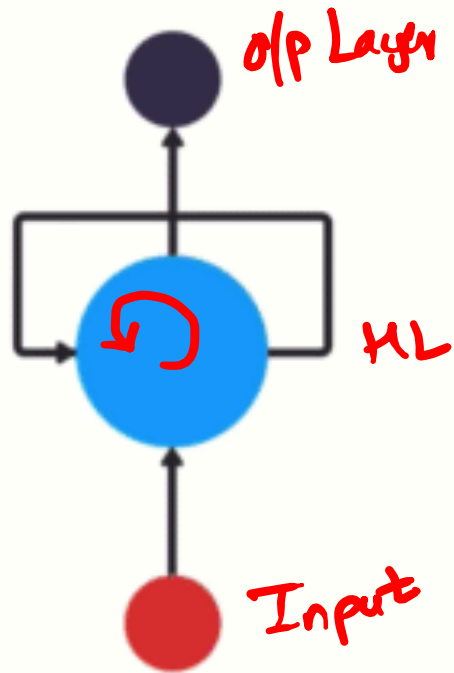


DEEP LEARNING – Recurrent Neural Network

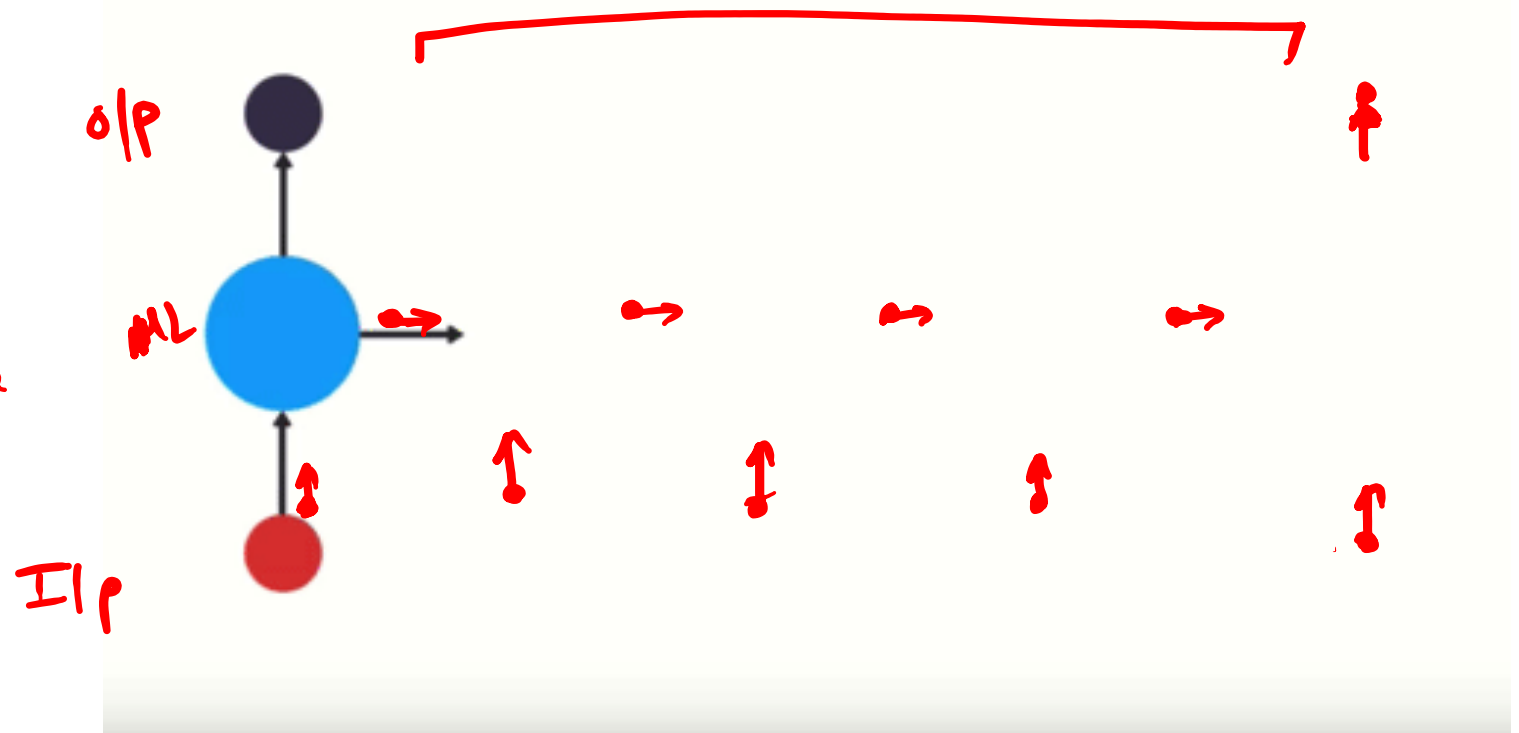
Trainer: Dr. Darshan Ingle.



Recurrent Neural Network



Unroll
→
are
same



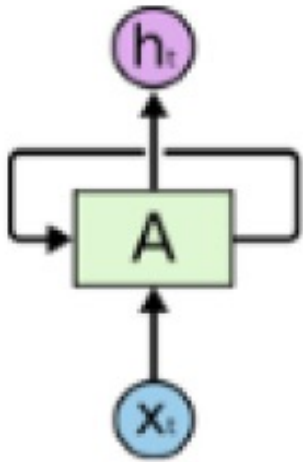
Recurrent Neural Network (RNN)

Humans don't start thinking from scratch every second.

Our thoughts have persistence.

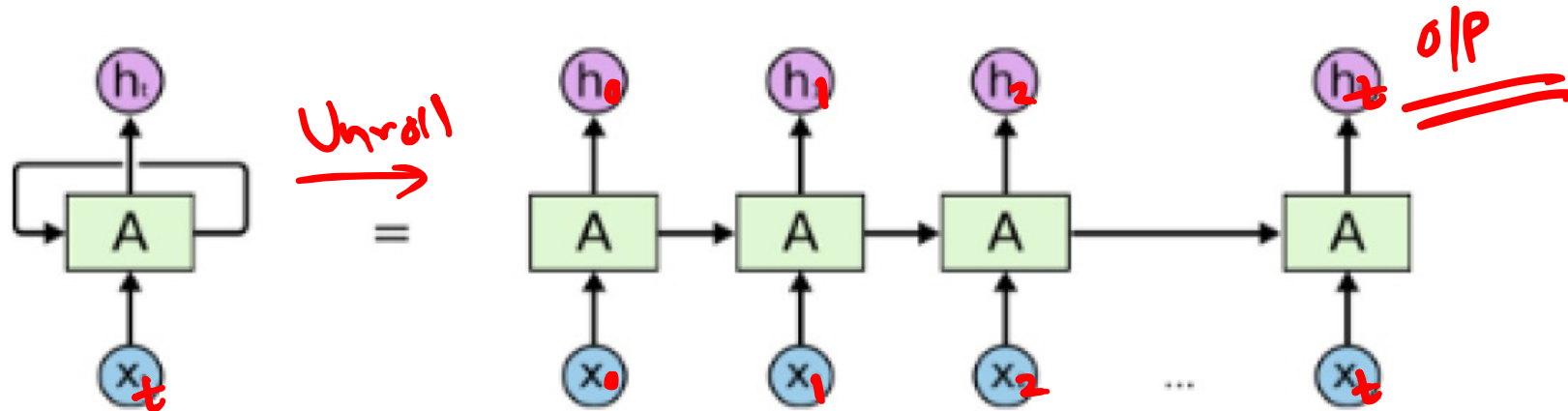
eg: What kind of event is happening at every point in a movie.

RNN can address this issue -



loop (they allow info. to persist)

RNN



An unrolled recurrent neural network.

Why RNN?

Sequence: It is a stream of data (finite/infinite) which are interdependent.
eg: Time Series, Conversation, informative pieces of strings, etc.

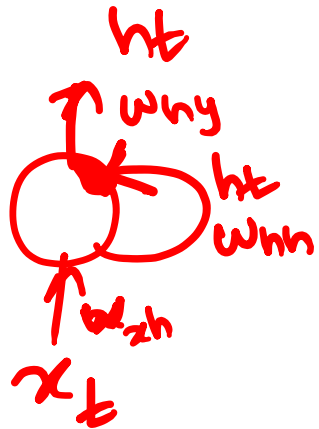
Why not CNN? Why go to RNN?

Soln: CNN don't perform well when input data is interdependent in a sequential pattern.
∴ all the outputs are self dependent.

Example

Predict what is the next letter, after a sequence of letters.

N A M A S T E
1 2 3 4 5 6 7 8th



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

where h_t = new state

h_{t-1} = previous state

x_t = input at time t .

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

$$y_t = w_{hy} \cdot h_t$$

Example

RNN Types

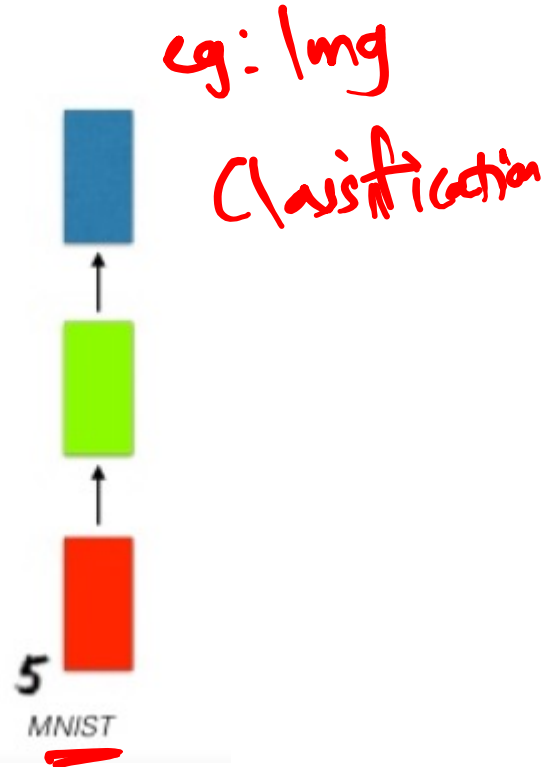
Each rectangle is a vector.

Arrows represents functions (eg: Mat. Mult.)

Input vectors → Red

O/P vectors → Blue

RNN State → Green.



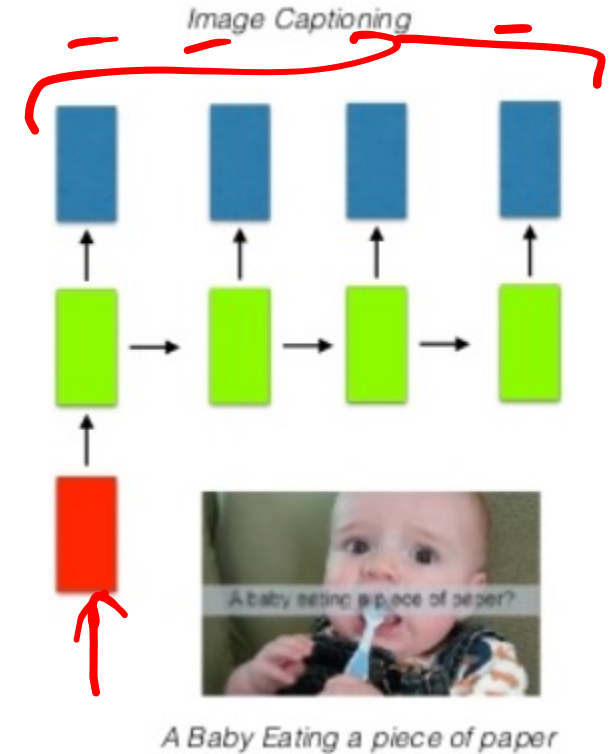
① One to One: Vanilla mode of processing w/o RNN.

from fixed sized ip to fixed size o/p

RNN Types

2. One to Many: Sequence o/p.

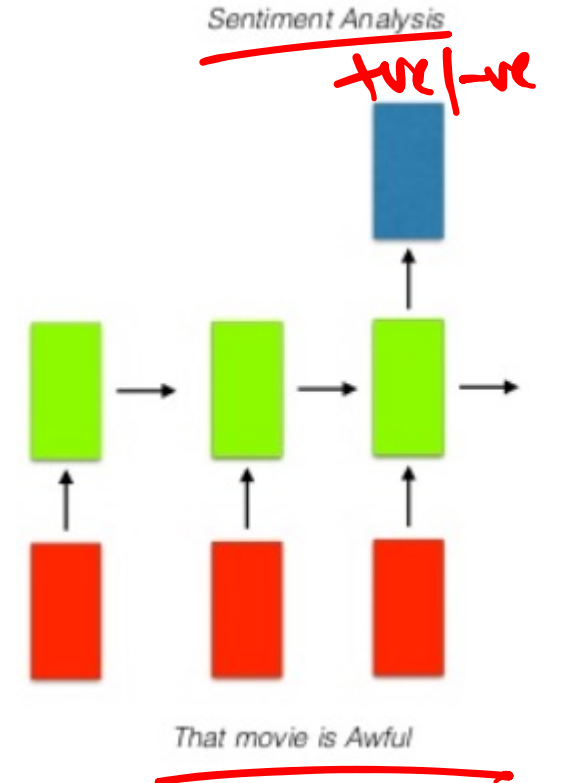
eg: Img Captioning



RNN Types

3. Many to One: Seq. input

eg: Sentiment analysis



RNN Types

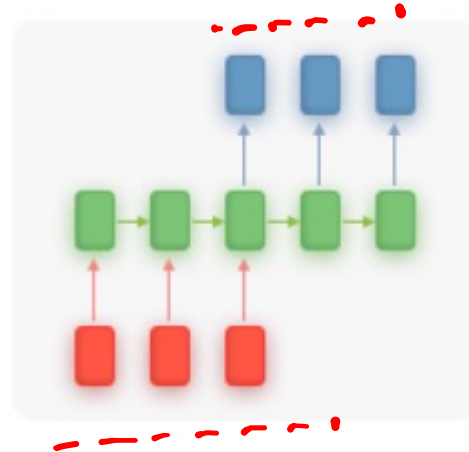
4.) Many to Many

a.) Seq. input

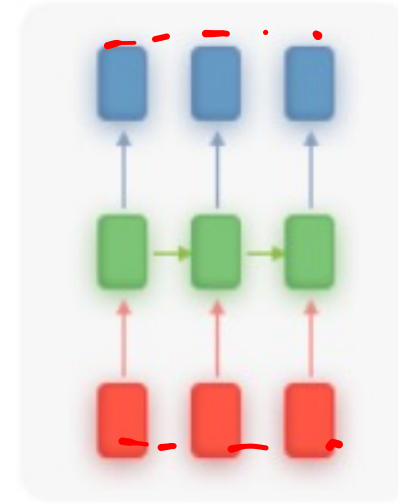
Seq. output

eg: MLC

Translation.



Many to many



b.) Synched

Seq. input

Seq. O/P

eg: Video

Classification.

Why RNN?

NLP: Input Data

Used popularly used in NLP Problems



processed $X = \text{Text format}$
 $X = \text{Number format}$ } preprocessing
 + Bag of Words
 (Count Vectorizer)
 Naive Bayes Algo.

eg: 0 - I love playing
 1 - we love playing cricket
 2 - Playing is fun.
 Preprocess: ↓ lower, rem. stopwords,
 ↓ apply stemming

0 - love play
 1 - love play cricket
 2 - play fun

0 love play
 1 love play cricket
 2 play fun

	love	play	cricket	fun
0	1	1	0	0
1	1	1	1	0
2	0	1	0	1
<u>Sum:</u>	2	3	1	1

Desc. order.

Seq. info is lost.

	play	love	cricket	fun
0	1	1	0	0
1	1	1	1	0
2	1	0	0	1

0 - I love playing $\rightarrow \begin{bmatrix} 1 & 1 & 0 & 0 \end{bmatrix}$
 1 - we love playing cricket $\rightarrow \begin{bmatrix} 1 & 1 & 1 & 0 \end{bmatrix}$
 2 - Playing is fun $\rightarrow \begin{bmatrix} 1 & 0 & 0 & 1 \end{bmatrix}$

Why RNN?

Summary

Summary

Red Ink: FP

Blue Ink: BP

FP to HL: w_{xh} , HL to HL: w_{hh} , HL to OP: w_{hy} .

$$\frac{\partial L}{\partial w_{hy}} = \frac{\partial L}{\partial g} \cdot \frac{\partial g}{\partial w_{hy}}$$

$$w_{hy \text{ new}} = w_{hy \text{ old}} - \eta \cdot \frac{\partial L}{\partial w_{hy \text{ old}}}$$

$$\frac{\partial L}{\partial w_{xh}} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial o_4} \cdot \frac{\partial o_4}{\partial w_{xh}}$$

$$w_{xh \text{ new}} = w_{xh \text{ old}} - \frac{\partial L}{\partial w_{xh}}$$

$\frac{\partial L}{\partial g}$ can be computed directly w/o chain rule.



$$o_1 = f[(x_0 \cdot w_{xh} + b_{xh}) + (o_0 \cdot w_{hh} + b_{hh})]$$

$$o_2 = f[(x_1 \cdot w_{xh} + b_{xh}) + (o_1 \cdot w_{hh} + b_{hh})]$$

$$o_3 = f[(x_2 \cdot w_{xh} + b_{xh}) + (o_2 \cdot w_{hh} + b_{hh})]$$

$$\hat{y} = f[o_5 \cdot w_{hy} + b_{hy}]$$

RNN Architecture (Fwd Prop over Time)

RNN Architecture (Fwd Prop over Time)

RNN Architecture (Back Prop over Time)

RNN Architecture (Back Prop over Time)

Problems with RNN

① $\tanh : [-1, +1]$
Der. of $\tanh : [0, 1]$ } Vanishing Gradient Problem.
- * - * - * ... = very small gradient

Exploding Gradient Problem
- caused due to hugely assigned
weights