#### **Stochastic Process**

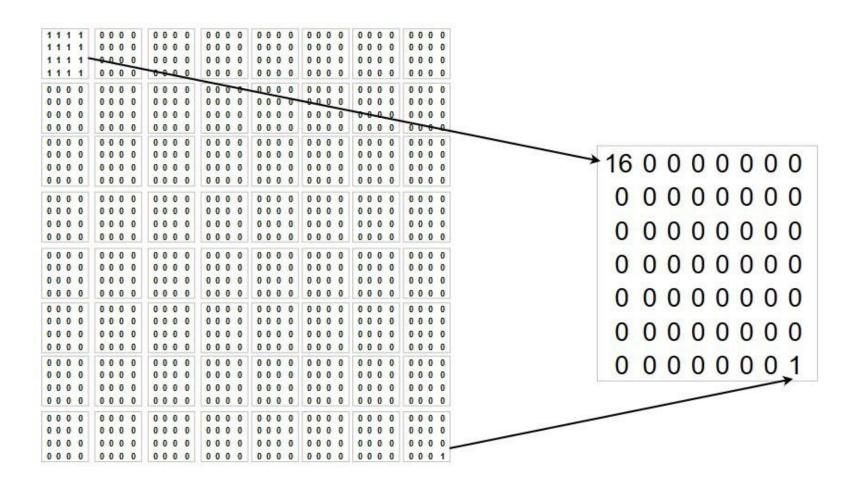
# Markov Recurrent Neural Networks

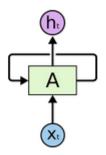
Handwriting Recognition

Ridho Gani Ferlinda Feliana A.R Duto Pamungkas **MNIST** 

8 8 

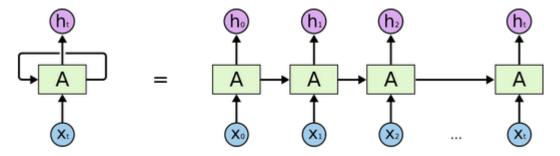
**MNIST** 





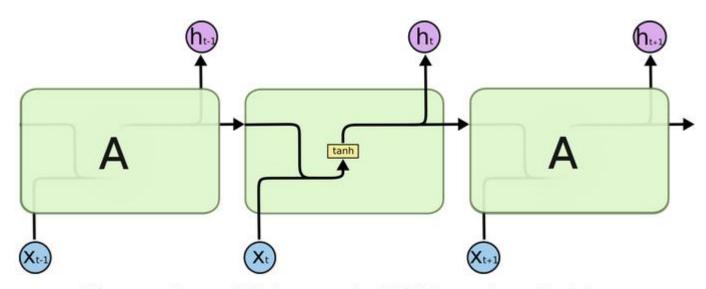
Recurrent Neural Networks have loops.

# RNN

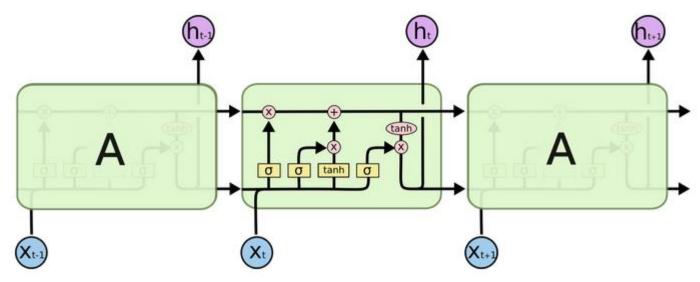


An unrolled recurrent neural network.

# LSTM

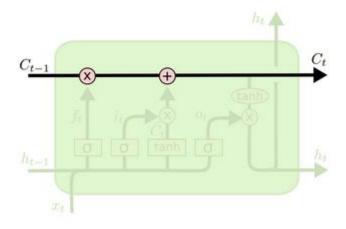


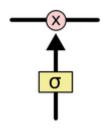
The repeating module in a standard RNN contains a single layer.

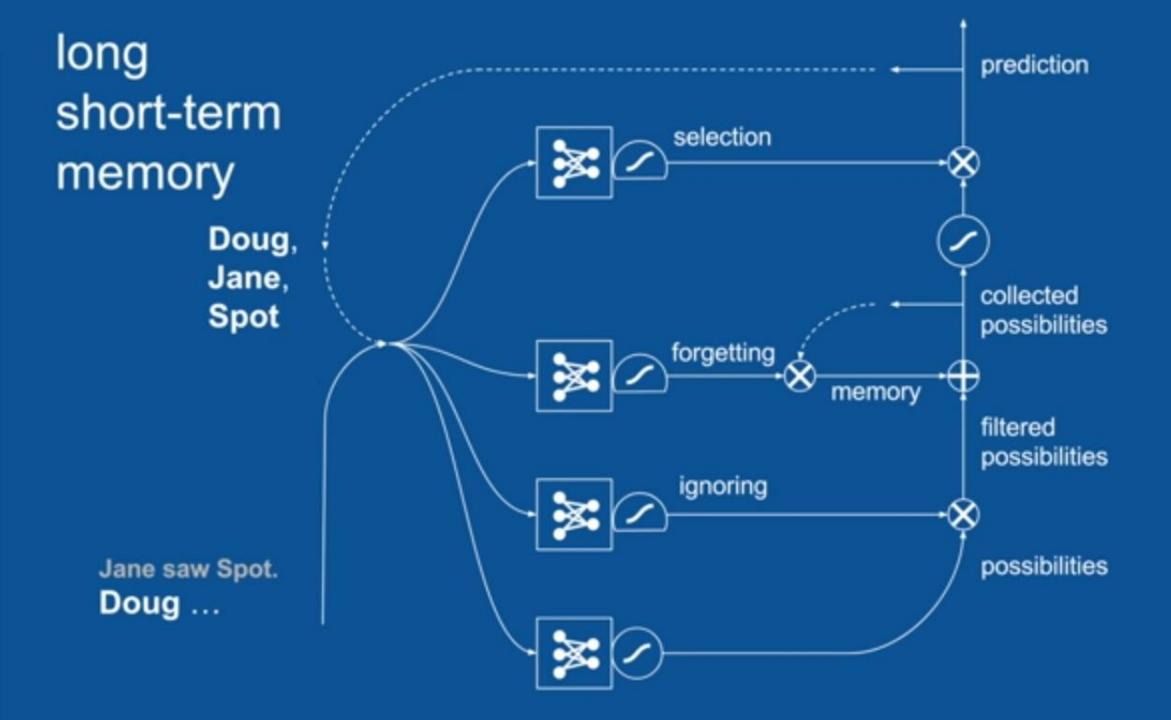


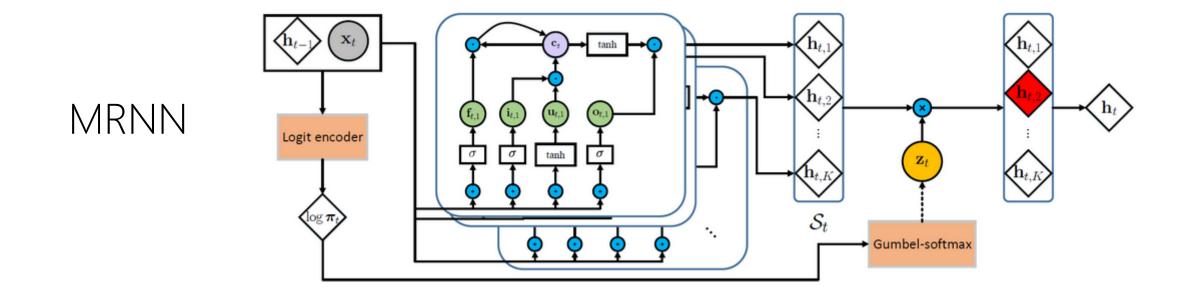
The repeating module in an LSTM contains four interacting layers.

LSTM Key: cell states









## MARKOV CHAIN

MRNN is constructed with a state space which allows stochastic transition among multiple states  $\{ht1, \dots, htK\}$  at each time t. Transition of a stochastic state zt in MRNN complies with the property of Markov chain

$$p(\mathbf{z}_t|\mathbf{z}_{1:t-1},\mathbf{x}_{1:t}) = p(\mathbf{z}_t|\mathbf{z}_{t-1},\mathbf{x}_t).$$

The probability of choosing a state  $\mathbf{z}_t$  depends only on previous state  $\mathbf{z}_{t-1}$  and current input  $\mathbf{x}_t$ .

## MARKOV CHAIN

Stochastic state variable  $zt = \{ztk\}Kk = 1$  consisting of binary indicator  $ztk \in \{0, 1\}$  for each state k. The state space at each time t consists of all deterministic states  $\{ht1, \ldots, htK\}$  as basis vectors

$$\mathcal{S}_{t} \triangleq \begin{bmatrix} \mathbf{h}_{t1}^{\top} \\ \mathbf{h}_{t2}^{\top} \\ \vdots \\ \mathbf{h}_{tK}^{\top} \end{bmatrix} = \begin{bmatrix} \text{LSTM}(\mathbf{h}_{t-1}, \mathbf{x}_{t}, \boldsymbol{\Theta}_{1}) \\ \text{LSTM}(\mathbf{h}_{t-1}, \mathbf{x}_{t}, \boldsymbol{\Theta}_{2}) \\ \vdots \\ \text{LSTM}(\mathbf{h}_{t-1}, \mathbf{x}_{t}, \boldsymbol{\Theta}_{K}) \end{bmatrix}$$

Each hidden state htk is encoded by an individual LSTM using the previous state ht-1, the current input xt and the corresponding parameters  $\Theta k$ .

# MARKOV CHAIN

For simplify this problem, let's look this one

 $[next\ state] = [matrix\ of\ transition\ probabilities][current\ state]$ 

$$\begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} x0 & y0 & z0 \\ x1 & y1 & z1 \\ x2 & y2 & z2 \end{bmatrix} \begin{bmatrix} A \\ B \\ C \end{bmatrix}$$

$$\begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} x0 & y0 & z0 \\ x1 & y1 & z1 \\ x2 & y2 & z2 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

Pixel

X Y Z

**Transition Probability** 

X X X0
X Y Y0
X Z Z0
Y Y Y1
Y X X1
Y Z Z1
Z Z Z2
Z Y Y2
Z X X2

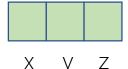
next state

matrix of transition probabilities

current state

$$\begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} x0 & y0 & z0 \\ x1 & y1 & z1 \\ x2 & y2 & z2 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

Pixel



**Transition Probability** 

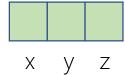
Χ	Χ	80%
Χ	Υ	10%
Χ	Z	10%
Υ	Υ	70%
Υ	Χ	20%
Υ	Z	10%
Z	Z	60%
Z	Υ	30%
Z	Χ	10%

next state

current state

$$\begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} x0 & y0 & z0 \\ x1 & y1 & z1 \\ x2 & y2 & z2 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

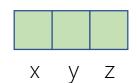
Pixel



**Transition Probability** 

From	То	value
Χ	Χ	80%
Χ	Υ	10%
Χ	Z	10%
Υ	Υ	70%
Υ	Χ	20%
Υ	Z	10%
Z	Z	60%
Z	Υ	30%
Z	Χ	10%

Pixel



Then, value for each pixel are (value of pixel are determined by how much the ink fill that pixel) For this example,

Pixel x = 200Pixel y = 120

Pixel z = 180

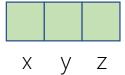
next state

matrix of transition probabilities

current state

$$\begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} x0 & y0 & z0 \\ x1 & y1 & z1 \\ x2 & y2 & z2 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

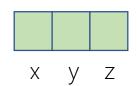
Pixel



**Transition Probability** 

From	То	value
Χ	Χ	80%
Χ	Υ	10%
Χ	Z	10%
Υ	Υ	70%
Υ	Χ	20%
Υ	Z	10%
Z	Z	60%
Z	Υ	30%
Z	Χ	10%

Pixel



Pixel x = 200Pixel y = 120Pixel z = 180

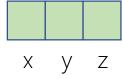
After that, every pixel must be devided by sum of all pixel value to get the probability value of pixel fragment Pixel x = 200/500 = 0.40

Pixel y = 120/500 = 0.24

Pixel z = 180/500 = 0.36

$$\begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} 0.8 & 0.2 & 0.1 \\ 0.1 & 0.7 & 0.3 \\ 0.1 & 0.1 & 0.6 \end{bmatrix} \begin{bmatrix} 0.40 \\ 0.24 \\ 0.36 \end{bmatrix}$$

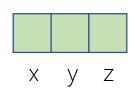
Pixel



**Transition Probability** 

From	То	value
Χ	Χ	80%
Χ	Υ	10%
Χ	Z	10%
Υ	Υ	70%
Υ	Χ	20%
Υ	Z	10%
Z	Z	60%
Z	Υ	30%
Z	X	10%

Pixel



Pixel x = 200Pixel y = 120Pixel z = 180

After that, every pixel must be devided by sum of all pixel value to get the probability value of pixel fragment Pixel x = 200/500 = 0.40

Pixel y = 120/500 = 0.24

Pixel z = 180/500 = 0.36

$$\begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} 0.8 & 0.2 & 0.1 \\ 0.1 & 0.7 & 0.3 \\ 0.1 & 0.1 & 0.6 \end{bmatrix} \begin{bmatrix} 0.40 \\ 0.24 \\ 0.36 \end{bmatrix}$$

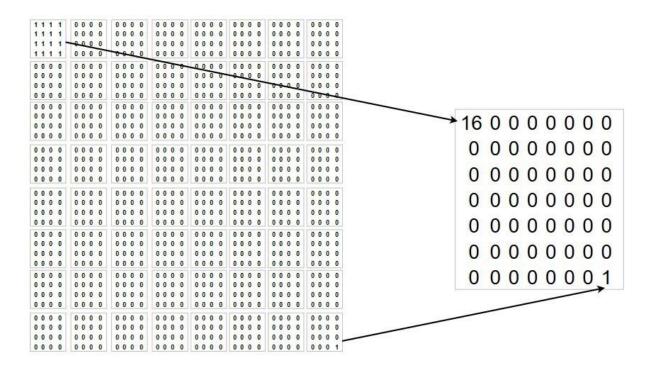
$$\begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} 0.404 \\ 0.316 \\ 0.280 \end{bmatrix}$$

Well done! we get the probability of next state
Then, we can give this next state data to RNN model
to get the prediction what the digit is

$$\begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} 0.8 & 0.2 & 0.1 \\ 0.1 & 0.7 & 0.3 \\ 0.1 & 0.1 & 0.6 \end{bmatrix} \begin{bmatrix} 0.40 \\ 0.24 \\ 0.36 \end{bmatrix}$$
$$\begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} 0.404 \\ 0.316 \\ 0.280 \end{bmatrix}$$

Prediction is based on MNIST dataset. If prediction value equal 1 or almost 1, it means good/accurate.

All this example is looks simply because we only use 3-pixel 😂



And it will become a nightmare when we use real case 64-pixel. That's way, we also use LSTM to determine probability value of next state

## Overall probability of which LSTM being chosen



