Deep Learning for Computer Vision

Recurrent Neural Networks: An Introduction

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Review: Questions

How to find bias in a model?

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How to find bias in a model?

Change a particular attribute/feature in question, and see if the prediction changes!

Acknowledgements

- This lecture's slides are based on:
  - **Lecture 10** of Stanford's **CS231n** course Fei-Fei Li
  - **Lecture 13** of IIT Madras' **CS7015** course by Mitesh Khapra

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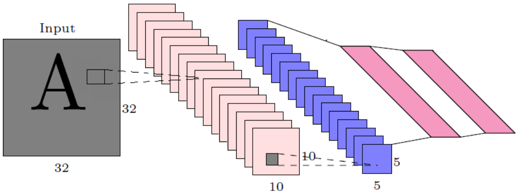

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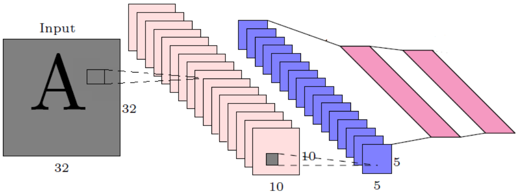

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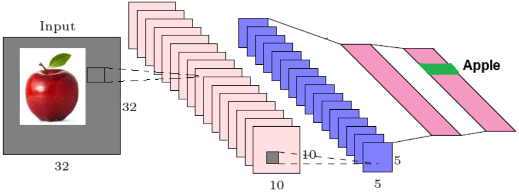

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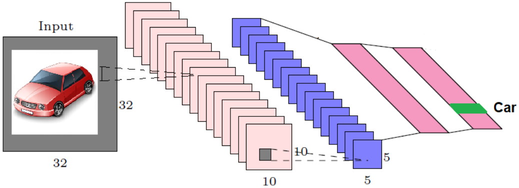

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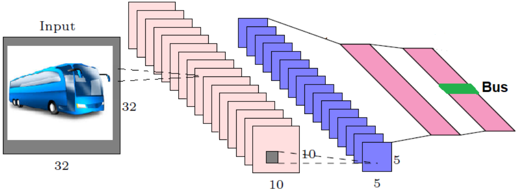
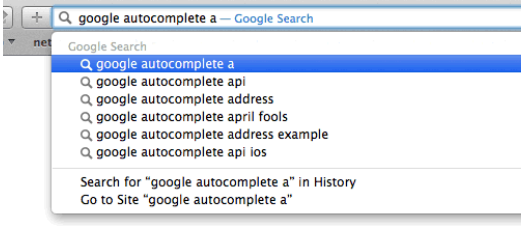


Sequence Learning Problems

- Consider task of text auto completion



Credit: John Johnston

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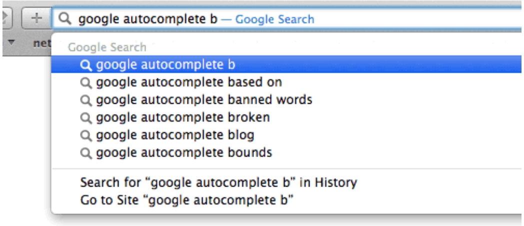

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Sequence Learning Problems

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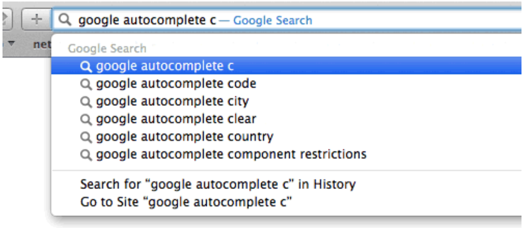
- Successive inputs are no longer independent!



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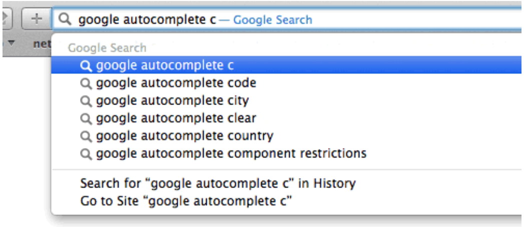

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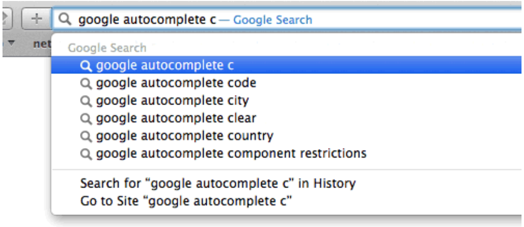
- Underlying model is performing same task across all contexts (*input:* character, *output:* character)



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Sequence Learning Problems

- Consider task of text auto completion
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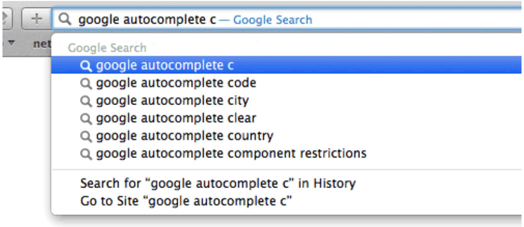
- Underlying model is performing same task across all contexts (*input:* character, *output:* character)
- Known as **sequence learning problems**



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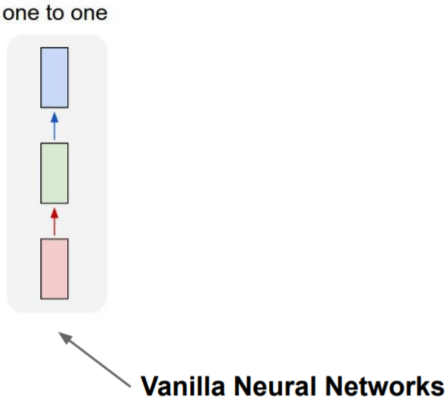
Recurrent Neural Networks: Variants



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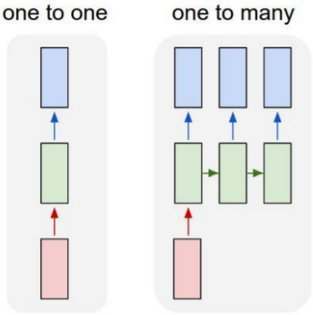
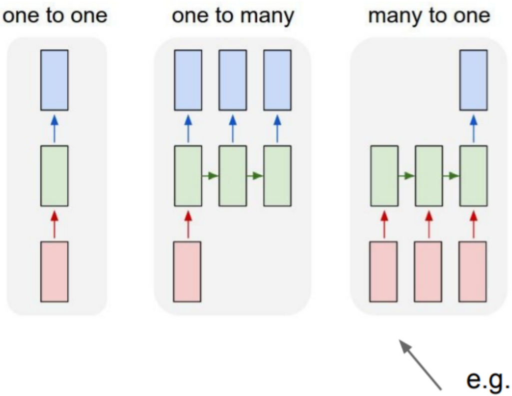


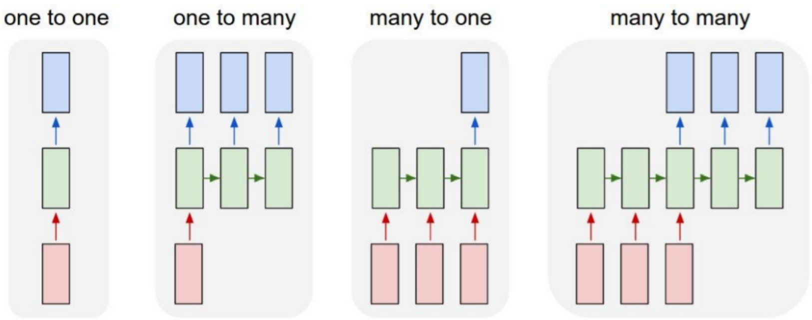
e.g. **Image Captioning**
image -> sequence of words

Recurrent Neural Networks: Variants



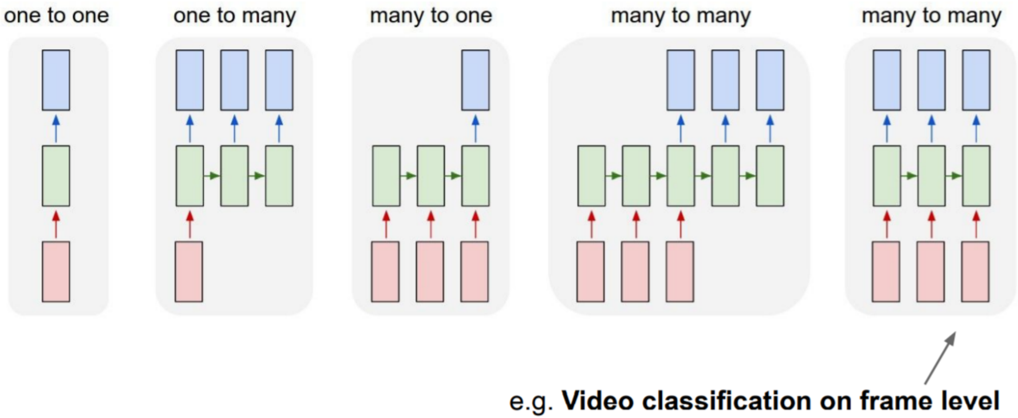
e.g. **action prediction**
sequence of video frames -> action class

Recurrent Neural Networks: Variants



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

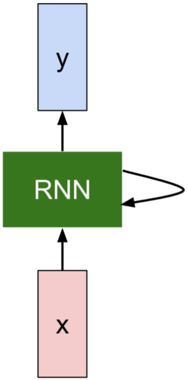
Recurrent Neural Networks: Variants



How do we model such tasks involving sequences?

- Account for dependence between inputs
- Account for variable number of inputs
- Make sure that function executed at each time step is the same. Why?

Recurrent Neural Network



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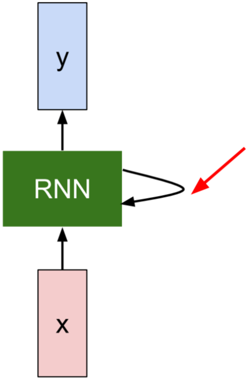
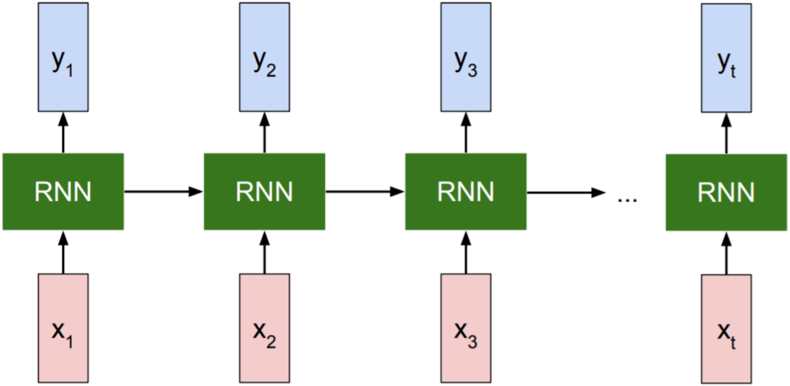


Key idea: RNNs have an "internal state" that is updated as a sequence is processed

Recurrent Neural Network: Unfolded



Recurrent Neural Network

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

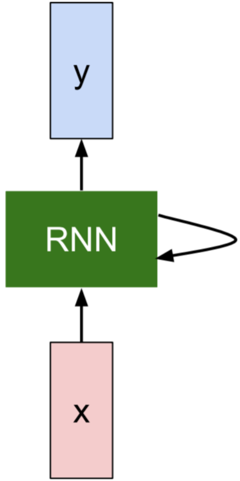
$$\boxed{h_t} = \boxed{f_{UW}}(\boxed{x_t}, \boxed{h_{t-1}})$$

new state

input vector at some time step

old state

some function with parameters U&W



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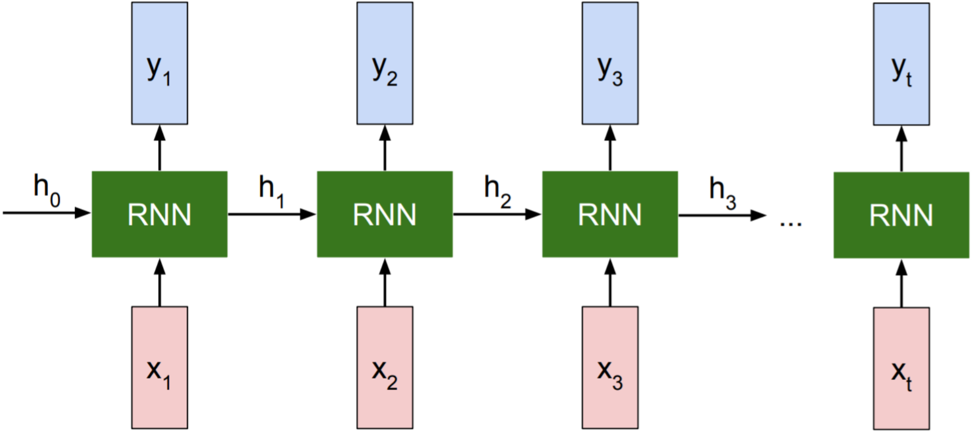

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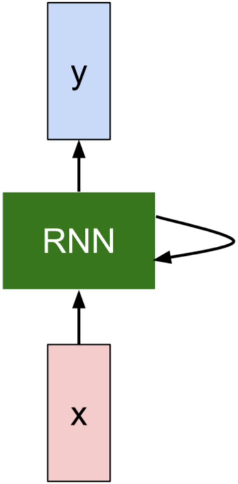
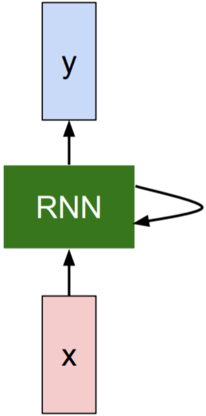
Notice: the same function and the same set of parameters are used at every time step.



(Simple) Recurrent Neural Network

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



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

$$\downarrow$$

$$h_t = \tanh(U x_t + W h_{t-1})$$

$$y_t = SoftMax(V h_t)$$

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

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- Values that are fed into nodes and come out of nodes called **tensors** (multi-dimensional array)
  - Subsumes scalars, vectors and matrices as well
- Can be instantiated to do two types of computation
  - Forward
  - Backward

Computational Graphs: Creating Expressions

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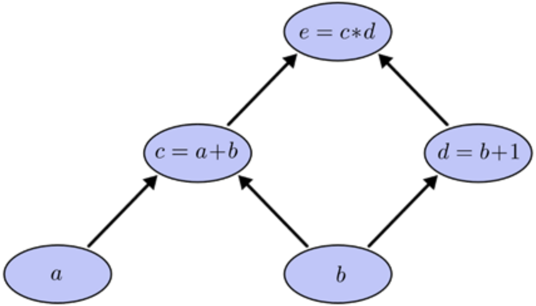

Credit: Christopher Olah

Computational Graphs: Evaluating Expressions

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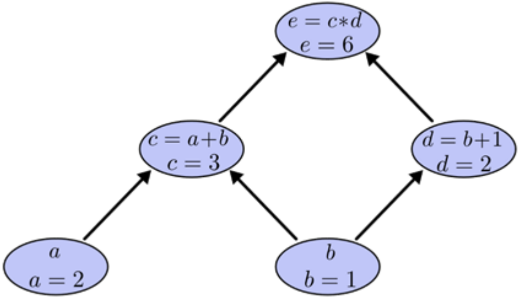

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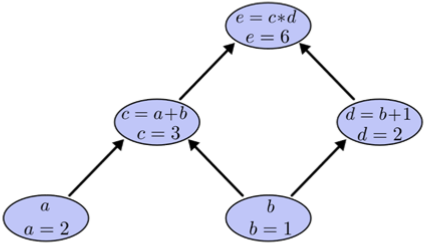
Computational Graphs: Computing Derivatives

- How?



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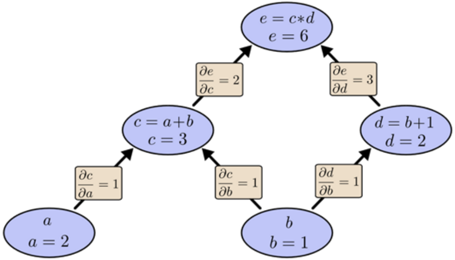

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- How?
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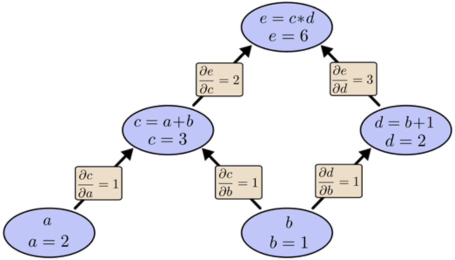

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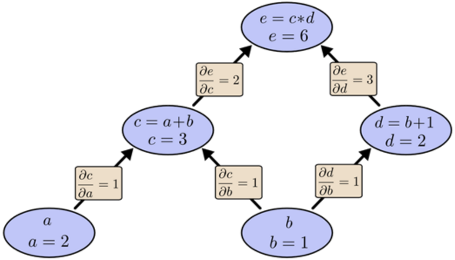

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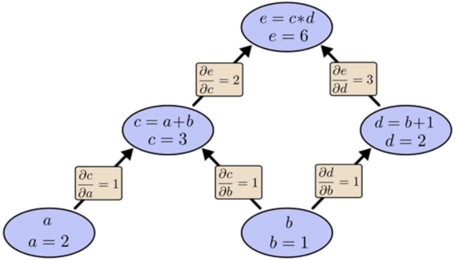
- E.g. to get derivative of e w.r.t. b:

$$\frac{\partial e}{\partial b} = 1 * 2 + 1 * 3$$



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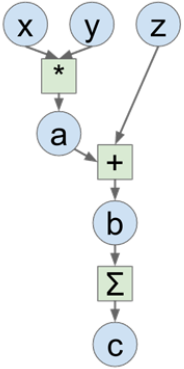
Computational Graphs: PyTorch Example

- In PyTorch, for e.g., changes are tracked on the go during forward pass allowing for dynamic graph creation
- Gradients are calculated only when **backward()** function is triggered




```python
import torch
from torch.autograd import Variable

#----- Define Variables to build computational graph -----#
x = Variable(torch.tensor([1.0, 2.0]).cuda(), requires_grad = True)
y = Variable(torch.tensor([2.0, 3.0]).cuda(), requires_grad = True)
z = Variable(torch.tensor([4.0, 3.0]).cuda(), requires_grad = True)

#----- Forward Pass -----#
a = x * y
b = a + z
c = torch.sum(b)

#----- Compute Gradients -----#
c.backward()

print(x.grad.data) # out = [2., 3.]
print(y.grad.data) # out = [1., 2.]
print(z.grad.data) # out = [1., 1.]
```

Computational Graphs: MLP

$$\mathbf{h} = \tanh(\mathbf{W}\mathbf{x} + \mathbf{b})$$
$$\mathbf{y} = \mathbf{V}\mathbf{h} + \mathbf{a}$$

Credit: Yoav Artzi CS5740

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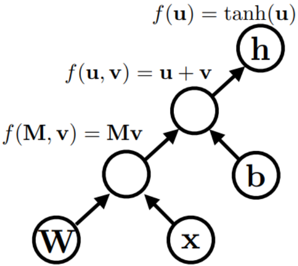

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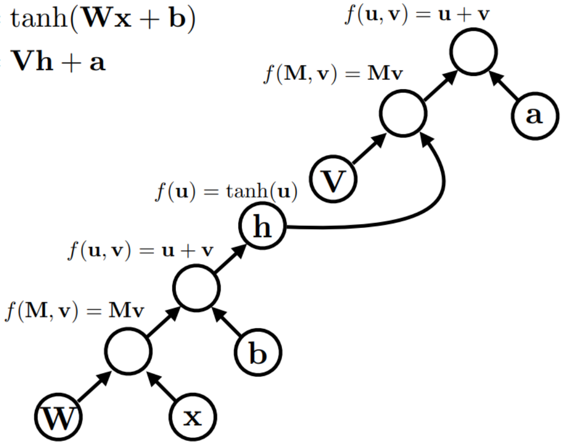

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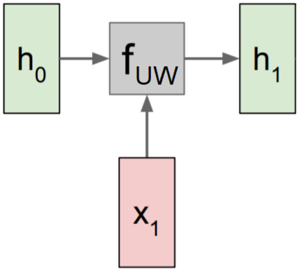
Back to RNNs: Computational Graph



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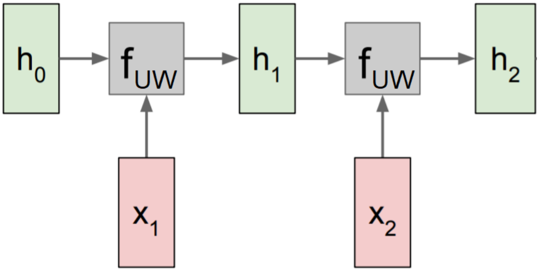

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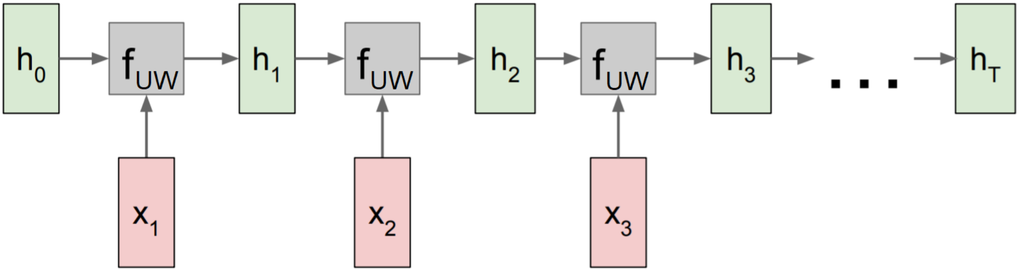
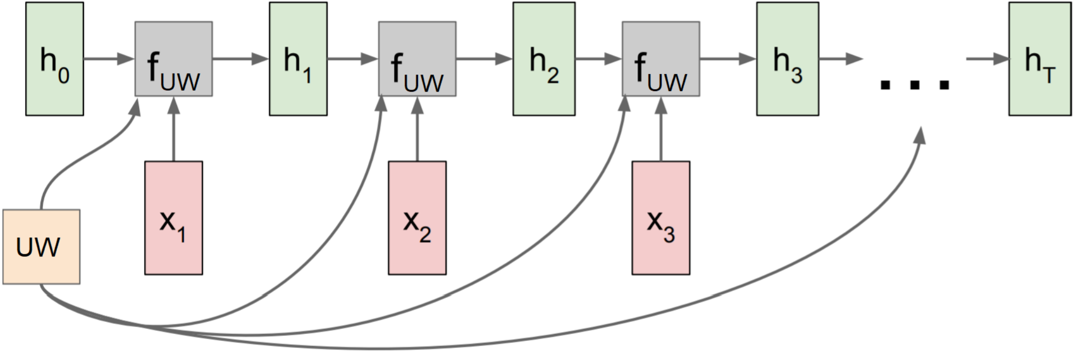
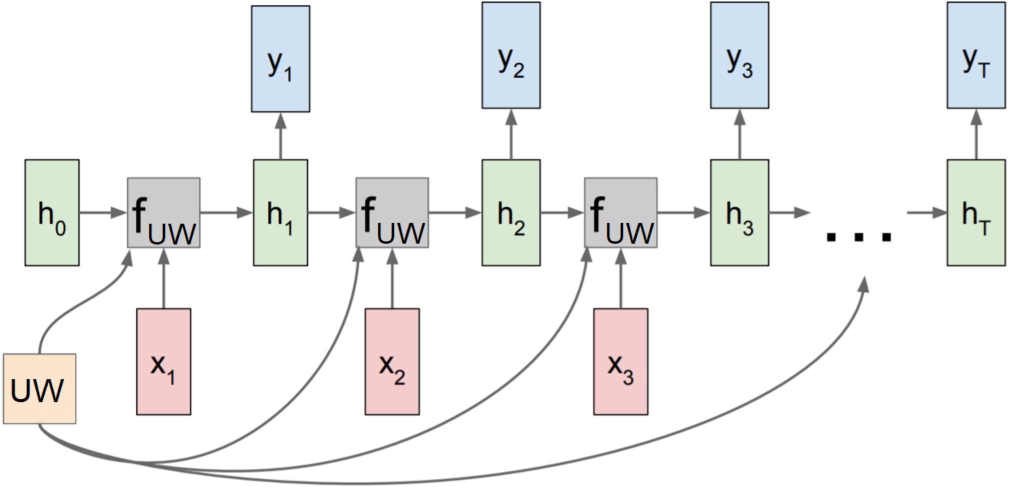


Back to RNNs: Computational Graph

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



RNN Computational Graph: Many-to-Many



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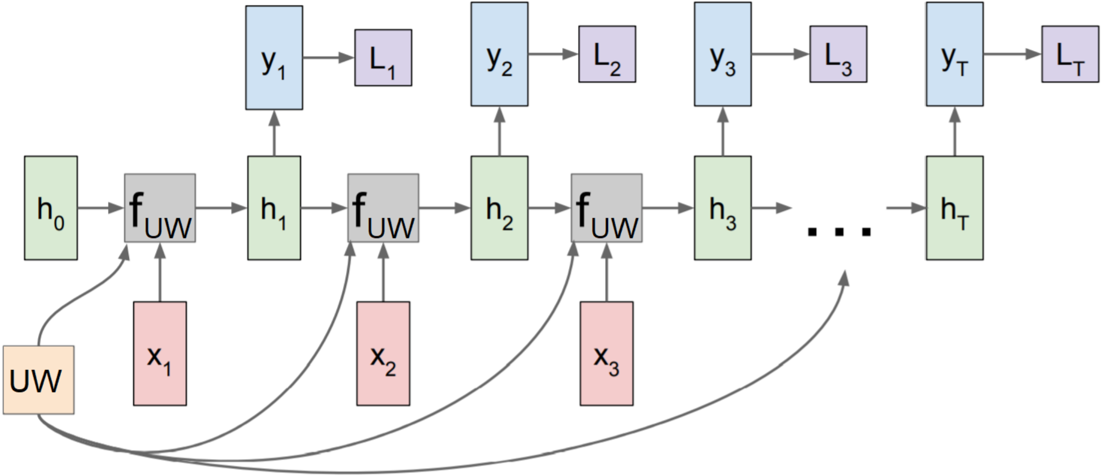

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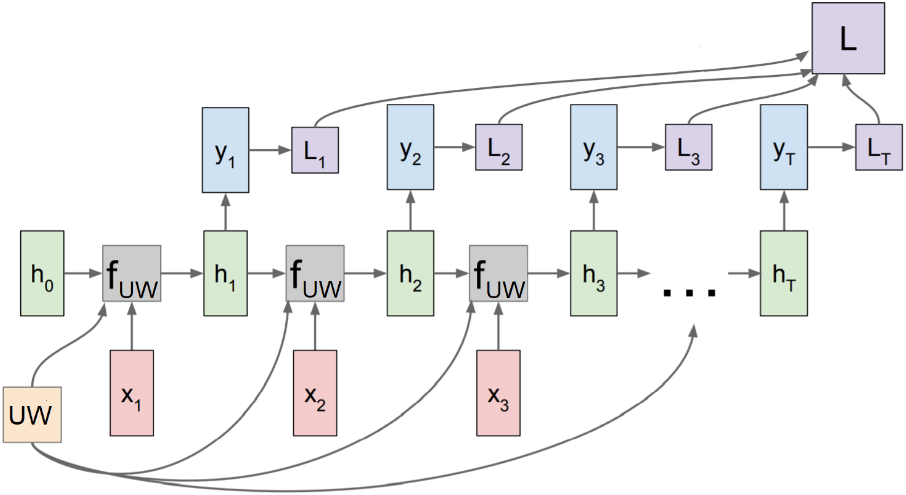

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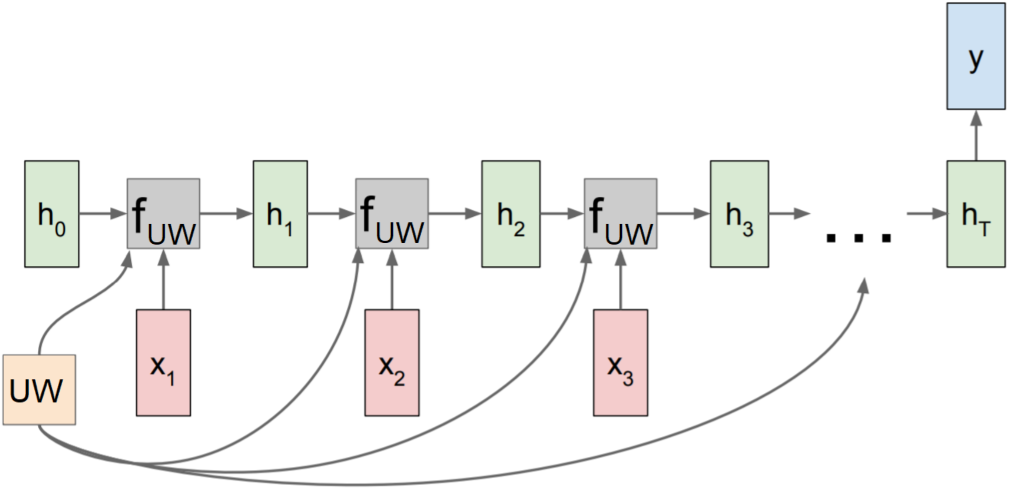

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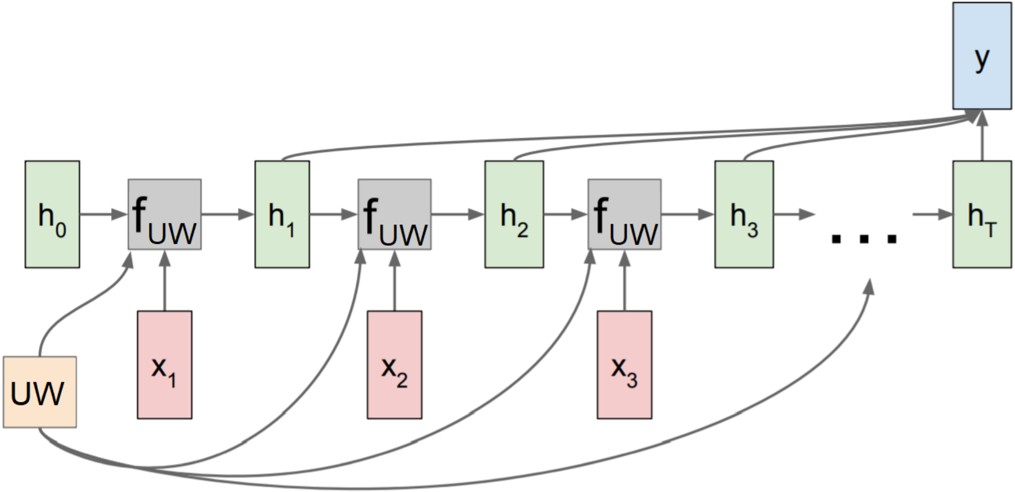

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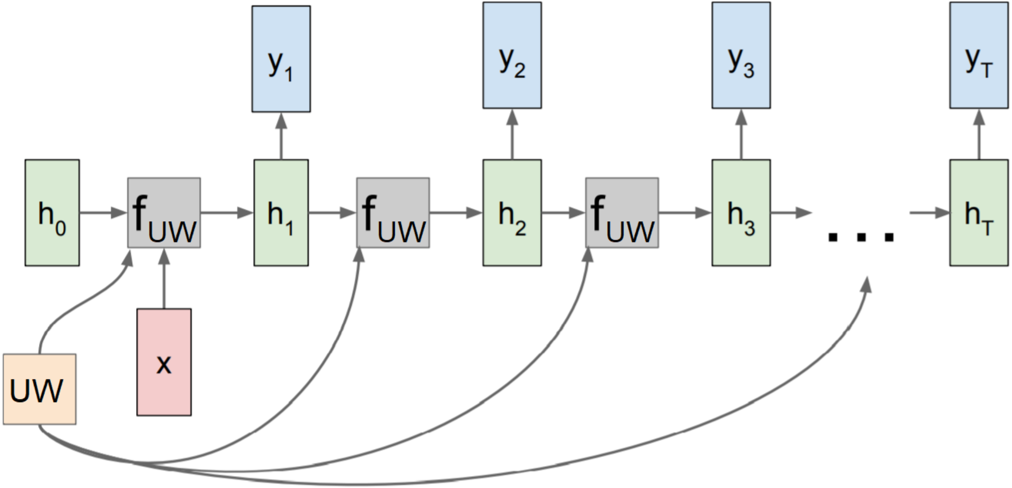

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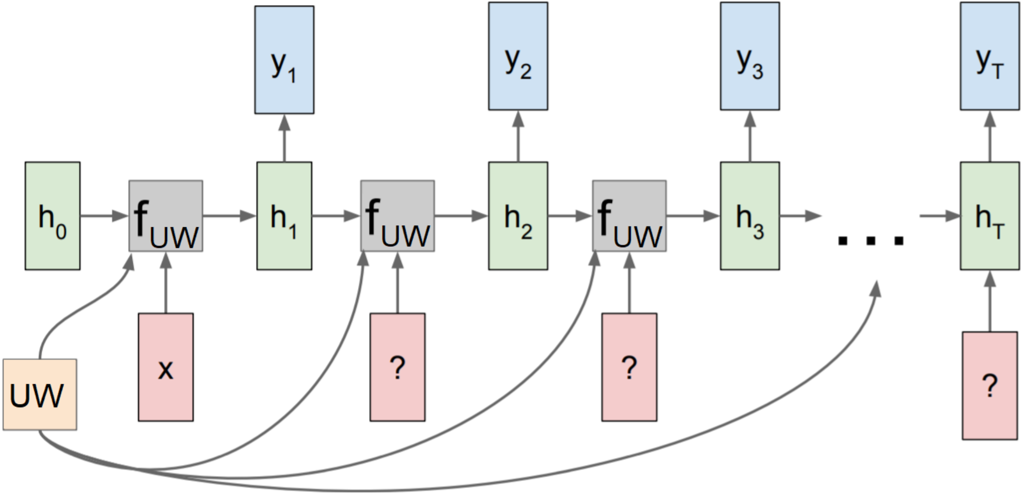

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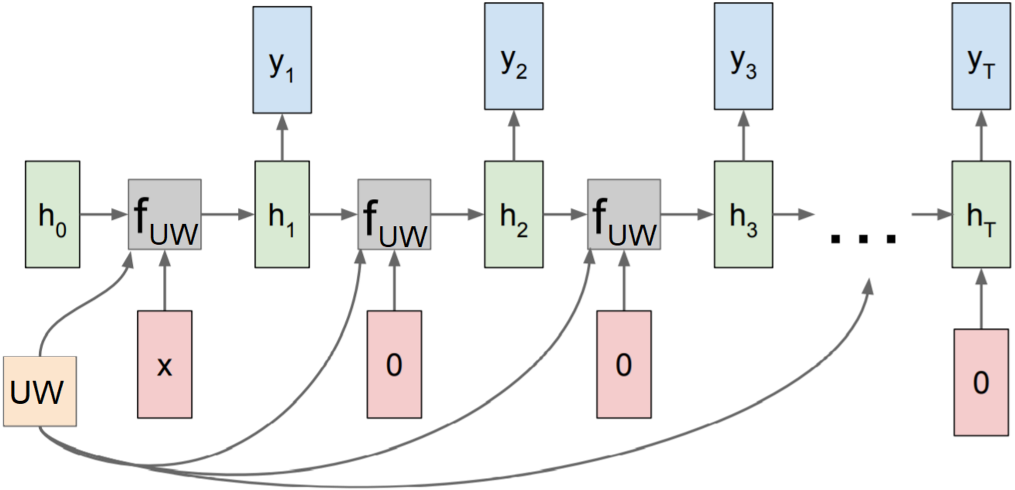

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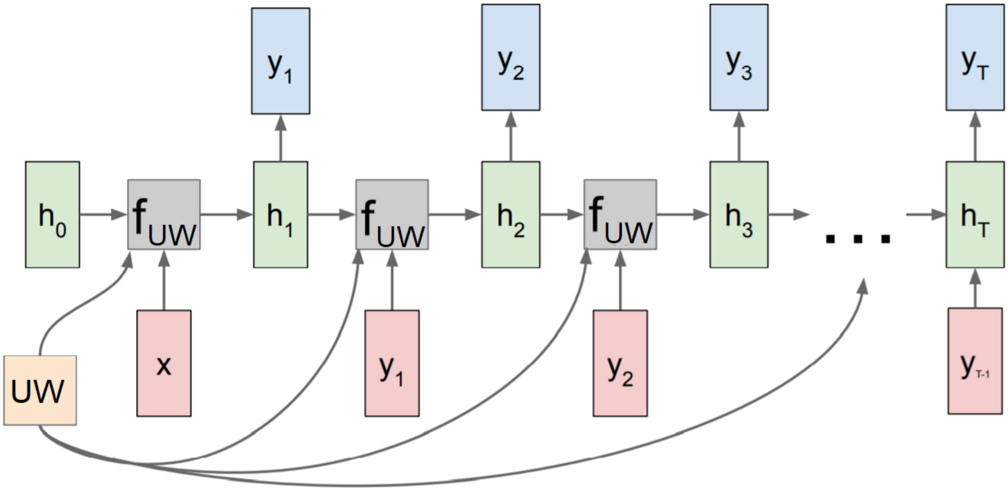
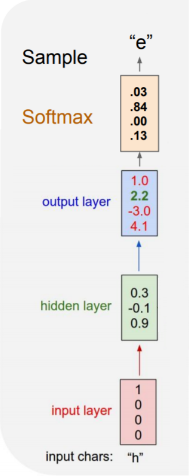


Example: Character-level Language Model

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



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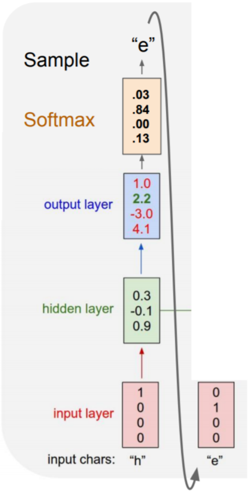

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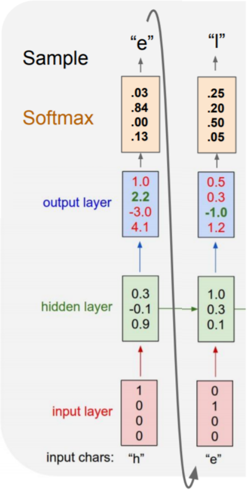
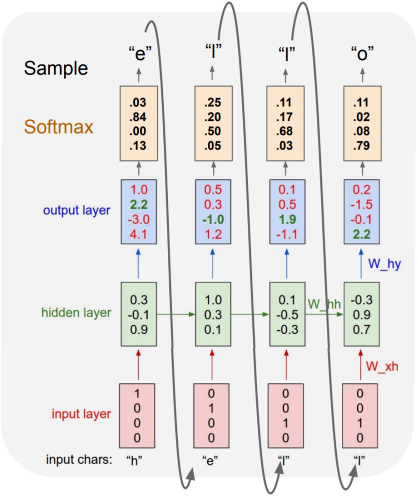


Example: Character-level Language Model

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



Homework

Readings

- Chapter 10 of Deep Learning Book (Goodfellow et al)
- Andrej Karpathy's blog post on RNNs (Important)
- (Additional) Lecture 10 - Stanford CS231n
- (Additional) Lecture 13 - IIT Madras CS7015

Questions

- Can RNNs have more than one hidden layer?
- The state (h_t) of an RNN records information from all previous time steps. At each new timestep, the old information gets *morphed* slightly by the current input. What would happen if we *morphed* the state too much?