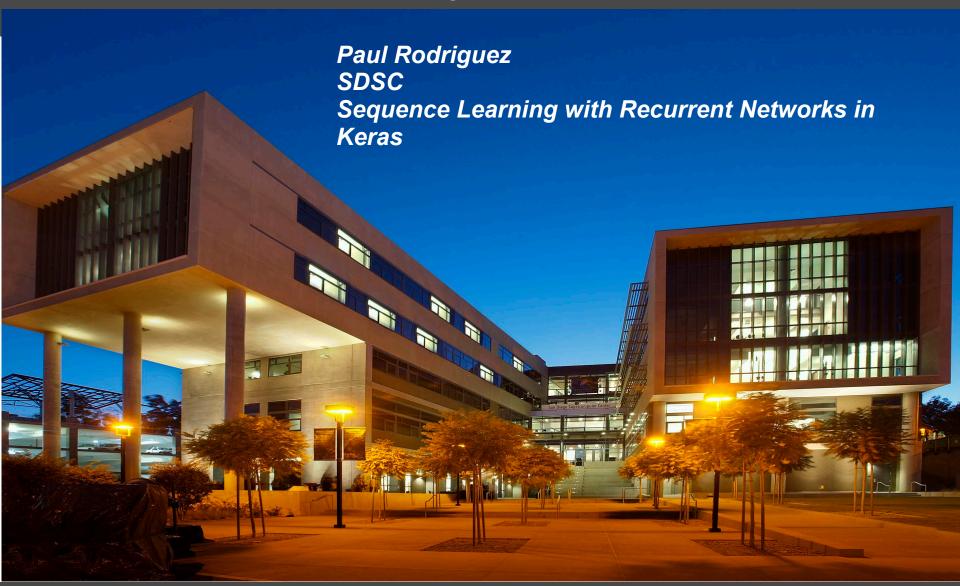
### CIML





### **Outline**

Applications of Sequence Learning

Recurrent Networks and Memory Units

Some Varieties of Recurrent Models

RNNs in Keras and exercise



### **Sequence Learning**

Language or grammar sequences

Time series, autoregressive models

**Machine Translation** 

Video, Image sequences

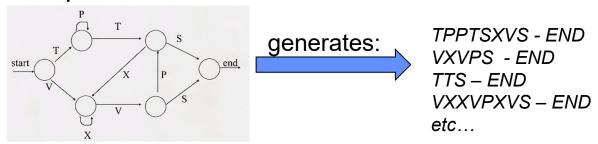
many others...

All involve learning about dependencies in time, often with variable length input



### **Artificial Grammar Learning:**

#### predict next letter and END-OF-SEQUENCE



#### Inputs and Outputs use 1 hot vectors of input

	Р	S	Т	V	X	END
Т	0	0	1	0	0	0
Р	1	0	0	0	0	0
Р	1	0	0	0	0	0
END	0	0	0	0	0	1

### Temporal Sequence Classification:

given a sequence of words can you classify the movie review sentiment

id	sentiment	review
4518_9	1	Adrian Pasdar is excellent is this film. He makes a fascinating woman.
874_1	0	Long, boring, blasphemous. Never have I been so glad to see ending credits roll.
3247_10	1	I don't know why I like this movie so well, but I never get tired of watching it.

1 hot encoding would be too large, so Inputs and Outputs use word embeddings (ie a reduced space of real values)

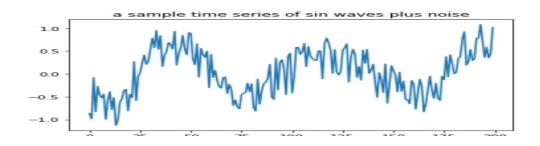
Long boring I have

H1	H2	Н3	H4	H5	
0.3	0.1	0.01	0.94	0.1	0.43
0.01	0.2	03	0.51	0.2	0.62

. . .

### Time series, autoregressive models

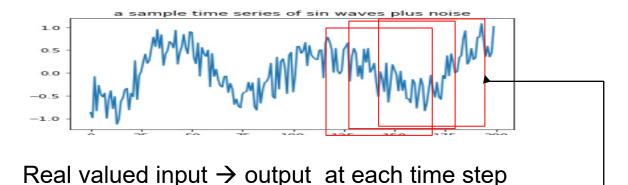
Predict rainfall for next hour, or next 24 hours (Kaggle)



Real valued input → output at each time step

### Time series, autoregressive models

Predict rainfall for next hour, or next 24 hours (Kaggle)

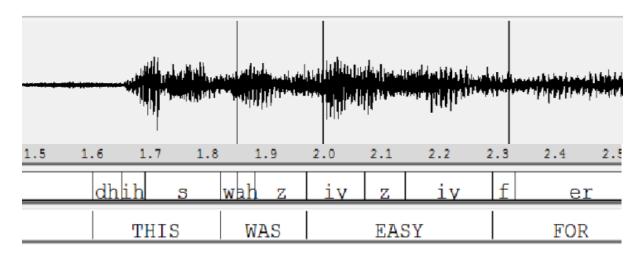


Or, you can feed in many time lags at once ("multi-step input")

This is like sliding a 1D convolution layer and getting a sequence of convolution outputs



#### Continuous speech phoneme/word recognition (TIMIT challenge)



RNNs with convolution were doing well, but lately (2020),

RNNs might be getting beat out by convolution over lagged inputs (of all time steps), with positional information.

But for more varied length input positional information might not generalize as well



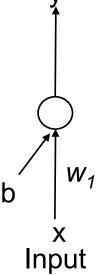
### What is a Recurrent Neural Network?



### First, recall a Neural Network node

Output (of the layer; not necessarily of the network)

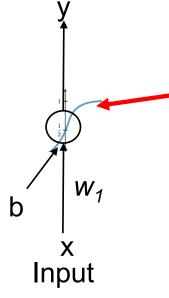
x,w,y are possibly vectors



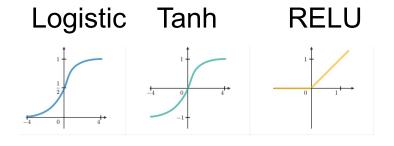
### First, recall a Neural Network node

Output (of the layer; not necessarily of the network)

x,w,y are possibly vectors



An activation function, usually one of these:



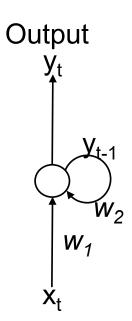
### Add recurrent connection

Let add feedback and work with discrete time steps

This is a dynamical system –

Y(t) depends on Y(t-1)

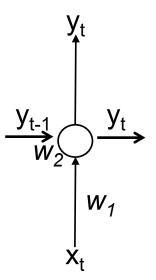
How does it learn?



This is a dynamical system – how does it learn?

Let's 'unroll' it in time by making copies.

Output at t

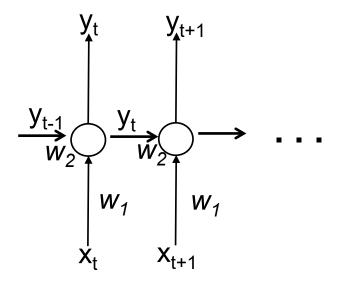


Input at t time

This is a dynamical system – how does it learn?

Let's 'unroll' it in time by making copies

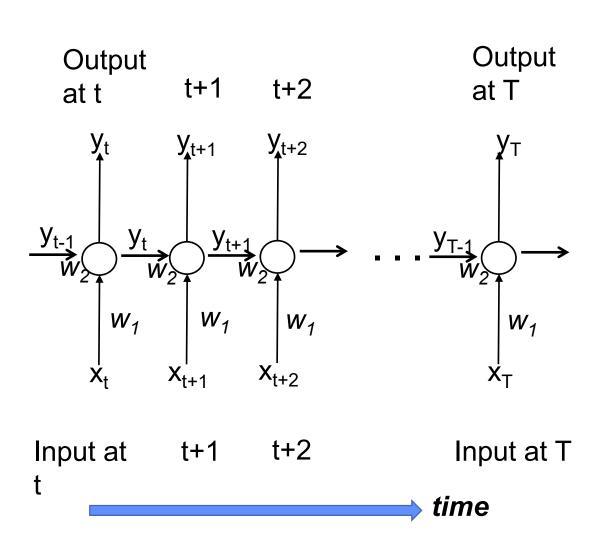
Output Output at t at t+1



Input at Input at t+1
t
t
time

This is a dynamical system – how does it learn?

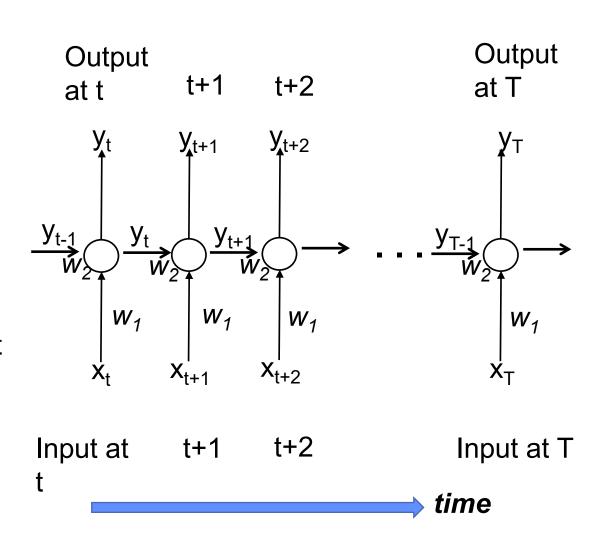
Let's 'unroll' it in time by making copies



This is a dynamical system – how does it learn?

Let's 'unroll' it in time by making copies

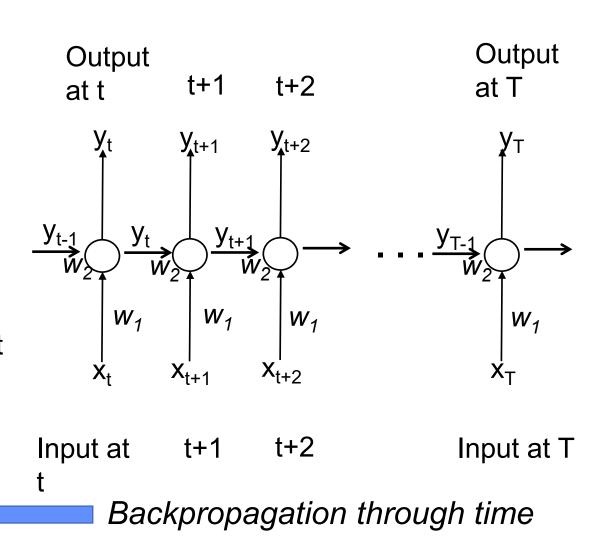
Can we see dependencies in time that backprop must learn?



This is a dynamical system – how does it learn?

Let's 'unroll' it in time by making copies

Can we see dependencies in time that backprop must learn?

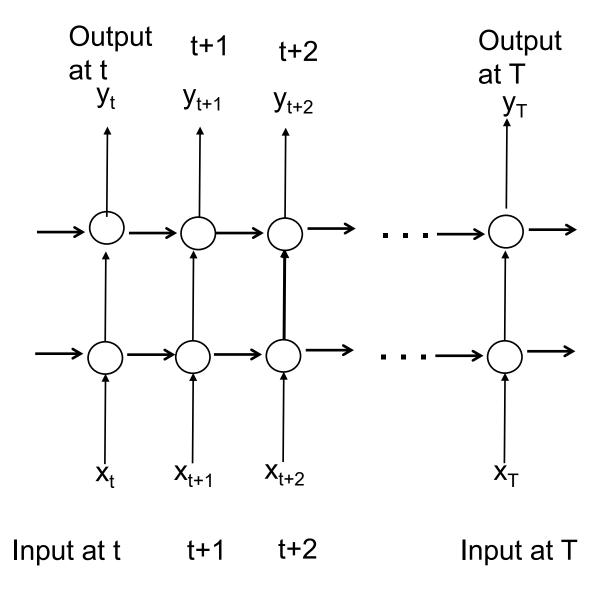




# **Deep RNN**

Layers can be added

Layers are 'unrolled' together



Can we make the feedback more like a memory unit?



# What would a 'memory' unit look like?

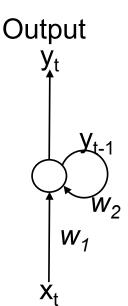
Consider:

Given an initial value of y<sub>t-1</sub>,

Given:

If you use a linear activation function:

What is  $y_t$ ?



# What would a 'memory' unit look like?

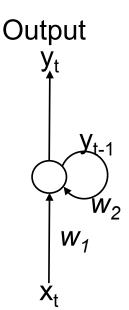
Consider:

Given an initial value of y<sub>t-1</sub>,

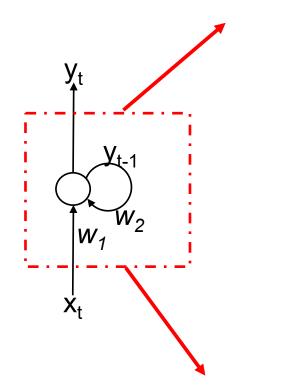
Given:

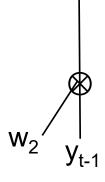
If you use a linear activation function:

What is  $y_t$ ? **Same as**  $y_{t-1}$ 



Use  $w_2$  as an 'update' gate on y



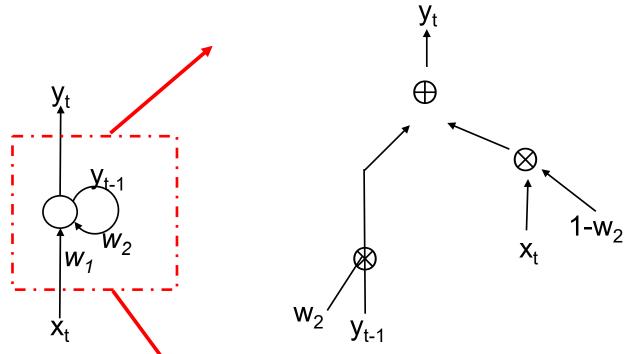


 $\bigoplus$  = element wise add

 $\otimes$  = element wise multiply

Use  $w_2$  as an 'update' gate on y

Let y<sub>t</sub> be weighted sum of y<sub>t-1</sub>and x<sub>t</sub>



- $\bigoplus$  = element wise add
- $\otimes$  = element wise multiply

 $W_2$  $y_{t-1}$  $\bigoplus$  = element wise add

Use  $w_2$  as an 'update' gate on y

Let y<sub>t</sub> be weighted sum of y<sub>t-1</sub>and x<sub>t</sub>

Use node to get  $w_2$ 

 $\otimes$  = element wise multiply

1-w<sub>2</sub>  $W_2$  $y_{t-1}$  $\bigoplus$  = element wise add  $\otimes$  = element wise multiply

Use  $w_2$  as an 'update' gate on y

Let y<sub>t</sub> be weighted sum of y<sub>t-1</sub>and x<sub>t</sub>

Use node to get w<sub>2</sub>

Use another node to combine y and x – with a 'relevance' gate on y<sub>t-1</sub>

1-w<sub>2</sub>  $W_2$  $y_{t-1}$  $y_{t-1}$  $\bigoplus$  = element wise add  $\otimes$  = element wise multiply

Use  $w_2$  as an 'update' gate on y

Let y<sub>t</sub> be weighted sum of y<sub>t-1</sub>and x<sub>t</sub>

Use node to get  $w_2$ 

Use another node to combine y and x – with a 'relevance' gate on y<sub>t-1</sub>

Use node to get  $r_t$ 

Use  $w_2$  as an 'update' gate on y

Let y<sub>t</sub> be weighted sum of y<sub>t-1</sub>and x<sub>t</sub>

Use node to get  $w_2$ 

Use another node to combine y and x – with a 'relevance' gate on y<sub>t-1</sub>

Use node to get  $r_t$ 

1-w<sub>2</sub>  $W_2$ **y**<sub>t-1</sub>  $y_{t-1}$  $y_{t-1}$ 

 $\bigoplus$  = element wise add

 $\otimes$  = element wise multiply

*'Gated Recurrent Unit'* (GRU)

Cho, Bengio 2015

### GRUs often drawn as circuit

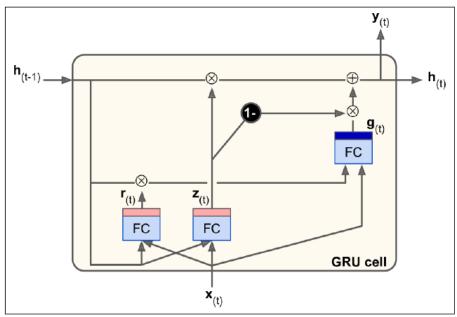


Figure 15-10. GRU cell

Image from Geron, 2019

# Long Short Term Memory (LSTM) has more parameters and gates

(Schmidhuber et al, 1997)

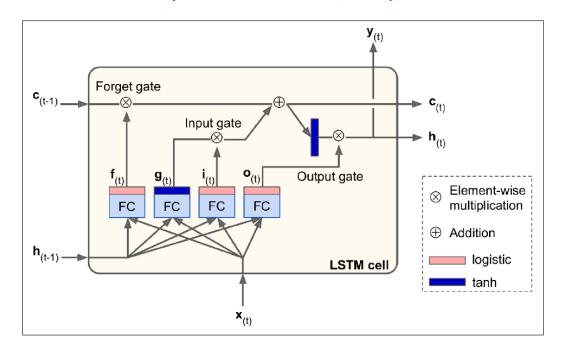


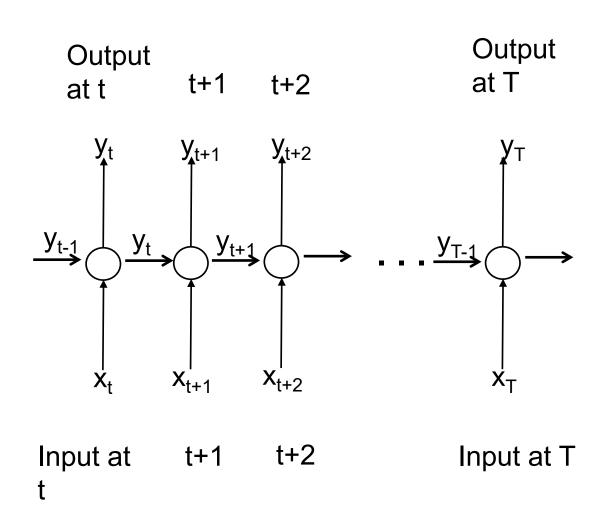
Image from Geron, 2019

### **Variations in RNN architectures**



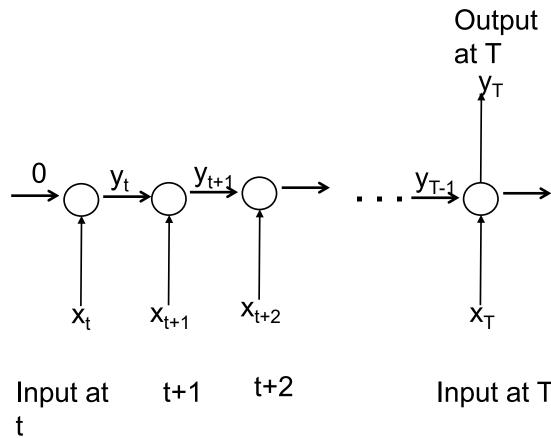
# Input Sequence to Output Sequence at each step

Often used to predict next input (self-supervised)



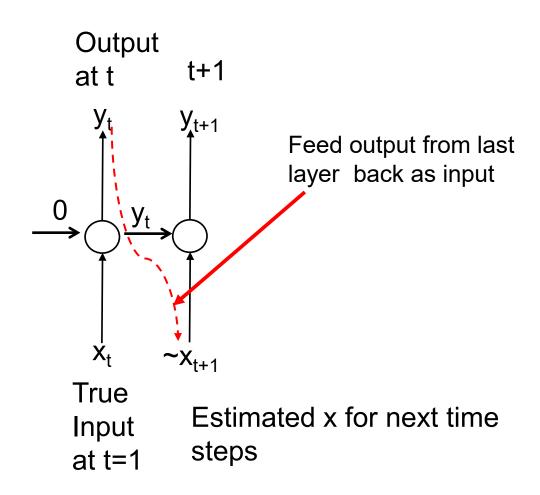
# Sequence to 1 output at end

Often used for time series classification



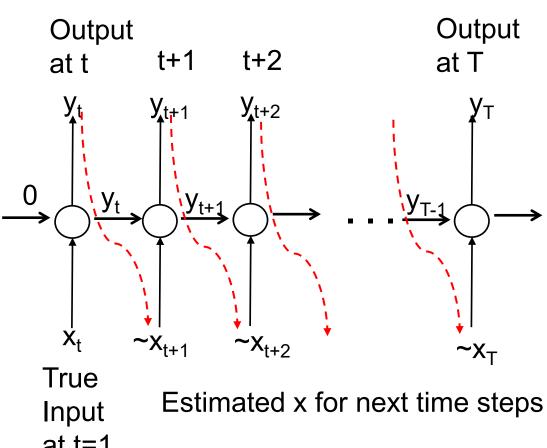
Input at T

# **Sequence Generation from 1 input**



### **Sequence Generation from 1 input**

Used for long term predictions or generating styles



at t=1

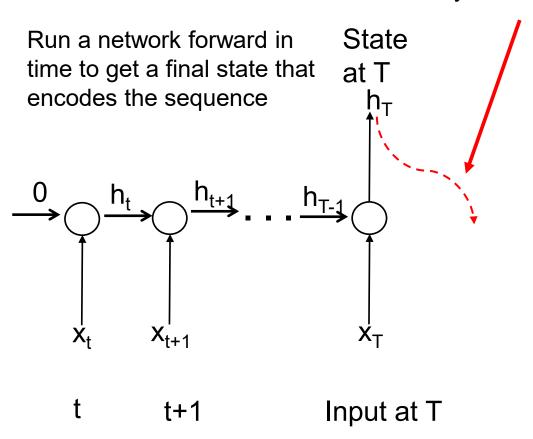


### **Encoding – Decoding sequence**

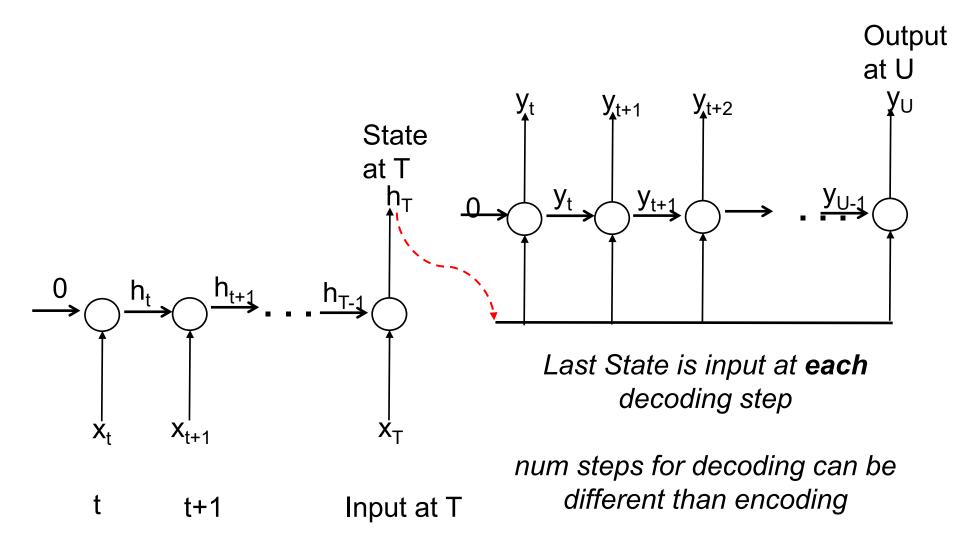
Run a network forward in State time to get a final state that at T encodes the sequence t+1 Input at T

# **Encoding – Decoding sequence**

Feed output from last layer as input to decoder



### **Encoding – Decoding sequence**



**Example: Machine Translation** 



# **Summary**

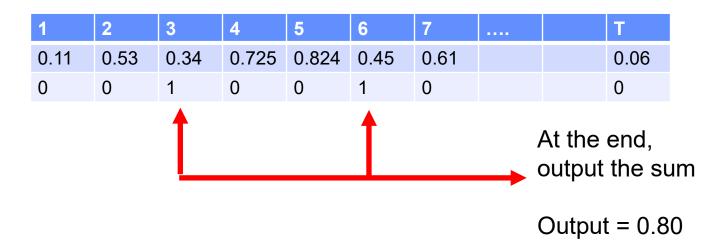
- RNNs can learn dependencies in time
- Long term dependencies can be hard because of vanishing gradients
- 'Simple' RNNs are unrolled in time
- 'Memory Unit' RNNs are built with "gate" multiplicative connections
- RNNs can be used for different input-output sequence mappings
- RNNs can be most useful for varying length sequences
- FeedForward NNs with lagged inputs compete with RNNs



### RNN exercise – the task

A toy problem: add two numbers in time

Inputs:
1 real
1 binary
indicator



# RNN exercise – the input

Generate Data as 3D array: N x T x 2

N samples

Inputs: 1 real 1 binary

1	2	3	4	5	6	7		T
0.11	0.53	0.34	0.725	0.824	0.45	0.61		0.06
0	0	1	0	0	1	0		0



#### The Script parameters

5

Inputs:
1 real
1 binary
indicator

0.11		0.34			0.45		0.61		0.06	
U		1	•••	•••	1	•••	1 • Su	m-0 3	0 1 <u>+</u> 0 1	5±0
						= 1	m=0.3 .41	470.4	<b>3</b> +0	

15

10

keras.layers.SimpleRNN(your-umber-of-units,
return\_sequences= True of False,
input\_shape = (None, your-number-of-variables))



keras.layers.SimpleRNN(your-umber-of-units,
return\_sequences= True of False,
input\_shape = (None, your-number-of-variables))

If TRUE then output at each time step
If FALSE then output only at T

Same options for:

keras.layers.GRU( ..... keras.layers.LSTM( ......



```
[12]:
     #a Simple RNN setup
     #set return_sequences=True for all recurrent layers
     #except the last one, if you only care about the last output
                    = P #set number of variables to P
     mysrn_model = keras.models.Sequential([
         keras.layers.SimpleRNN(numunits, return_sequences=True, input_shape=[None,nvar]),
         keras.layers.SimpleRNN(numunits),
         keras.layers.Dense(1,activation='linear')])
     # keras.layers.TimeDistributed(keras.layers.Dense(1 activation='sigmoid'))]) for pred at each step
[13]:
     mysrn model.summary()
     Model: "sequential"
                                                                             First RNN layer outputs 3D
                                                                             tensor
     Layer (type)
                                  Output Shape
                                                            Param #
     simple rnn (SimpleRNN)
                                  (None, None, 128)
                                                            16768
     simple rnn 1 (SimpleRNN)
                                  (None, 128)
                                                            32896
     dense (Dense)
                                  (None, 1)
                                                            129
     Total params: 49,793
     Trainable params: 49,793
     Non-trainable params: 0
```

```
[12]:
     #a Simple RNN setup
     #set return_sequences=True for all recurrent layers
     #except the last one, if you only care about the last output
                    = P #set number of variables to P
     mysrn model = keras.models.Sequential([
         keras.layers.SimpleRNN(numunits, return_sequences=True, input_shape=[None,nvar]),
         keras.layers.SimpleRNN(numunits),
         keras.layers.Dense(1,activation='linear')])
     # keras.layers.TimeDistributed(keras layers.Dense(1 activation='sigmoid'))]) for pred at each step
[13]:
     mysrn model.summary()
     Model: "sequential"
                                                                          First RNN layer outputs 3D
                                 Output Shape
     Layer (type)
                                                          Param #
                                                                          tensor
     simple rnn (SimpleRNN)
                                 (None, None, 128)
                                                          16768
                                                                          Second RNN layer outputs
     simple rnn 1 (SimpleRNN)
                                 (None, 128)
                                                          32896
                                                                          2D tensor
                                 (None, 1)
                                                          129
     dense (Dense)
     Total params: 49,793
     Trainable params: 49,793
                                                                          Last layer is class output
     Non-trainable params: 0
```



#### **Exercise**

- 1 Run the script
- 2. Run with different number-of-1's in binary variable or different ttime steps
- 3. Try different number of hidden units and/or layers
- 4. Compare LSTM and/or GRU

```
keras.layers.GRU( ..... keras.layers.LSTM( ......
```

```
inumepochs=100

my_model=mysrn_model #<<<<<<---- you can change the model here and run these cells #my_model=mygru_model

my_model.compile(optimizer='adam', #or just use 'adam' to get defaults</pre>
```