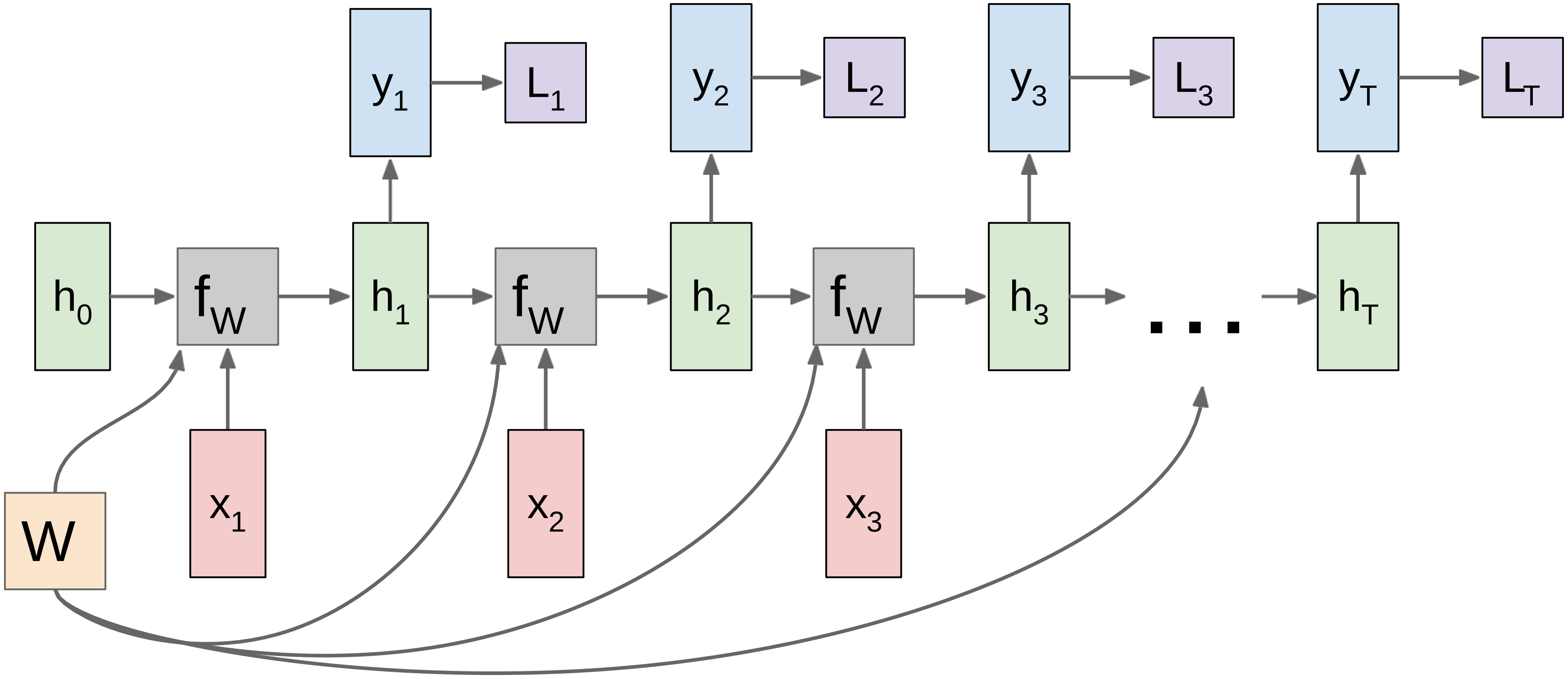
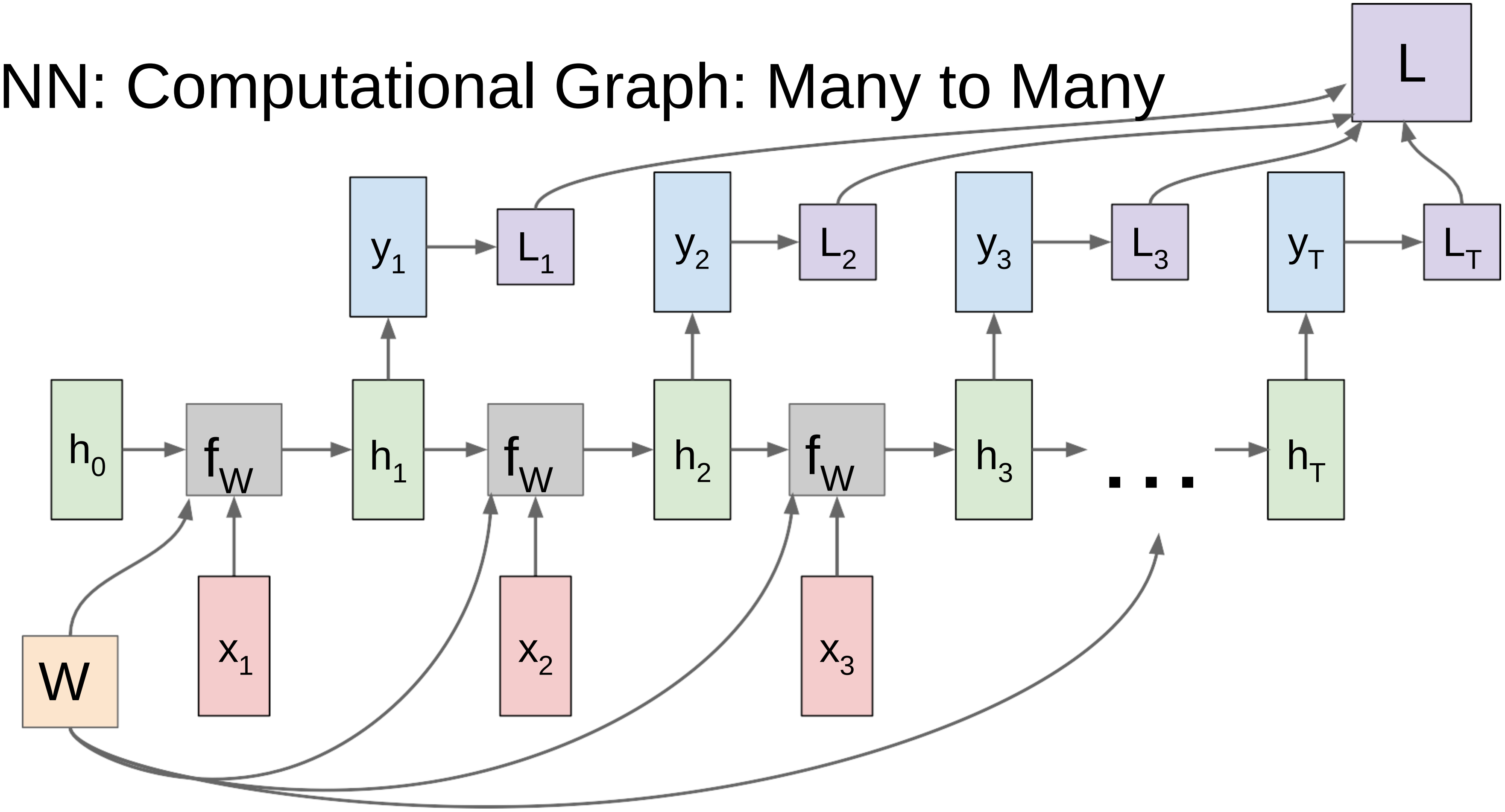
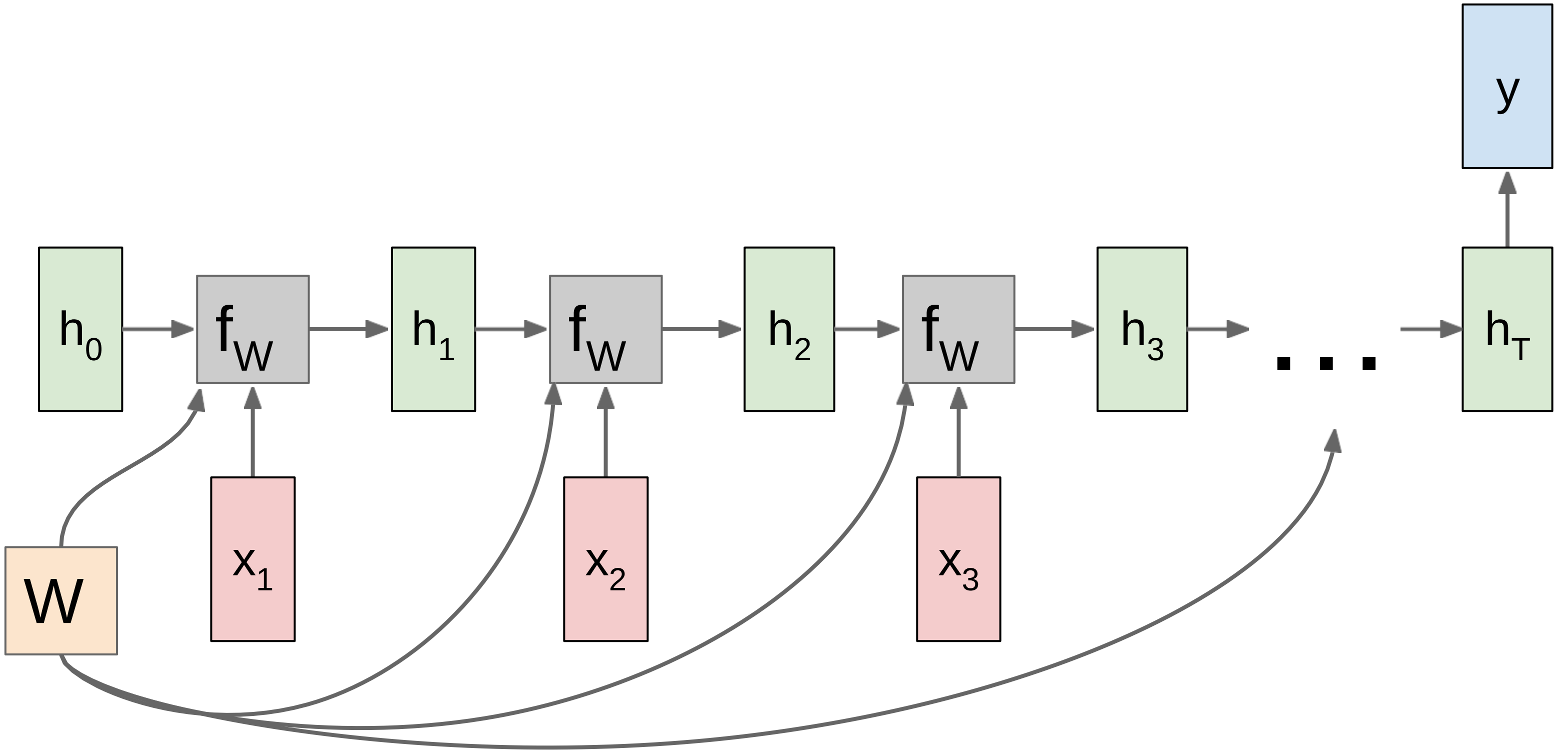


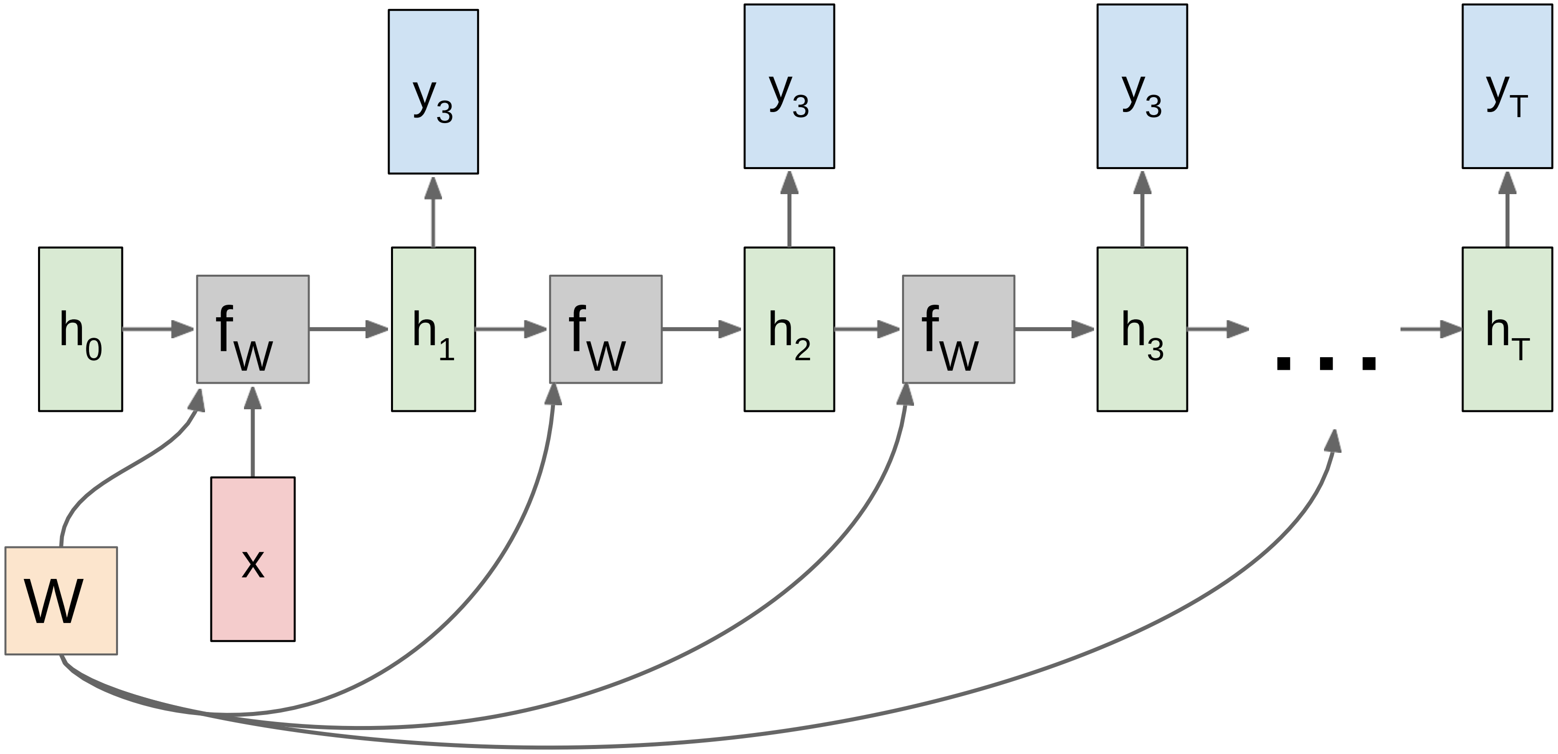
RNN: Computational Graph: Many to Many



RNN: Computational Graph: Many to One

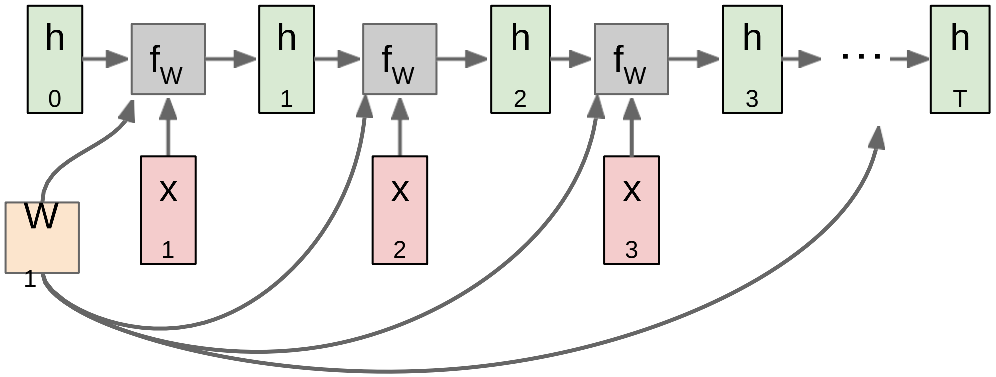


RNN: Computational Graph: One to Many



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

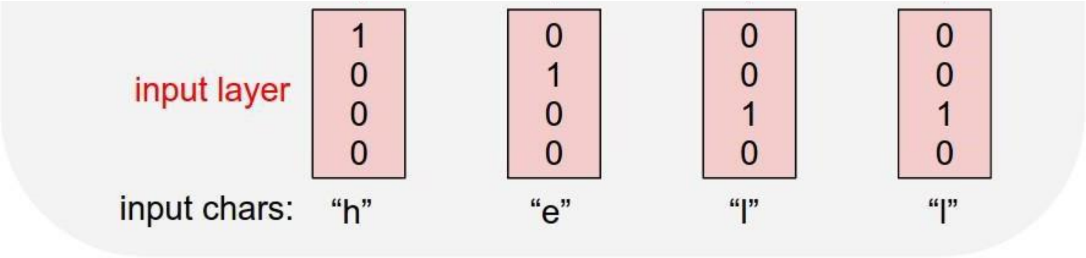
Many to one: Encode input sequence in a single vector



Example:
Character-level
Language Model

Vocabulary:
[h,e,l,o]

Example training sequence:
“hello”



Example:
Character-level
Language Model

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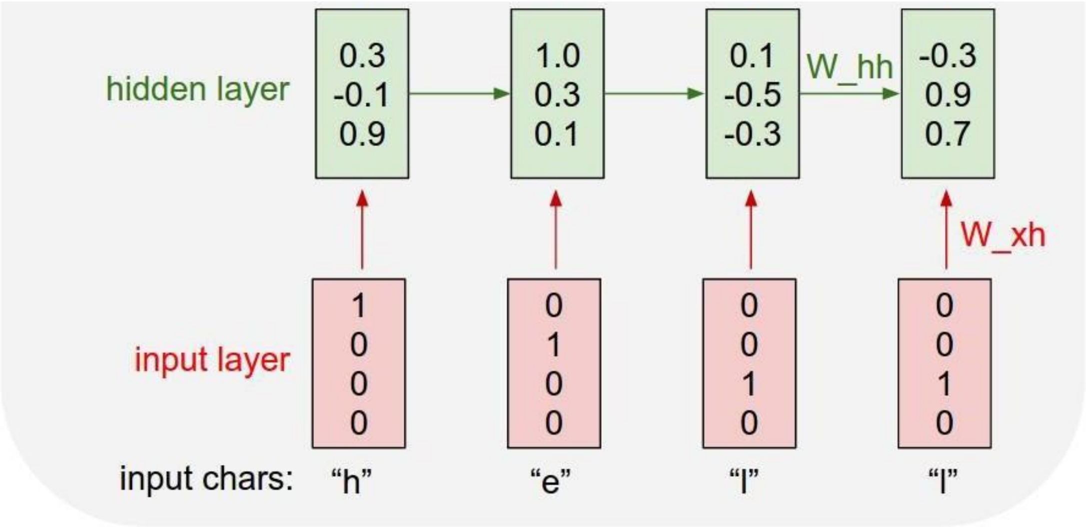
sequence:
“hello”



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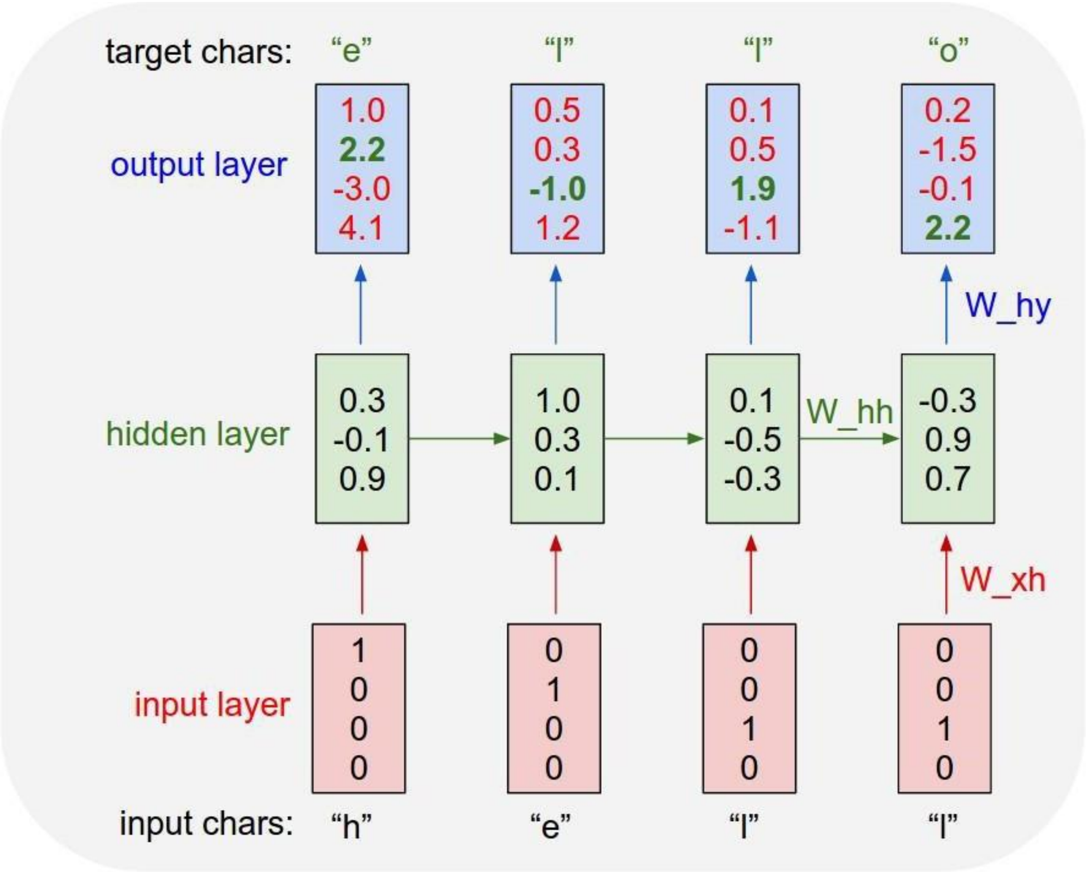
Vocabulary: [h,e,l,o]

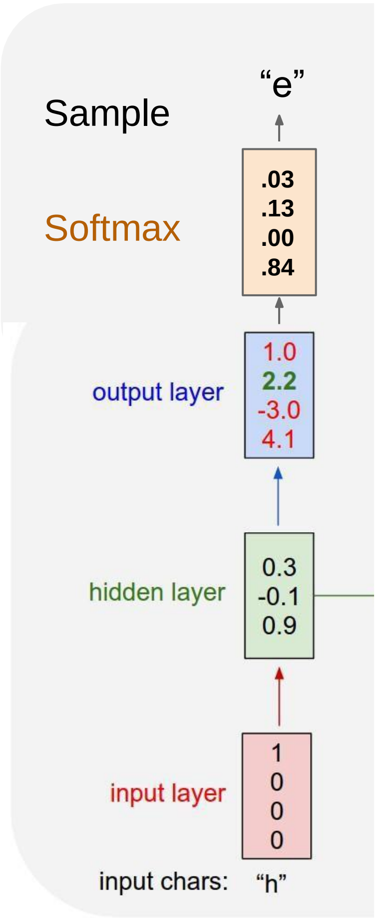
Example training sequence: **“hello”**



Example: Character-level Language Model Sampling

Vocabulary: [h,e,l,o]

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



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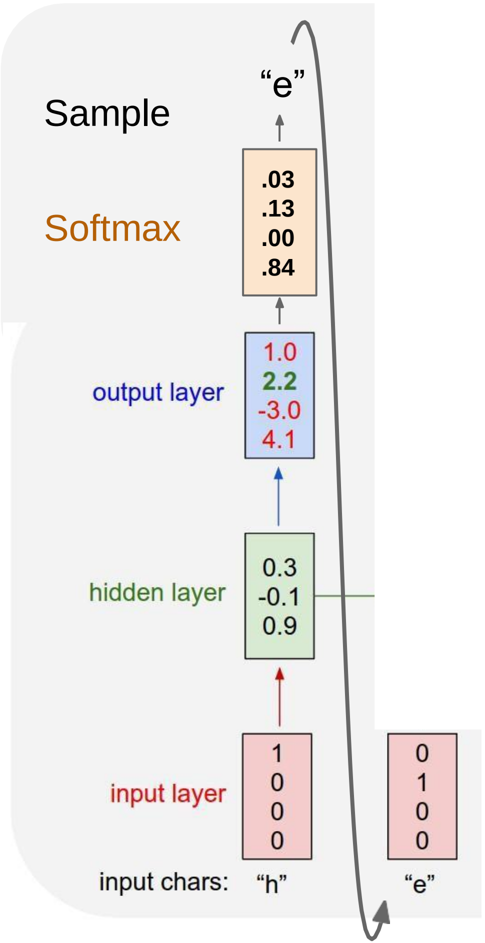

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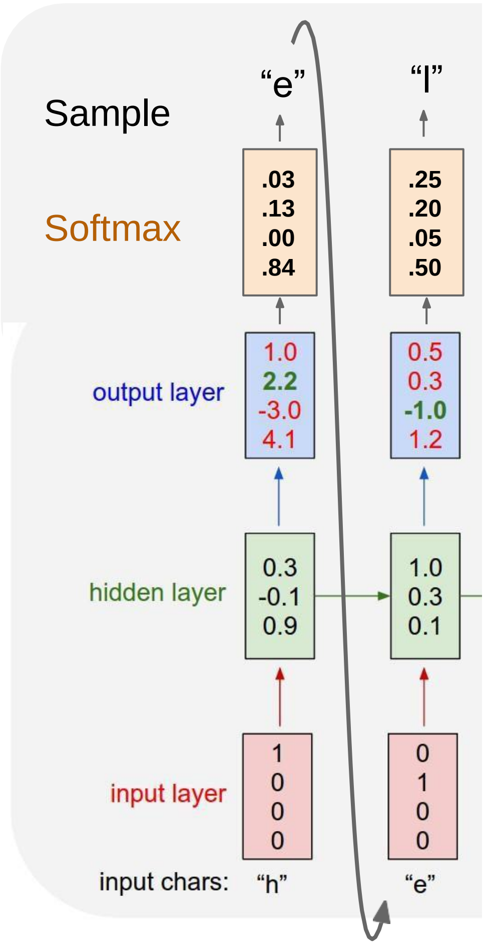

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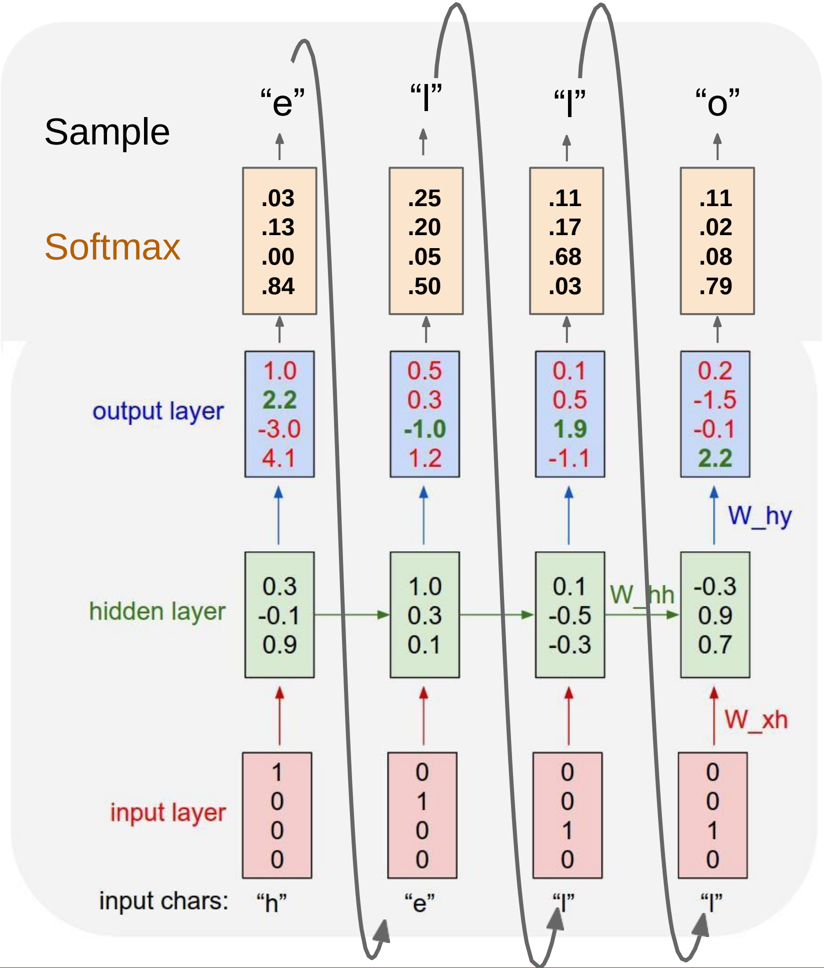
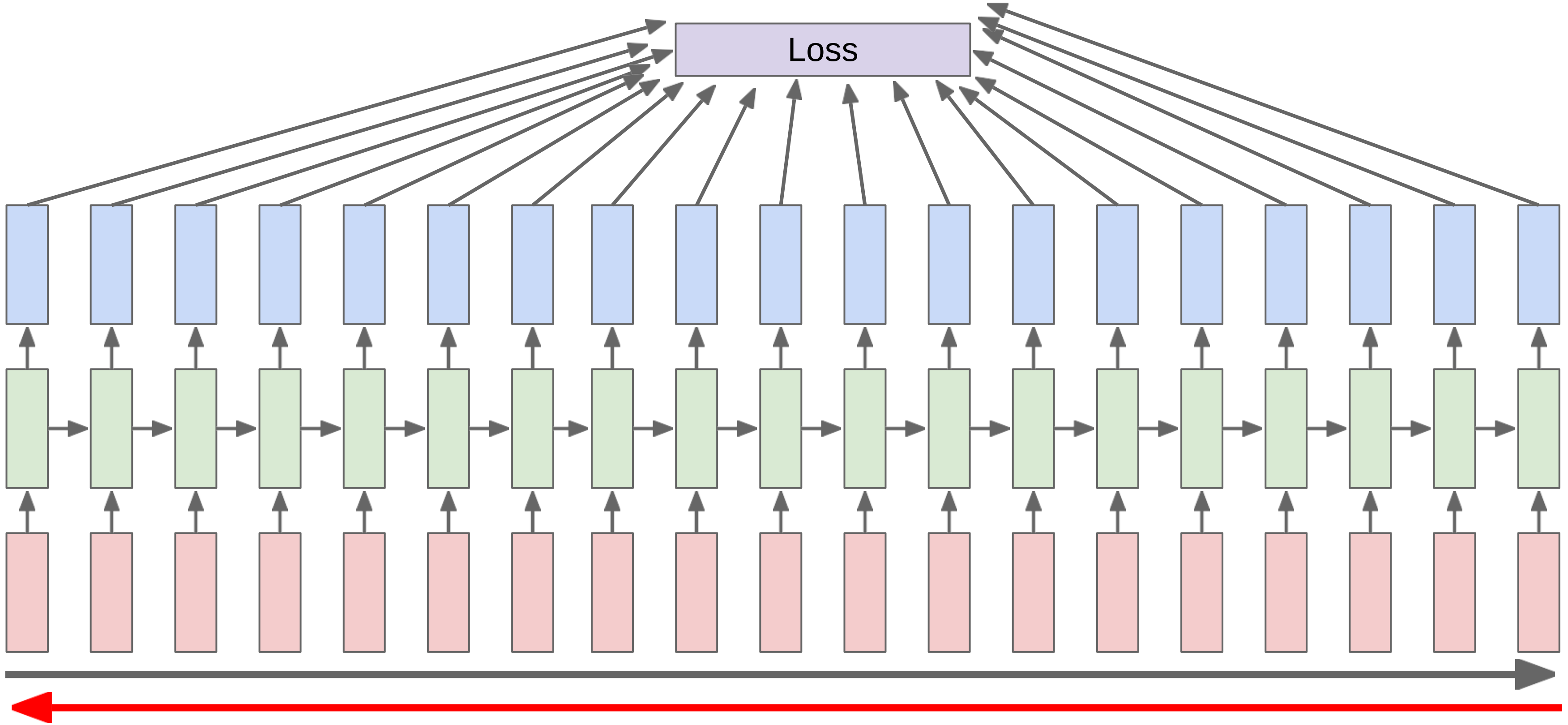


Backpropagation through time

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

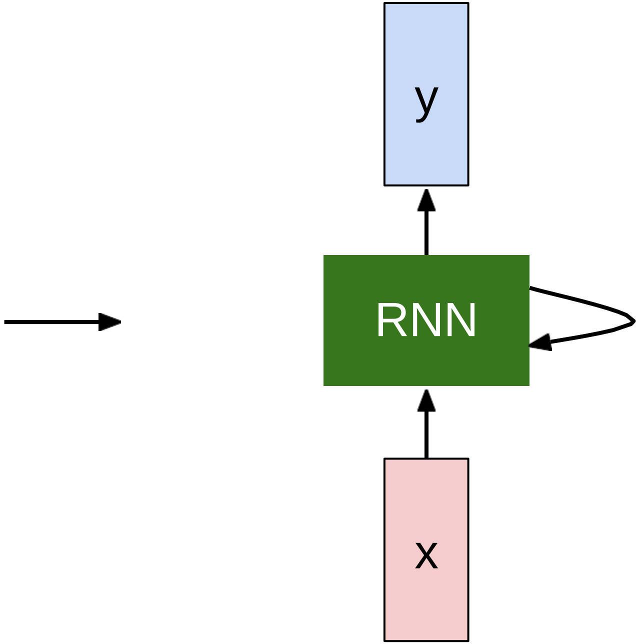


THE SONNETS

by William Shakespeare

From fairest creatures we desire increase,
That thereby beauty's rose might never die,
But as the riper should by time decease,
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 bud buriest 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-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."
```

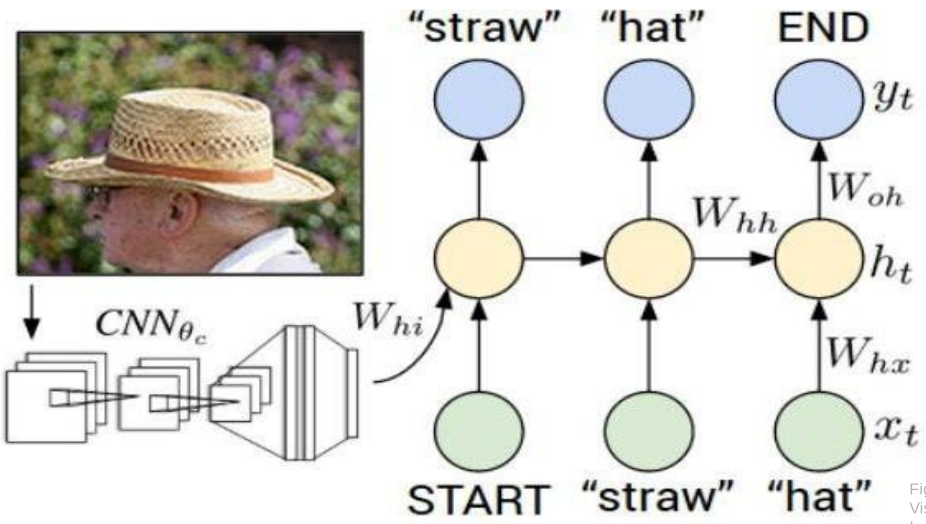
train more

```
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.
```

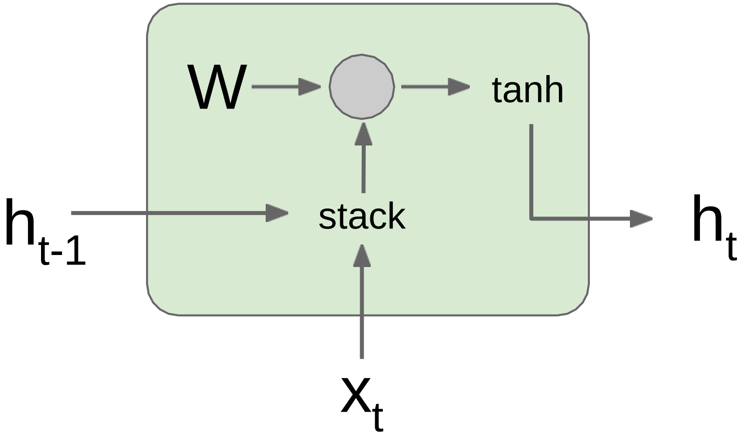
Image Captioning



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

Vanilla RNN Gradient Flow

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

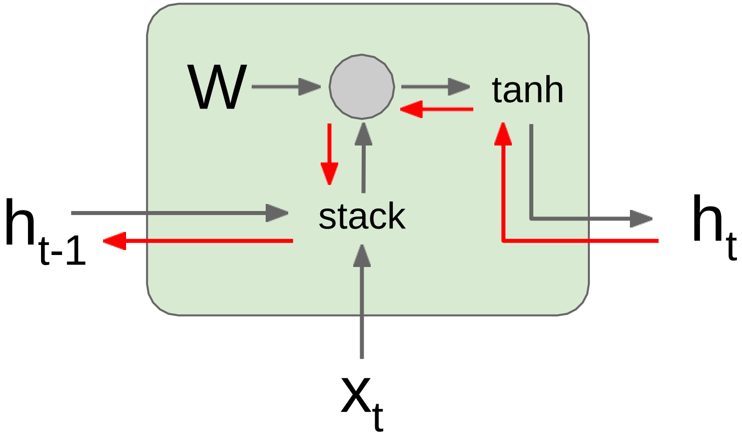


$$
\begin{aligned}
h_t &= \tanh(W_{hh} h_{t-1} + W_{xh} x_t) \\
&= \tanh\left(\begin{pmatrix} W_{hh} & W_{hx} \end{pmatrix} \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} \right) \\
&= \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} \right)
\end{aligned}
$$

Vanilla RNN Gradient Flow

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

Backpropagation from h_t to h_{t-1} multiplies by W (actually W_{hh}^T)



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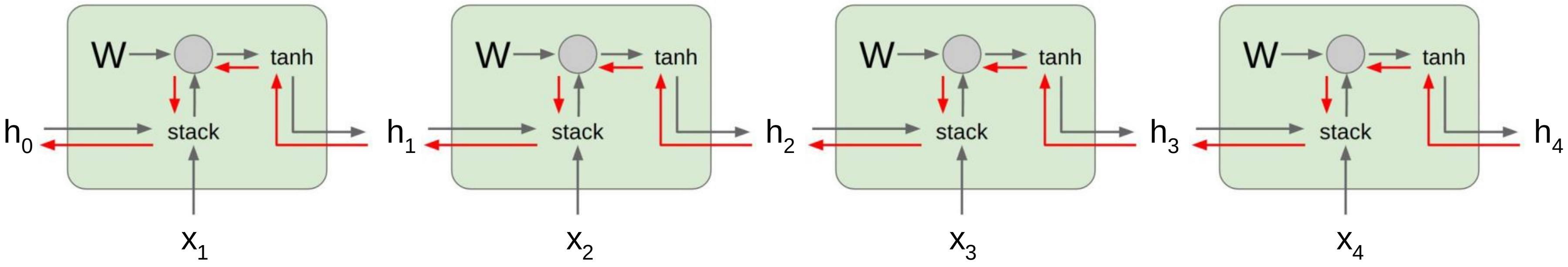
\begin{aligned}
h_t &= \tanh(W_{hh}h_{t-1} + W_{xh}x_t) \\
&= \tanh\left(\begin{pmatrix} W_{hh} & W_{hx} \end{pmatrix} \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right) \\
&= \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)
\end{aligned}
$$

Vanilla RNN Gradient Flow

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



Computing gradient of h_0 involves many factors of W
(and repeated tanh)

Vanilla RNN Gradient Flow

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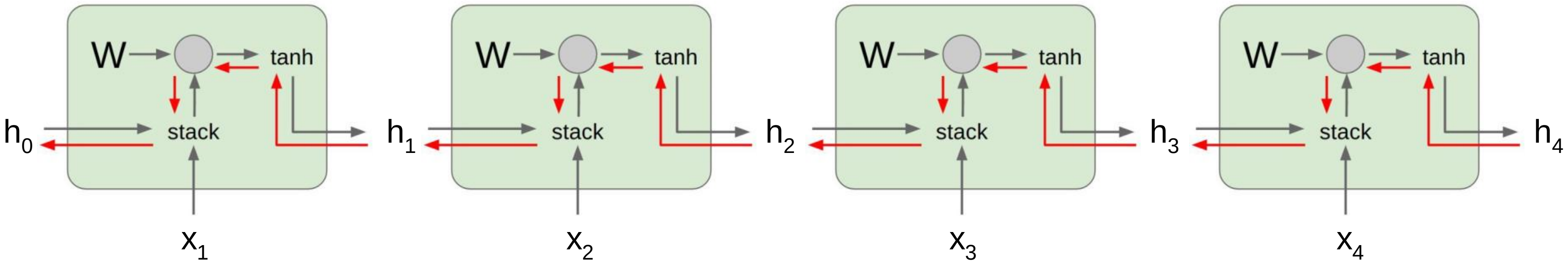

Computing gradient of h_0 involves many factors of W
(and repeated tanh)

Largest singular value > 1:
Exploding gradients

Largest singular value < 1:
Vanishing gradients

Vanilla RNN Gradient Flow

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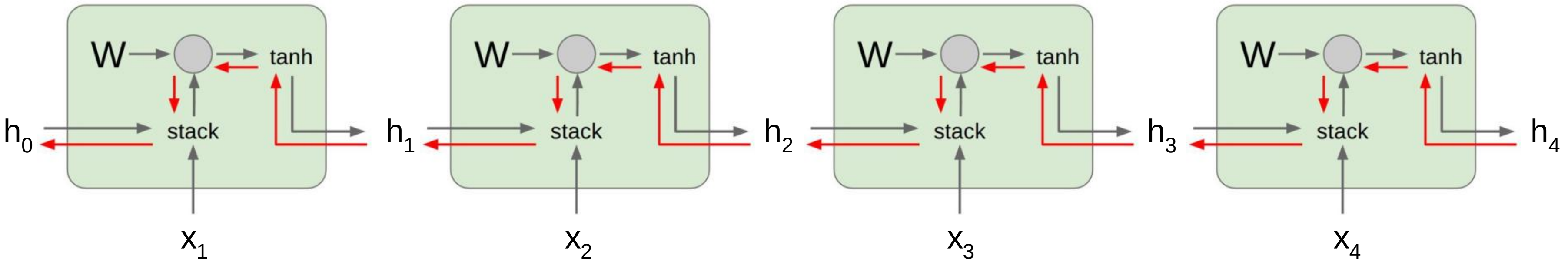

Computing gradient of h_0 involves many factors of W
(and repeated tanh)

Largest singular value > 1:
Exploding gradients

→ **Gradient clipping**: Scale gradient if its norm is too big

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

Largest singular value < 1:
Vanishing gradients

Vanilla RNN Gradient Flow

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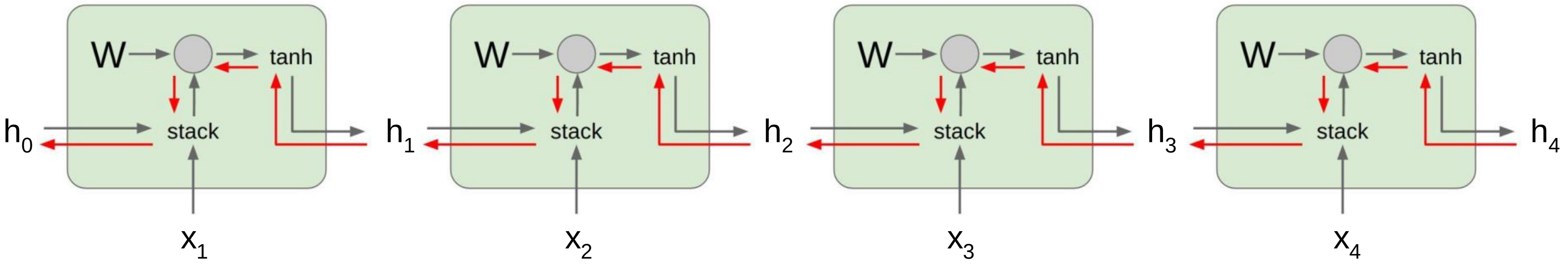
Pascanu et al, “On the difficulty of training recurrent neural networks”, ICML 2013



Computing gradient of h_0 involves many factors of W
(and repeated tanh)

Largest singular value > 1:
Exploding gradients

Largest singular value < 1:
Vanishing gradients

→ Change RNN architecture

Long Short Term Memory (LSTM)

Vanilla RNN

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

LSTM

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

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

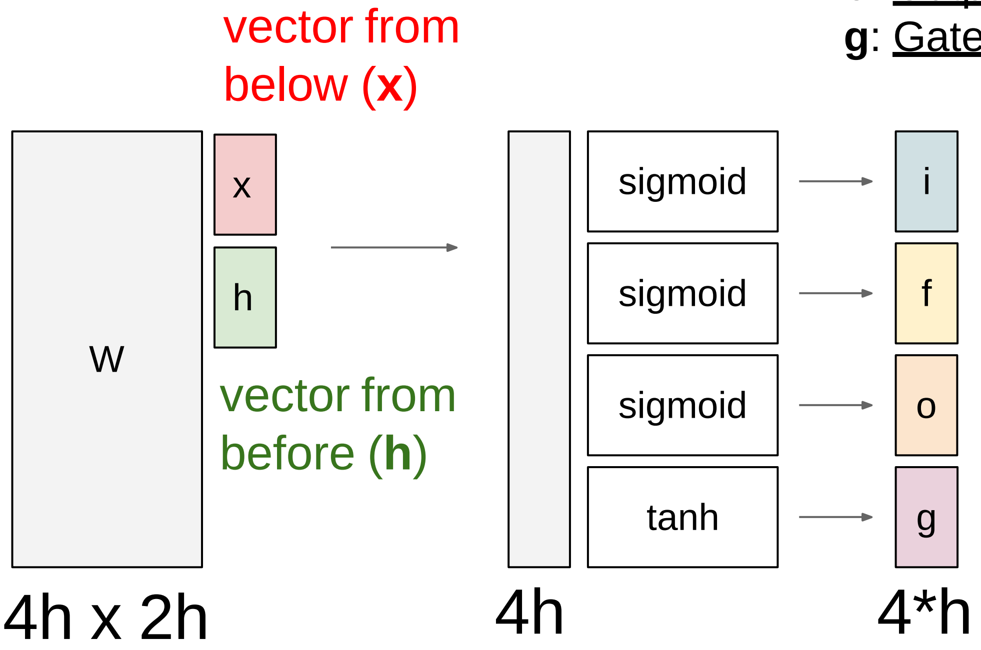
$$h_t = o \odot \tanh(c_t)$$

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

Long Short Term Memory (LSTM)

[Hochreiter et al., 1997]

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



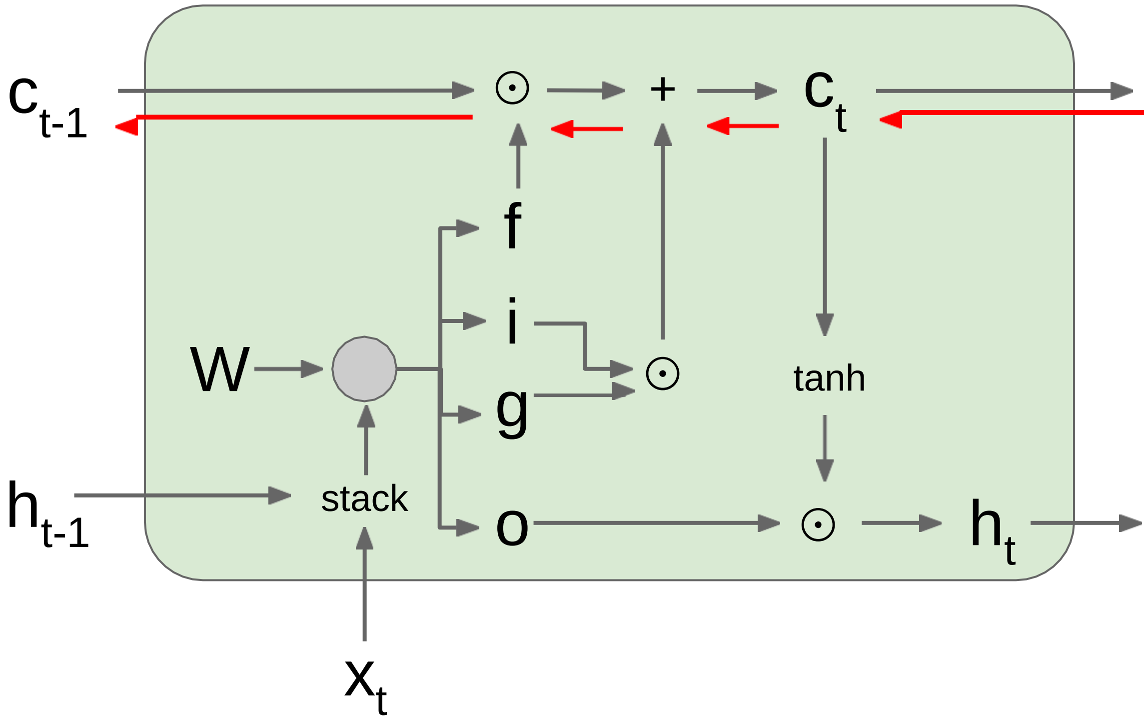
$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

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

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

Long Short Term Memory (LSTM): Gradient Flow

[Hochreiter et al., 1997]



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

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

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

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

Summary

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

Basic RNNs

Questions?