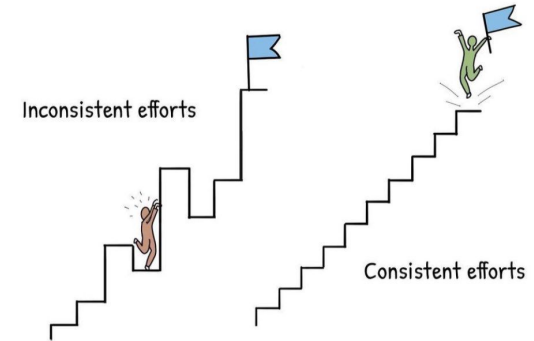


# Deep Sequence Modelling

B.Tech. Data Science, NMIMS

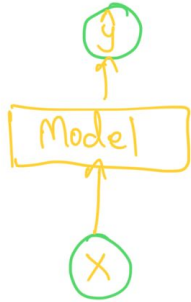
By,

Bilal Hungund, Data Scientist, Halliburton

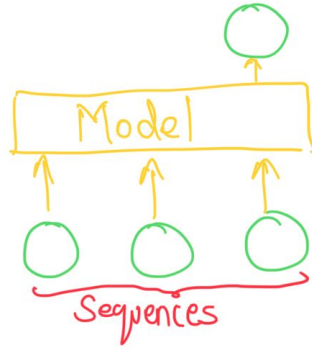


# Sequencing Modelling Applications

One to one  
(Classification)  
(Regression)

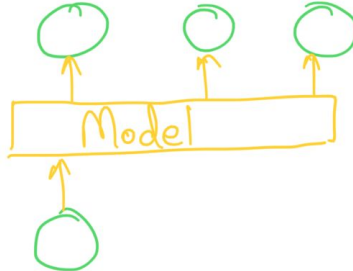


Many to One  
(Sentimental Analysis)



ScanNet uncovers binding motifs in protein structures with deep learning | Nature Methods  
[nature.com/articles/s41599-021-00159-0](https://www.nature.com/articles/s41599-021-00159-0)  
#DeepLearning

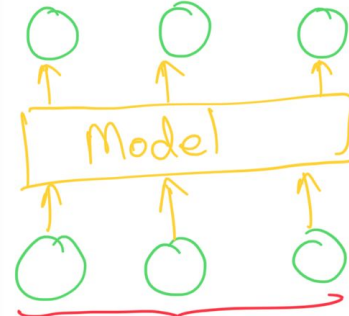
One to Many  
(Image Captioning)



Cat is sleeping



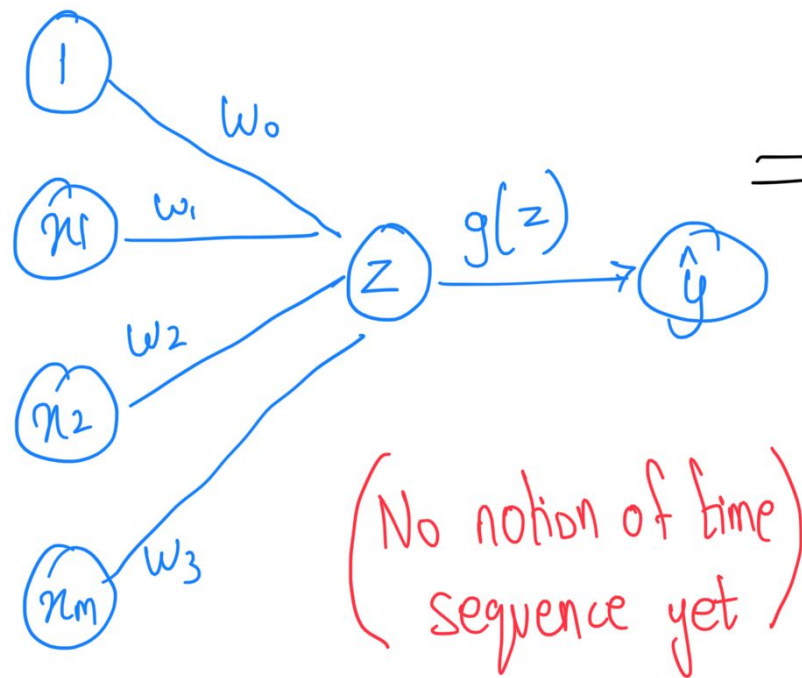
Many to Many  
(Language Modelling)



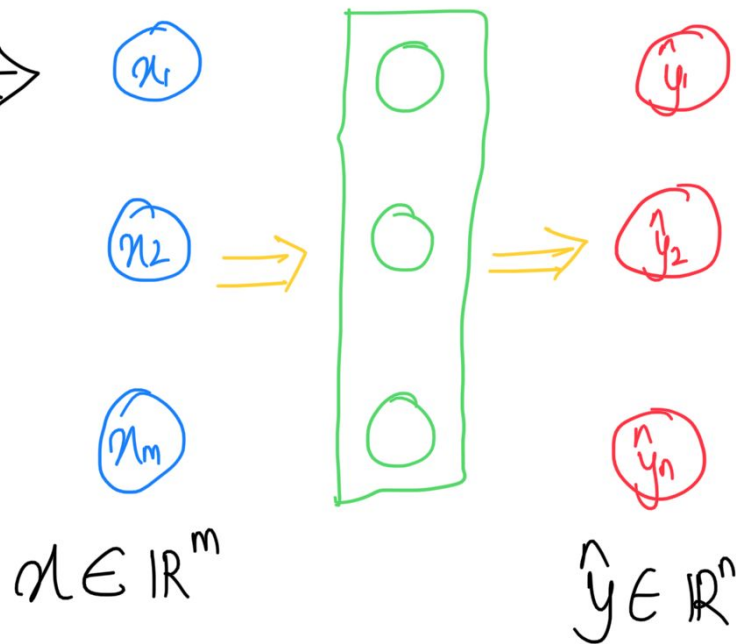
Temporal Space

English to Hindi  
Text

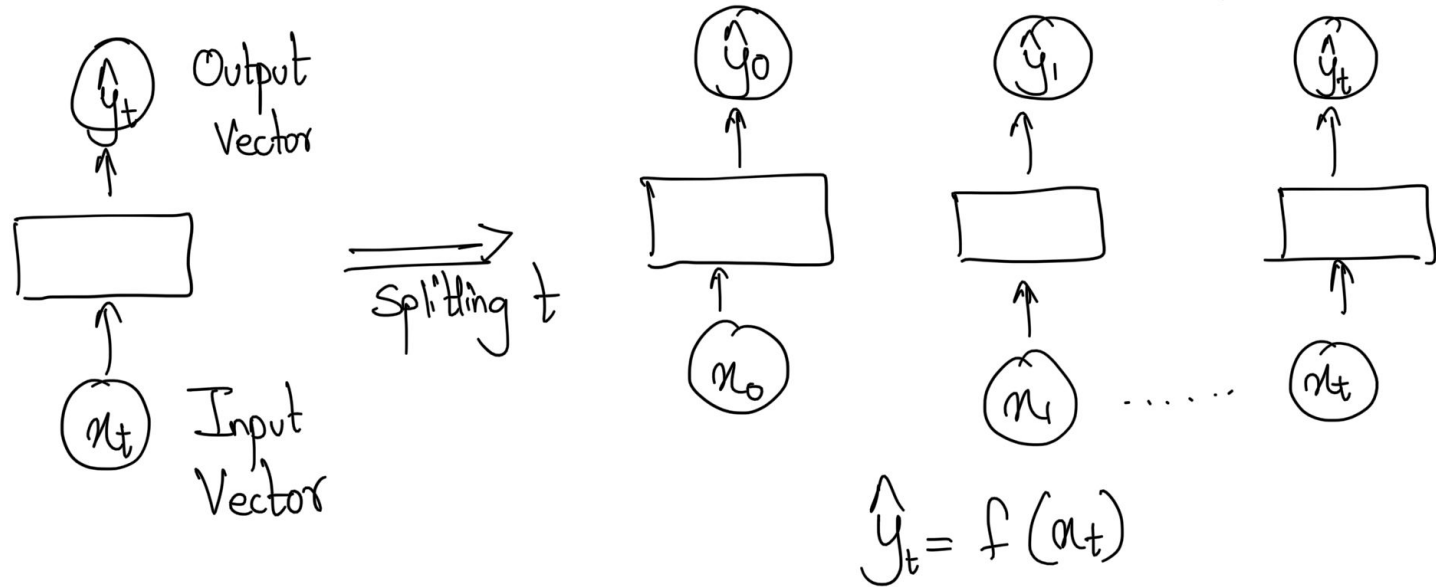
# Perceptrons Revisited



## Feed Forward Models

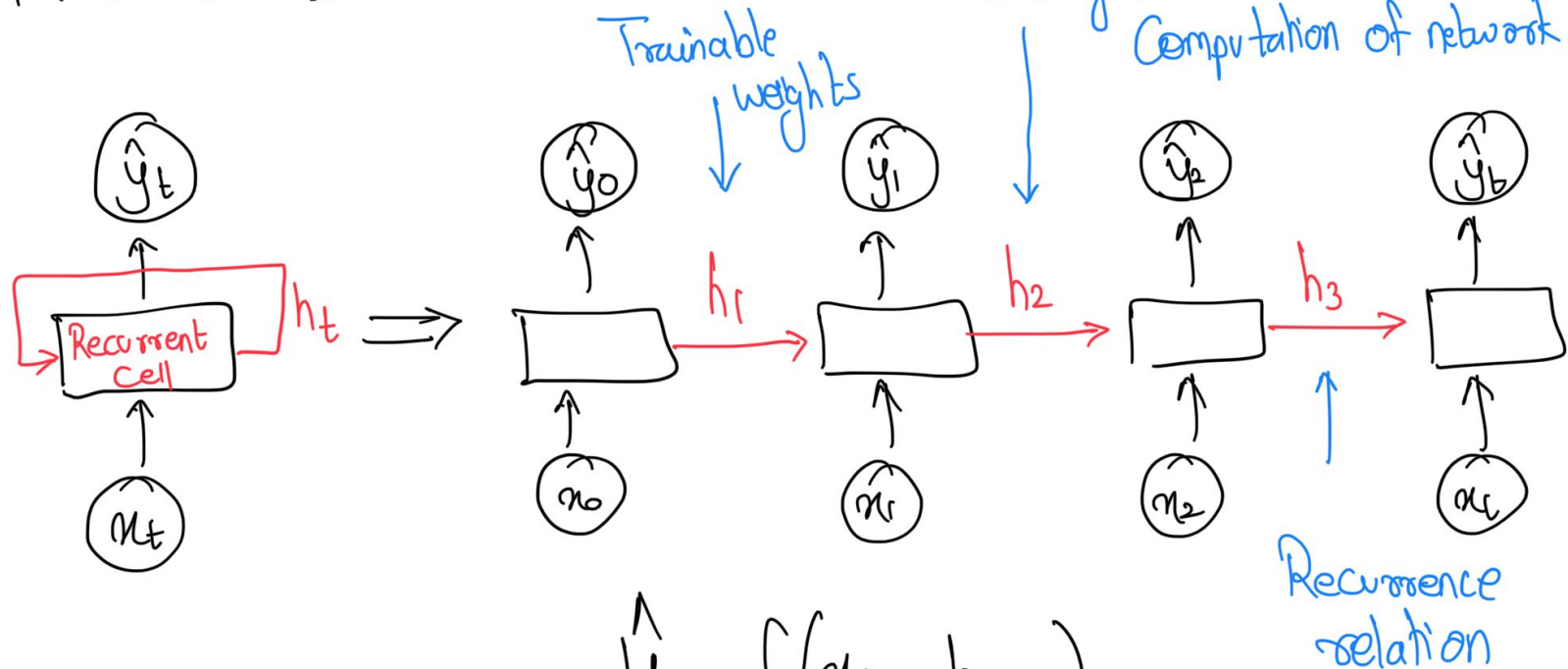


Handling with time steps (How to relate network computations?)  
Need some prior history



No interdependence or interconnectedness added yet

# Neurons with Recurrence



$$\hat{y} = f(x, h_{t-1})$$

Output      Input      past memory

# Recurrent Neural Networks (RNNs)

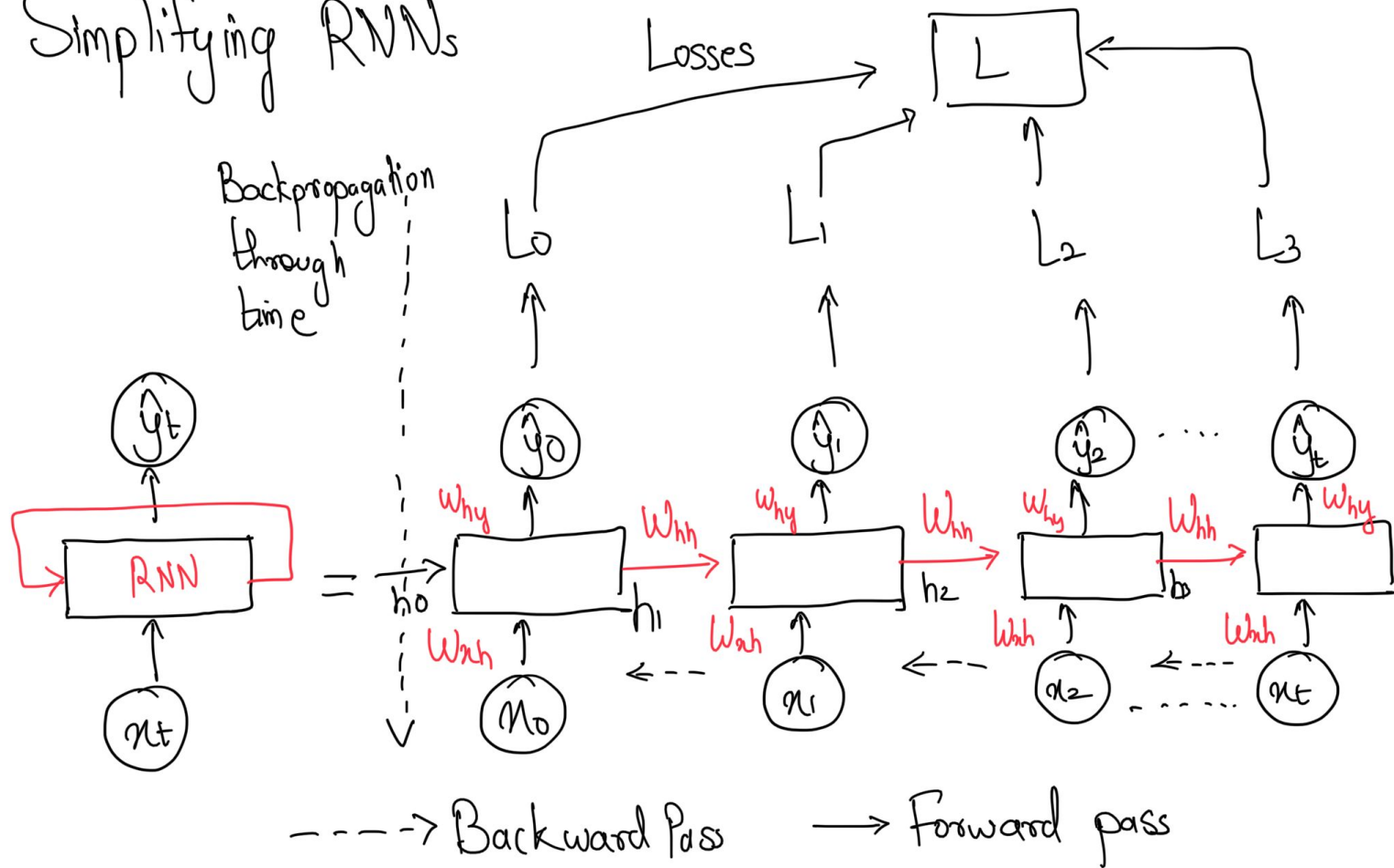
→ RNNs have a state  $h_t$ , that is updated at each time steps as a sequence

i.e.,

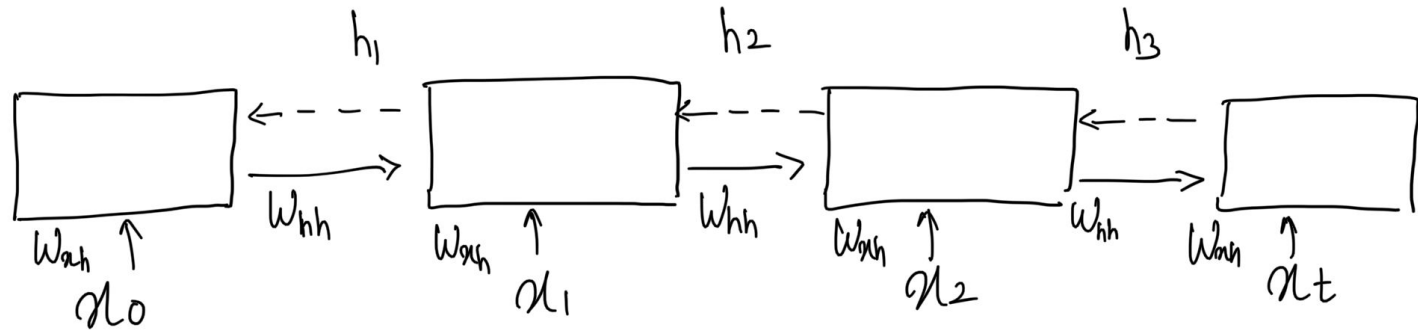
$$\underbrace{h_t}_{\text{cell state}} = \underbrace{f_w}_{\text{weight}} (\underbrace{x_t}_{\text{inputs}}, \underbrace{h_{t-1}}_{\text{old state}})$$

Input Vector	Update Hidden State	Output Vector
$x_t$	$h_t = \tanh(W_{hh}^T h_{t-1} + W_{xh}^T x_t)$	$\hat{y}_t = W_{hy}^T h_t$

# Simplifying RNNs



# Gradient issues



→ Exploding gradients (values  $> 1$ )

→ Gradient Clipping: Scale big gradients

→ Vanishing gradients (values  $< 1$ )

→ Activation Function, Weight initialization, Network architecture



→ Focusing on short-term dependencies and ignoring long term dependencies

Short term dependencies  
I love neural ?  
(network)

Ignorance  $\Rightarrow$

I studied data science and  
I am fluent in ?  
(ML, DL, ...)

→ Use of ReLU function as it prevents shrinking the gradients when  $x > 0$

→ Weight Initialization:

Initialize bias to zero and weights to identity matrix  
It prevents the weights from shrinking to zero

$$I_n = \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & & 0 \\ \vdots & & \ddots & \\ 0 & 0 & & 1 \end{bmatrix}$$

→ Gated Cells: (LSTM)

# Network Architecture

Use gates to add or remove information within each recurrent unit and to track information

# Design Criteria of RNNs

- Handle variable-length sequences
- Track long term dependencies
- Maintain order of information
- Sharing parameters

# Goals of Sequence Modelling

- Continuous stream
- Parallelization
- Long Memory

# Limitations of RNNs

- Encoding bottleneck
- Slow, no parallelization
- Not long memory

# NLP using RNN

## Tokenization, pad Sequences and Embeddings

F L O W  
001 002 003 004

Characters Tokens

W O L F  
004 003 002 001

Corpus/Vocabulary

I love neural network  
001 002 003 004

I love deep learning  
001 002 005 006

Sequences

$\begin{bmatrix} [001, 002, 003, 004] \\ [001, 002, 005, 006] \end{bmatrix}$

## Tokenization, pad Sequences and Embeddings

building vocabulary

I love neural network

I love deep learning

You love neural network

Do you think deep learning is good?

Tokens

love-1, i-2, you-3,  
neural-4, network-5,  
deep-6, learning-7,  
do-8, think-9, good-10  
is-11

Sequences

pad  
Sequences

$\begin{bmatrix} 2 & 1 & 4 & 5 \end{bmatrix}$

$\begin{bmatrix} 2 & 1 & 6 & 7 \end{bmatrix}$

$\begin{bmatrix} 3 & 1 & 4 & 5 \end{bmatrix}$

$\begin{bmatrix} 8 & 3 & 9 & 6 & 7 & 11 & 10 \end{bmatrix}$

$\begin{bmatrix} 0 & 0 & 0 & 2 & 1 & 4 & 5 \\ 0 & 0 & 0 & 2 & 1 & 6 & 7 \\ 0 & 0 & 0 & 3 & 1 & 4 & 5 \\ 8 & 3 & 9 & 6 & 7 & 11 & 10 \end{bmatrix}$

Pass to  
Embeddings