

Recurrent Neural Network

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AGENDA

Understanding Sequential Data

Working with Sequential Data

Understanding Recurrent Neural Network

Long Short Term Memory (LSTM)

Working with Time Series Data

Sequence to Sequence Models

Attention Mechanism

Gated Recurrent Unit (GRU)



Understanding Sequential Data

Guess the next word

The Sky is ____?

Exact same words but different meaning

I had fixed my laptop

I had my laptop fixed

Why???

Sequential Data

- Order of data points is important
- Number of data points in a sequence can vary

Example of Sequential Data



Music



Text



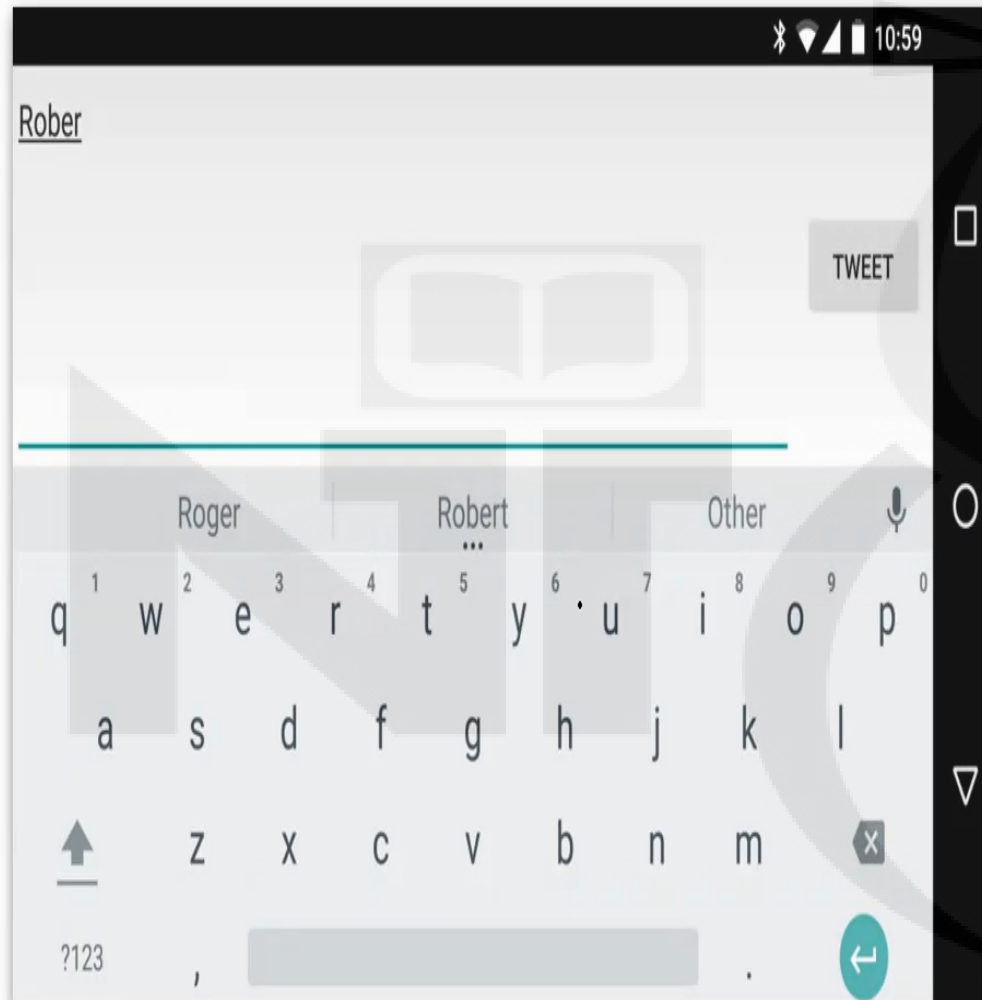
Voice



DNA sequence



Time related data



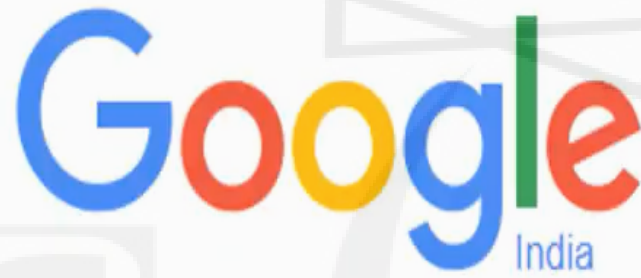
Mobile phone keyboard

Predict next word(s) as we type in...



Convert Speech to Text

e.g Alexa, Siri, Google Home



Recurrent Ne

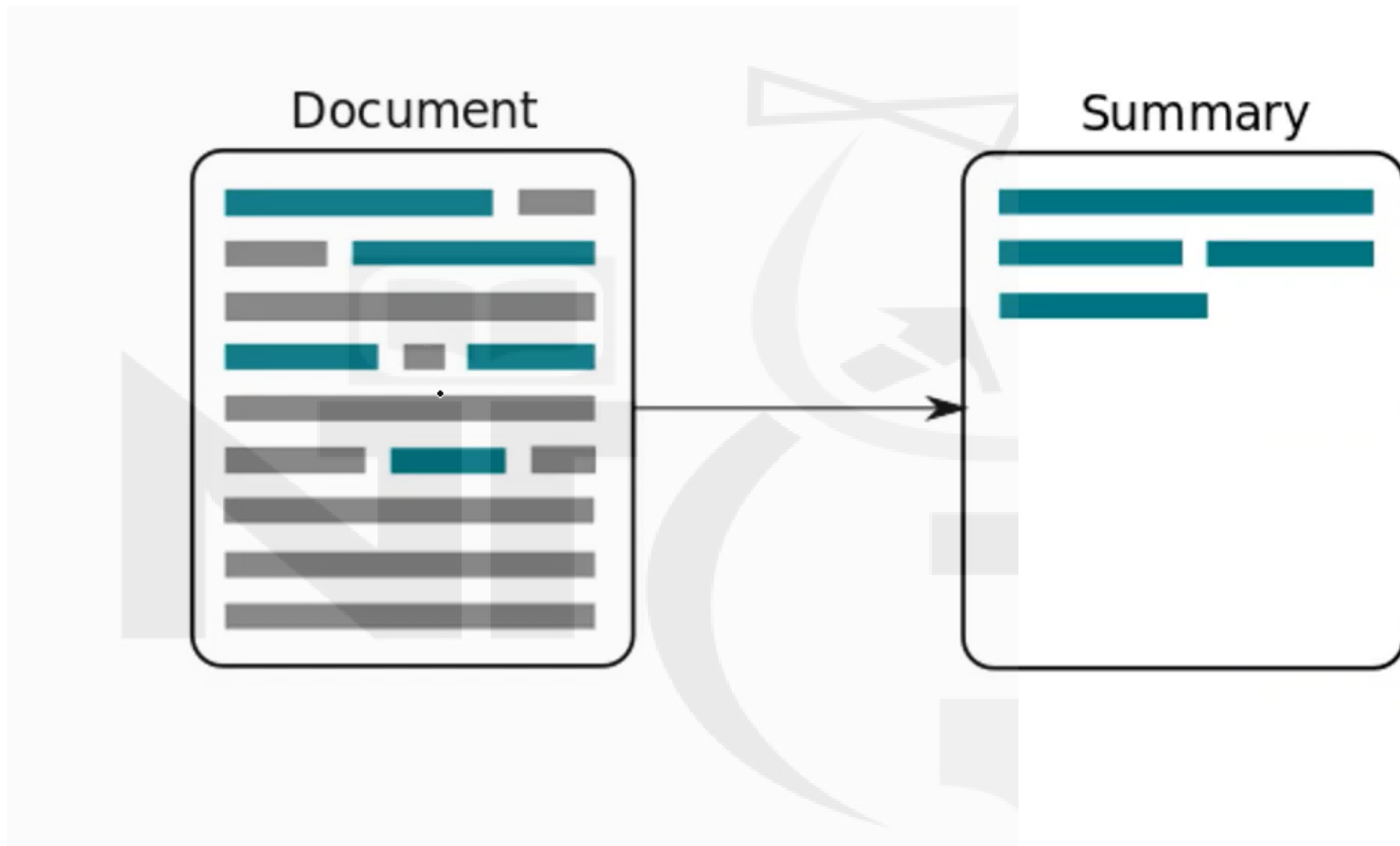


recurrent neural network
recurrent neural network tutorial
recurrent neural network pdf
recurrent neural network example

Google Search

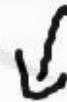
I'm Feeling Lucky

Search suggestions

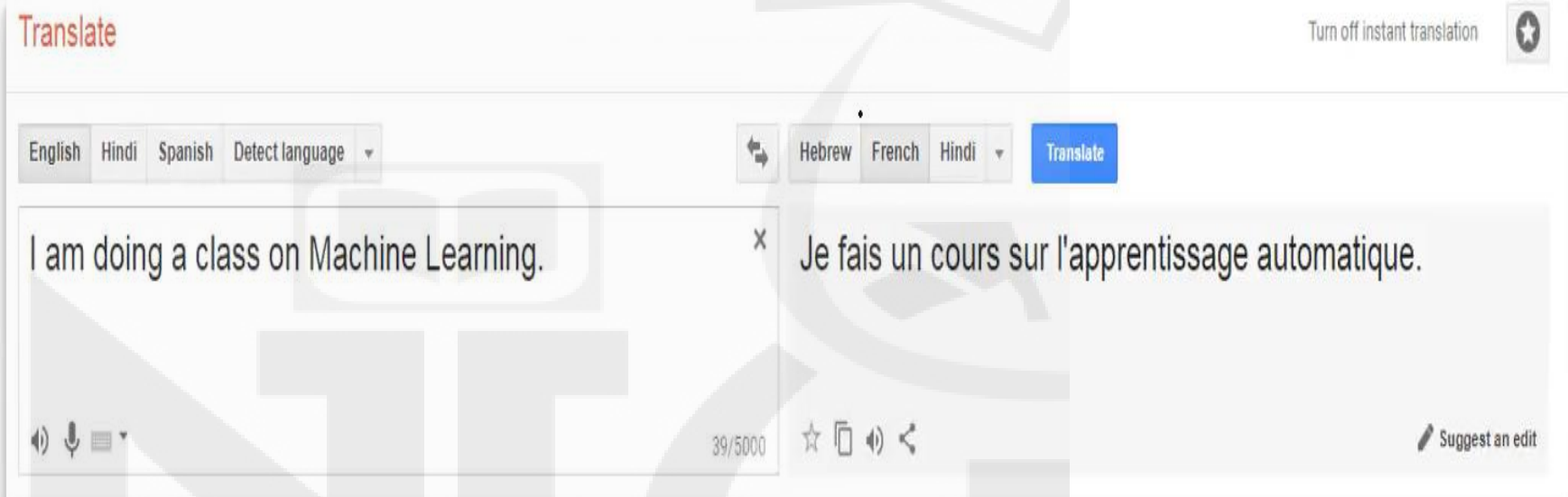


Text Summarization

Describe a picture



Tendulkar playing cricket



Language Translation



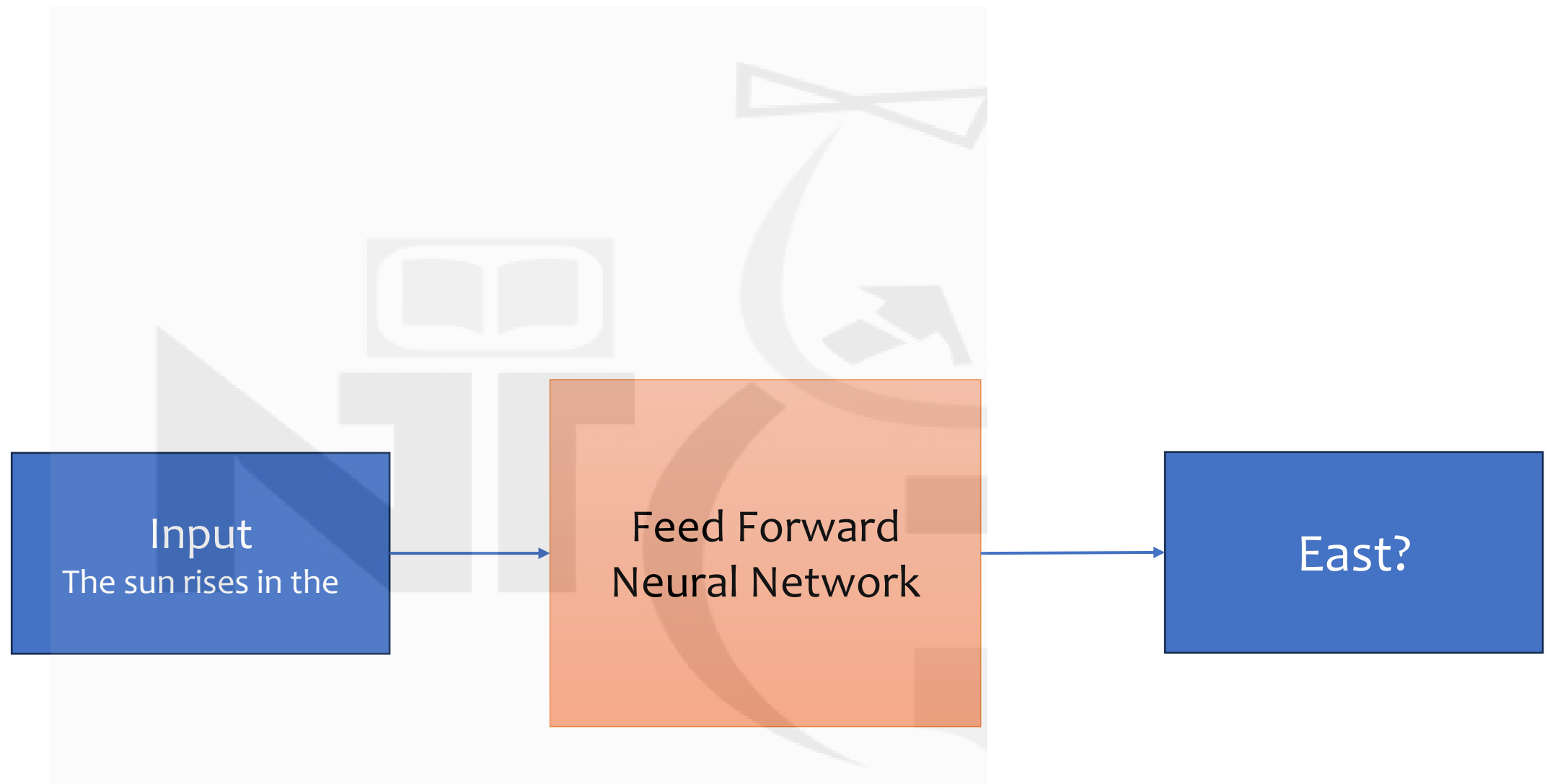
Demand forecasting

How much to build

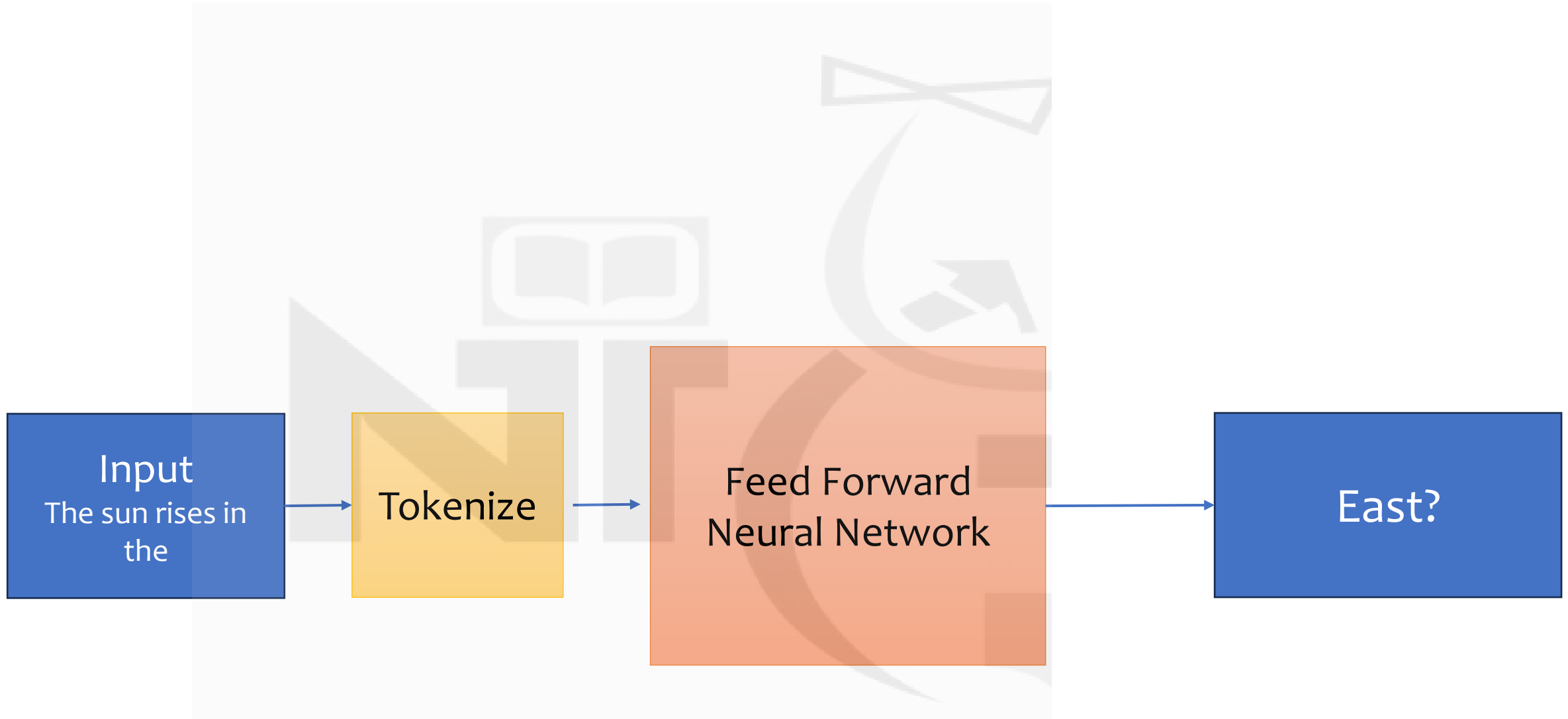
How do we make machine
understand....
Sequential data???



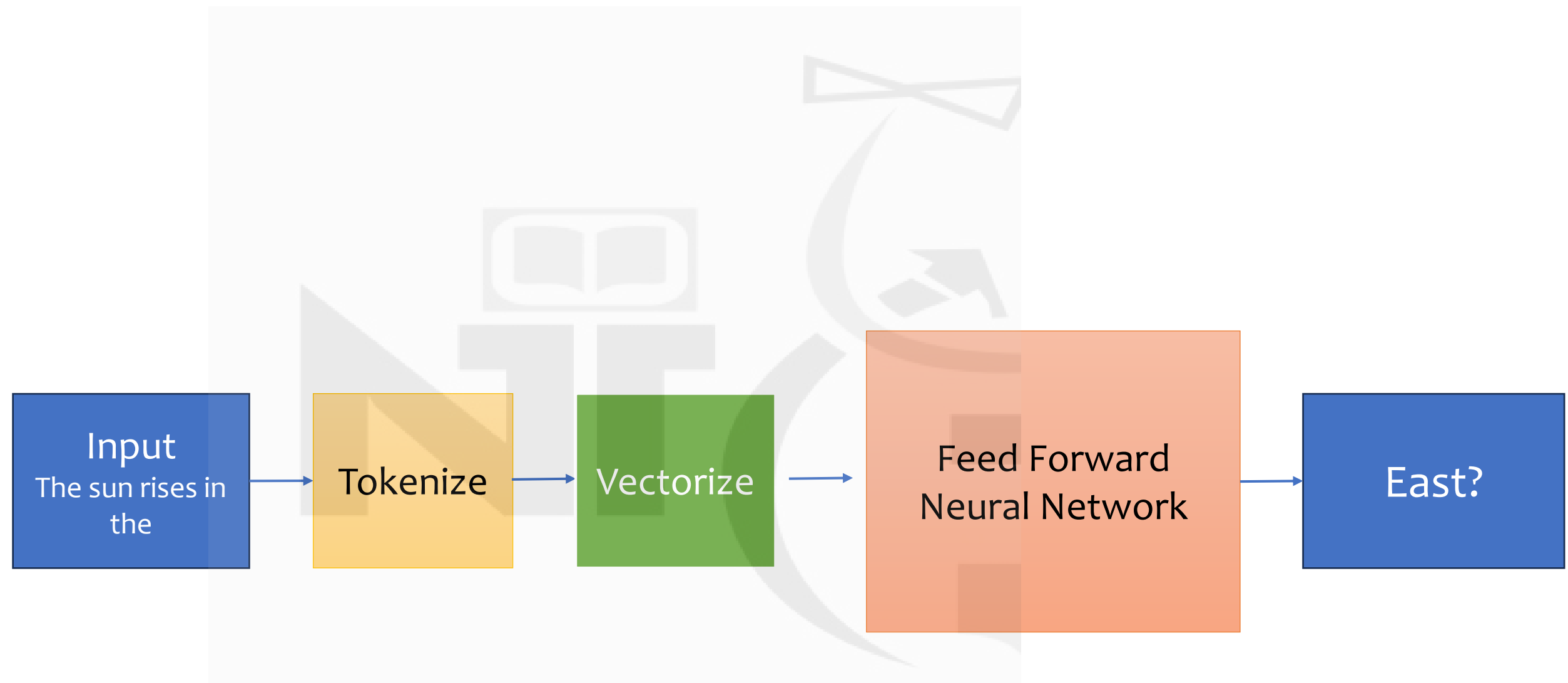
Let's try Word2Vec model



Feed Forward Dense Neural Network



Feed Forward Dense Neural Network



Feed Forward Dense Neural Network

What approaches available for **vectorization**?



What approaches available for **vectorization**?

1. **Count Vectorizer**
2. **TF-IDF**
3. **One hot encoding**
4. **Word2Vec**

What approaches will work with Sequential Data?

1. **Count Vectorizer**
2. **TF-IDF**
3. **One hot encoding**
4. **Word2Vec**

What approaches will work with Sequential Data?

1. Count Vectorizer ✗
2. TF-IDF ✗
3. One hot encoding
4. Word2Vec

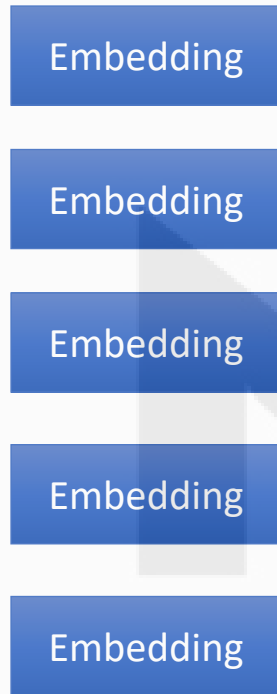
What approaches will work with Sequential Data?

-
- 1. Count Vectorizer **X**
 - 2. TF-IDF **X**
 - 3. One hot encoding
 - 4. Word2Vec → ML Logic
- Human Logic

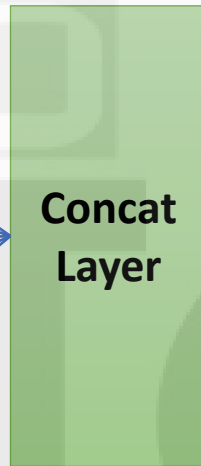
Word2Vec is most popular approach for vectorization of sequential data

Say the Embedding Size is 50

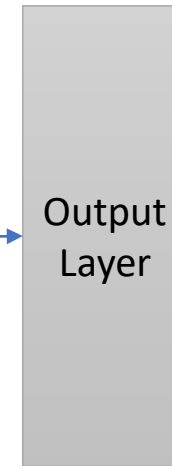
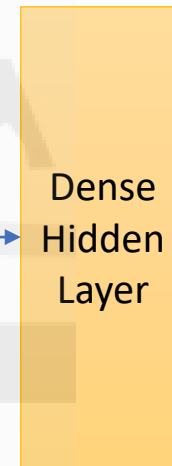
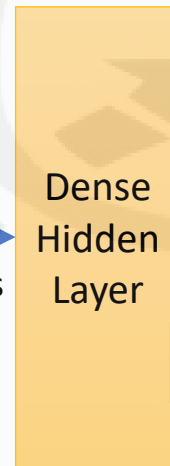
**The
Sun
rises
in
the**



50 numbers from every word



250
numbers



East?

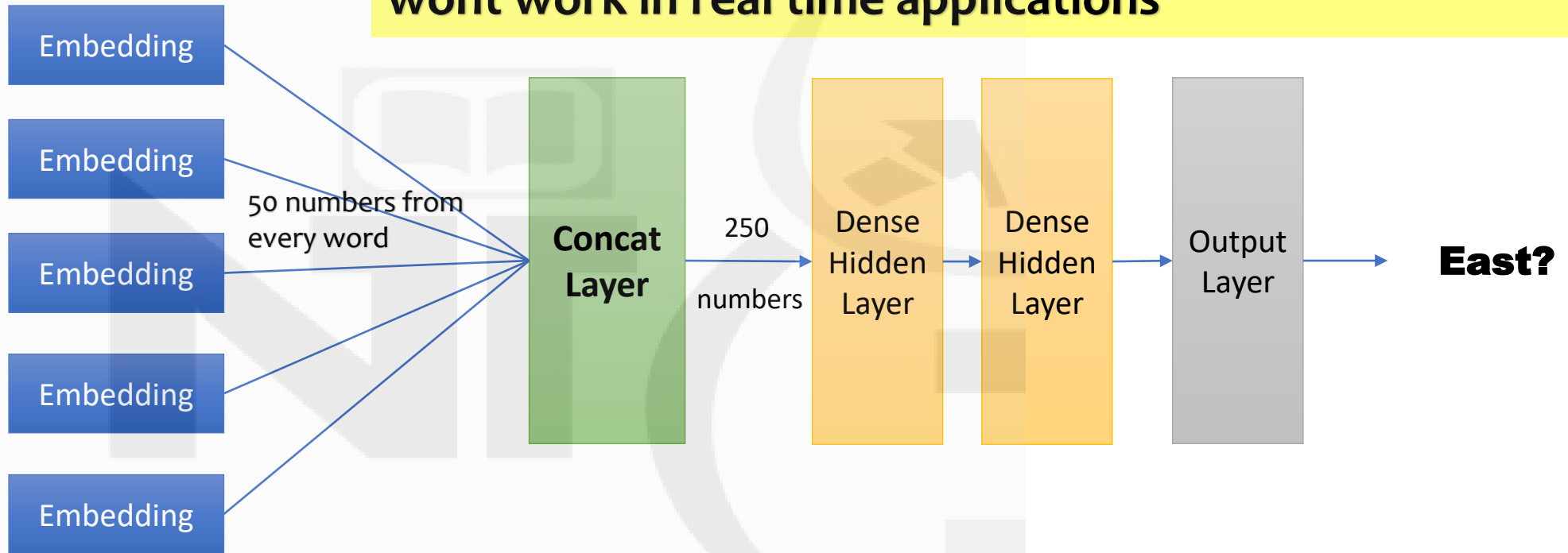
Feed Forward Network

with WordtoVec Embeddings

Say the Embedding Size is 50

When the number of words in the input change, we need to build a new model, this is not a generic model, wont work in real time applications

**The
Sun
rises
in
the**



Feed Forward Network

with Word2Vec Embeddings

We need a new layer ...

- Which can work with sequence of different lengths
- Number of weights should not change with number of inputs (words)

How do we build such a layer?



Why Dense layer uses more weights when sequence length increases?

Because a neuron looks at all the input words (features) in Dense layer at once

How do we solve this?

What if neuron looks at only one word at a time?

And remembers what it has looked so far?

This is the core idea behind RNN

RNN: A new kind of Neural Network

Can Remember Sequences and has memory

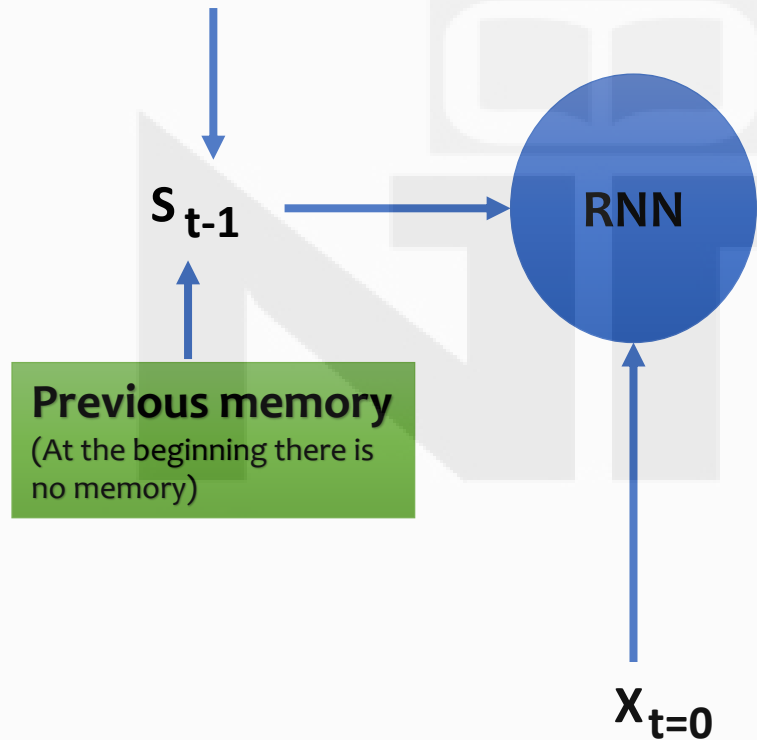


$x_{t=0}$

- RNN only looks at one input (one word) at a time

The input at step $t=0$

RNN uses its memory to
a sequence



RNN only looks at one input
(one word) at a time

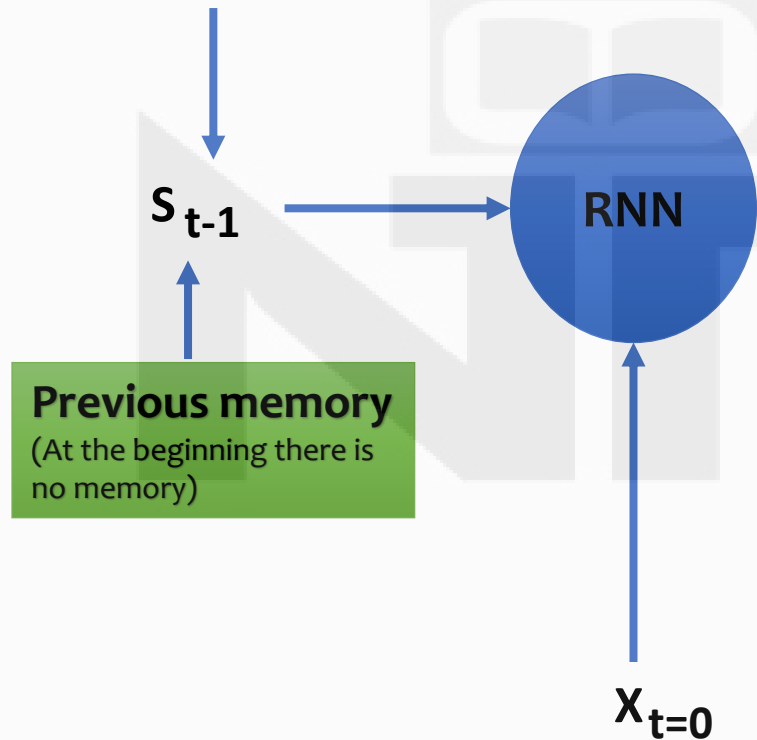
The input at step $t=0$



Now , lets feed the following sequence :

“The sun rises in the “

RNN uses its memory to
a sequence

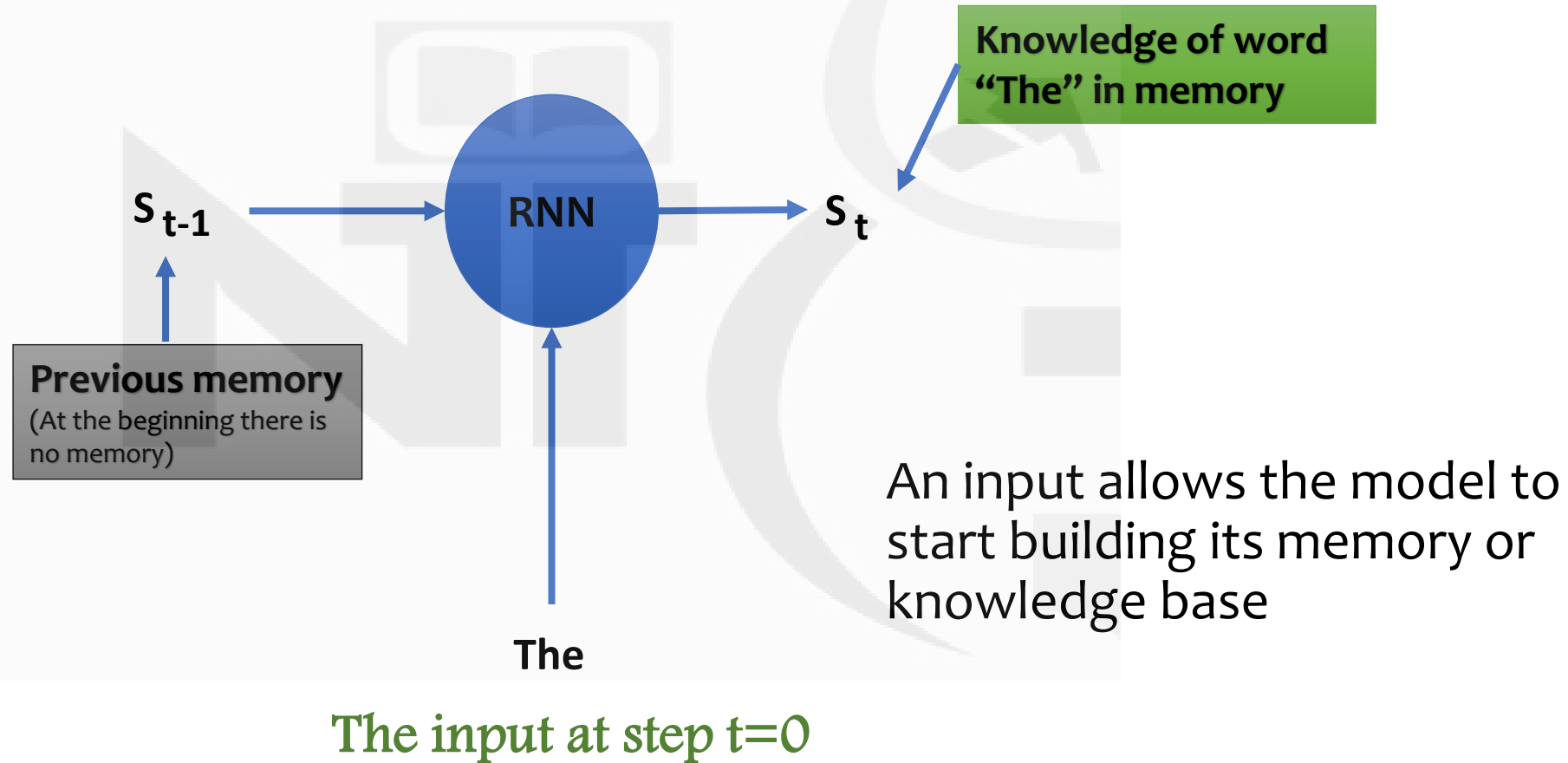


Inputs for RNN:

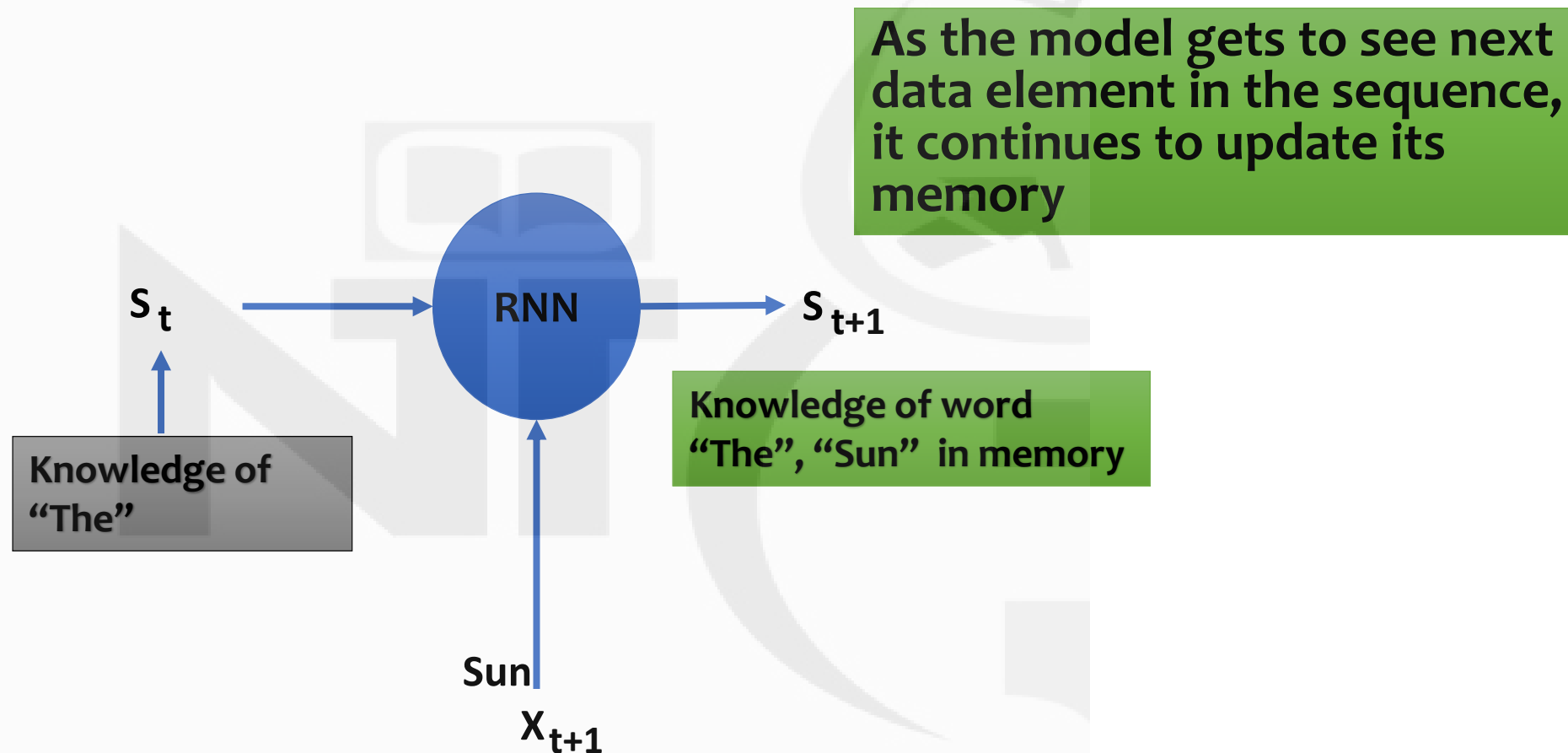
- A Word
- Previous Memory

The input at step $t=0$

Feeding the first word “The”

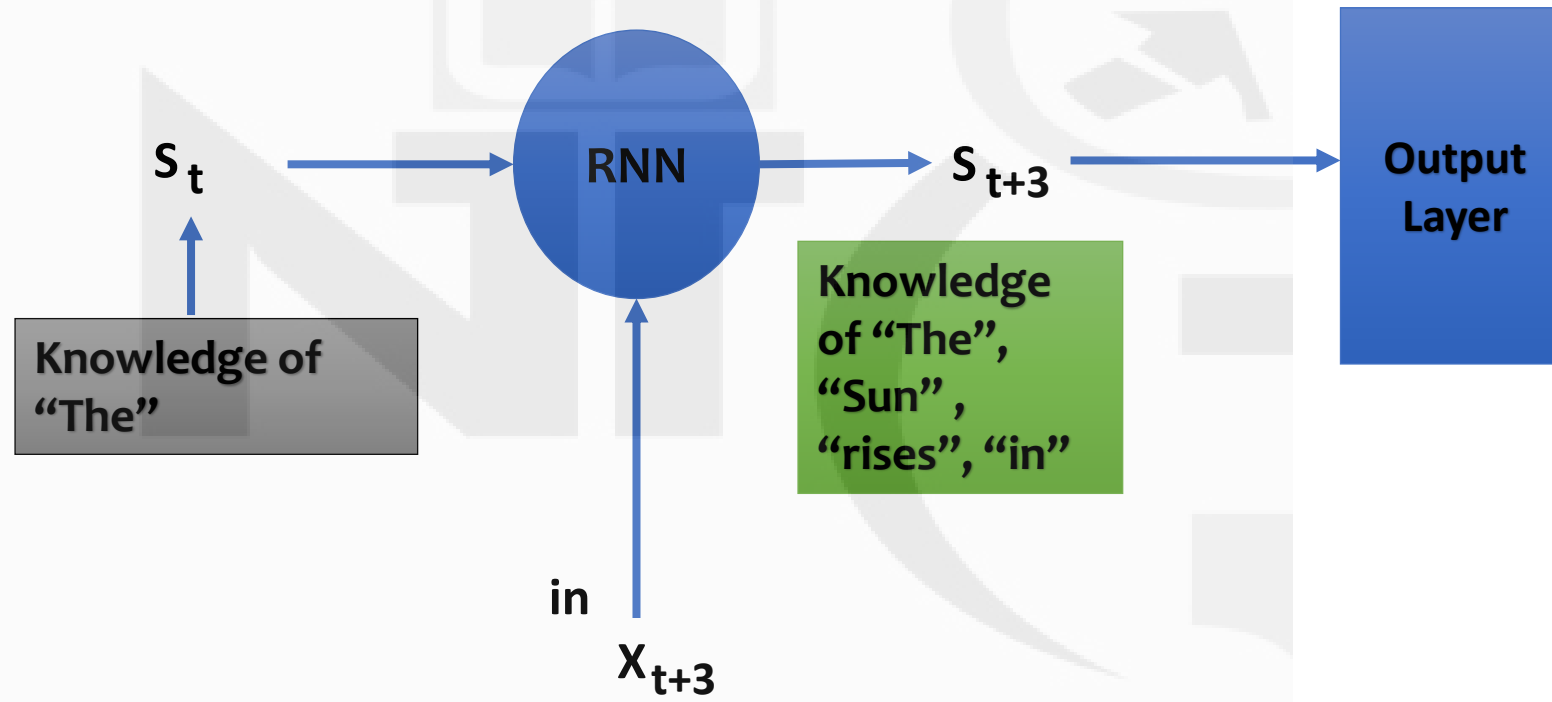


Next word “Sun”



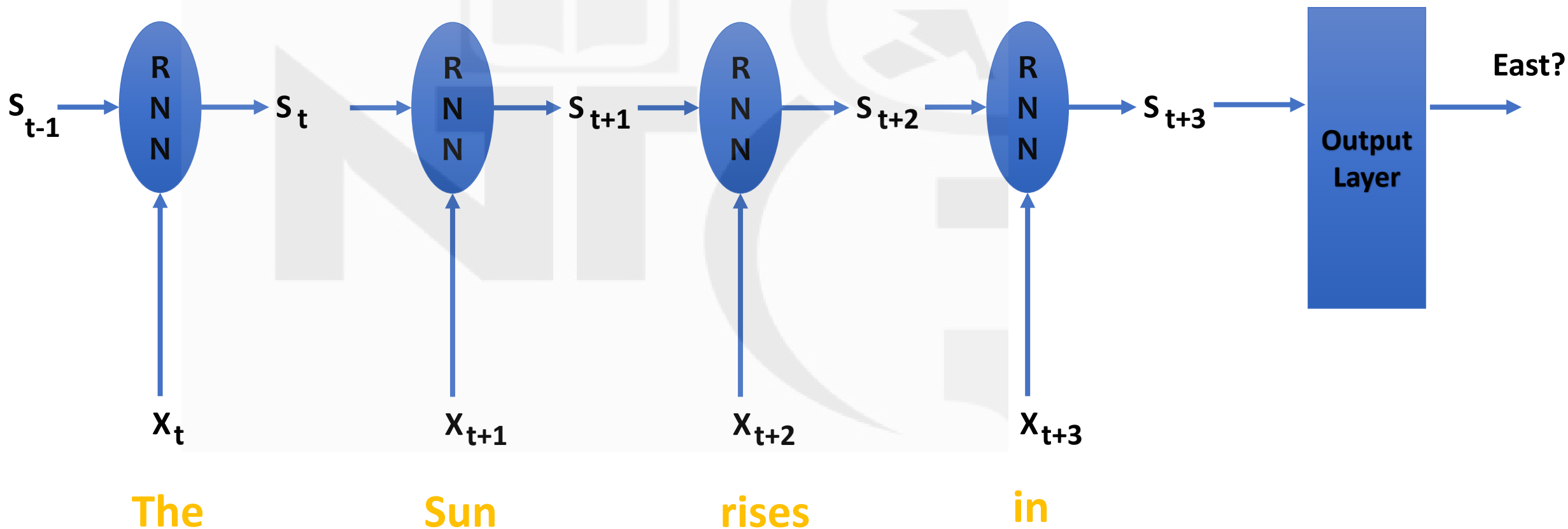
The input at step $t+1$

Once all the words have been fed, we can use the final memory state to generate the output through output layer

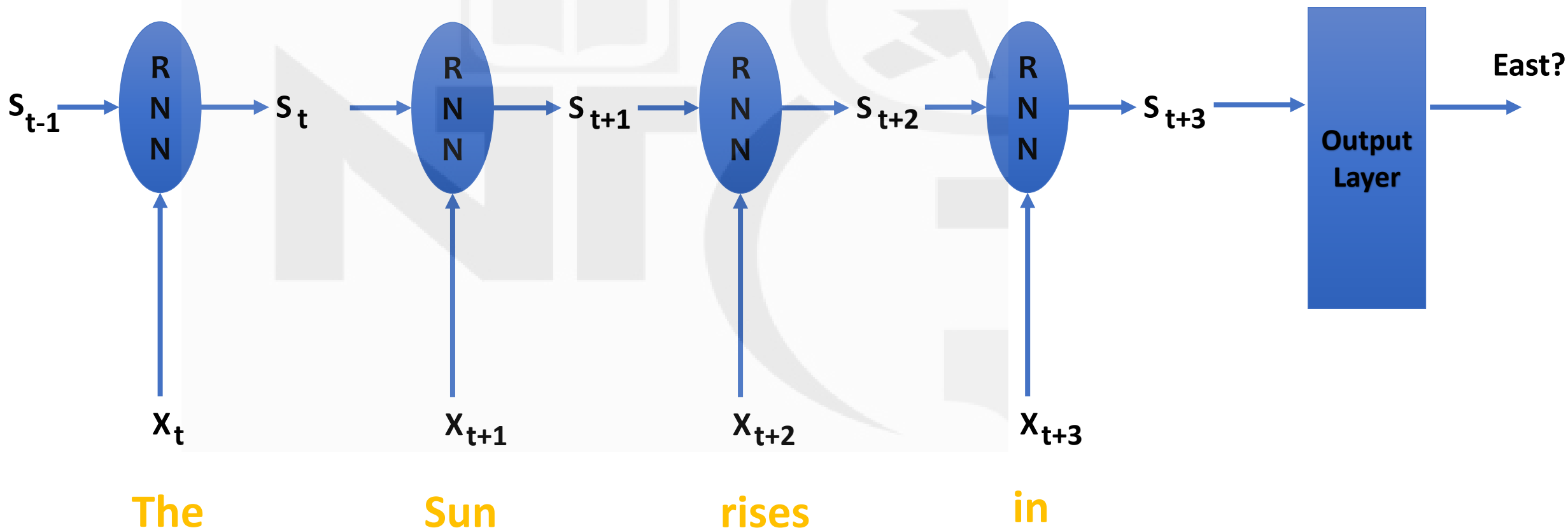


The input at step $t+1$

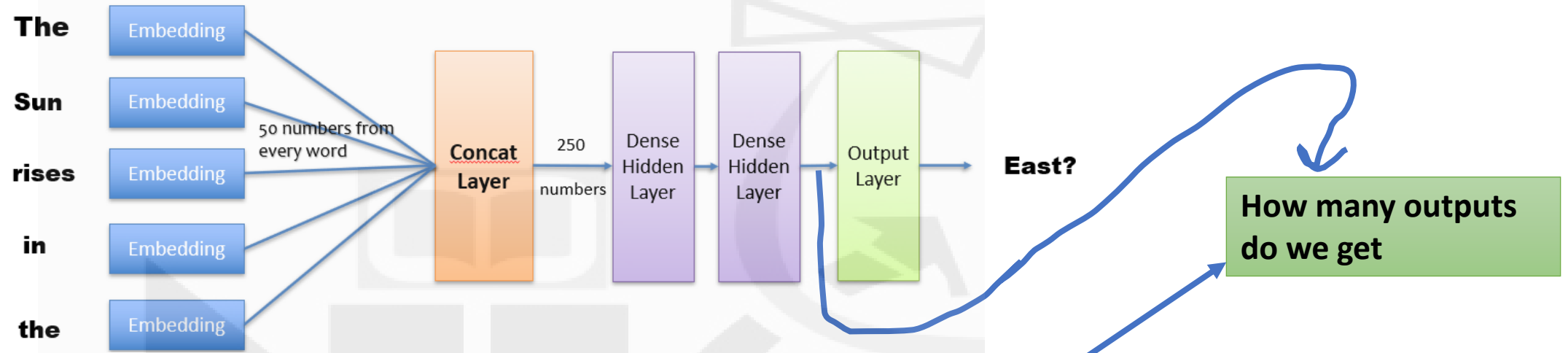
RNN over multiple time steps



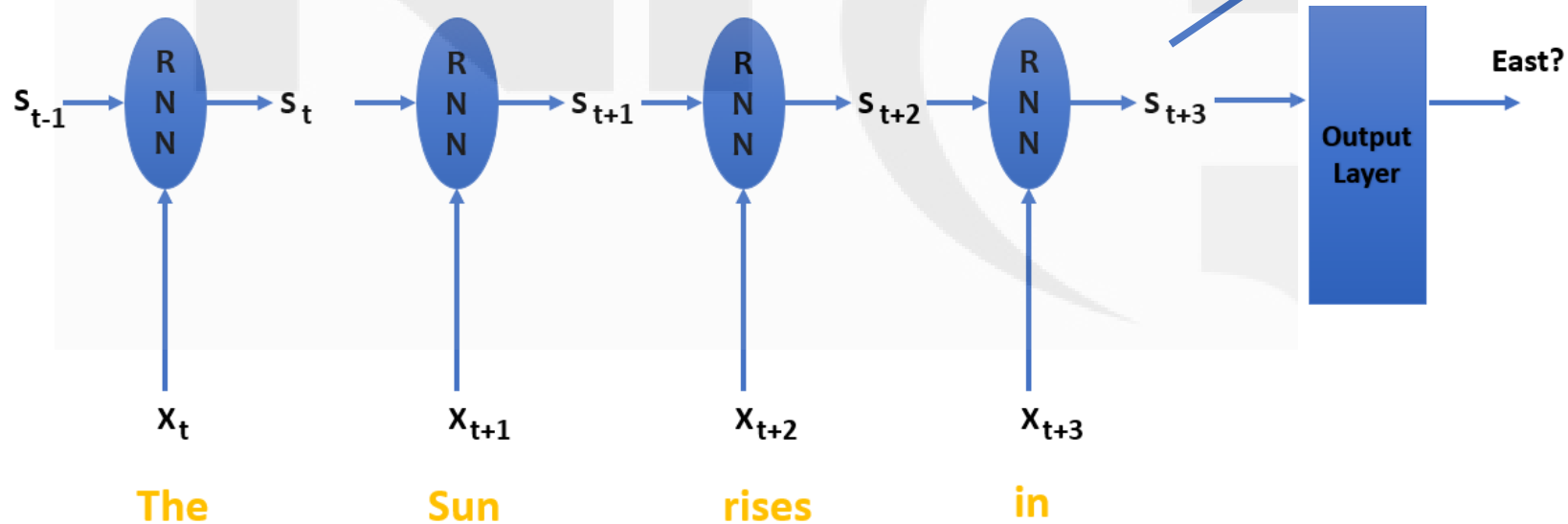
In this picture how many rnns are there?



Dense Neural Network(DNN)



Recurrent Neural Network(RNN)



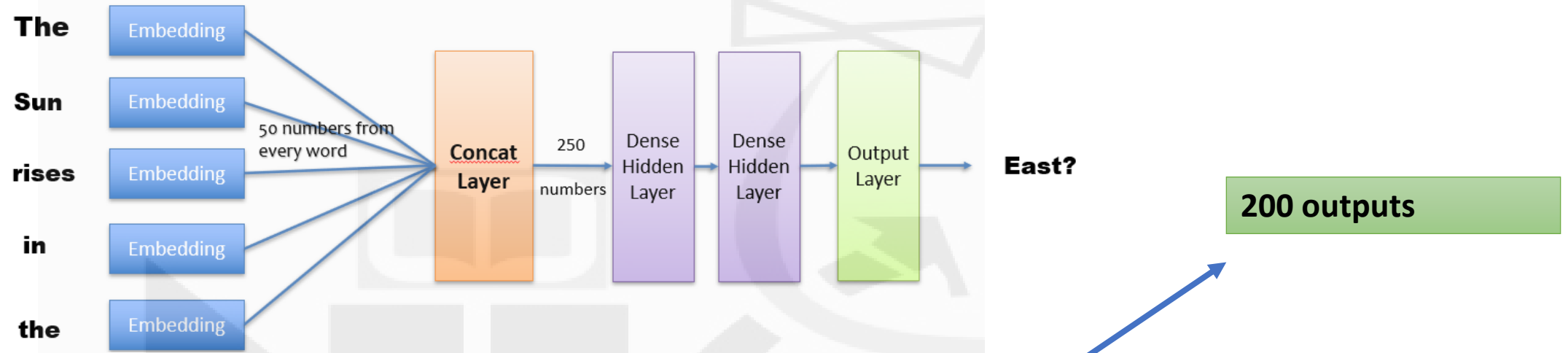
How many outputs do we get from RNN

Output of RNN is the final updated memory

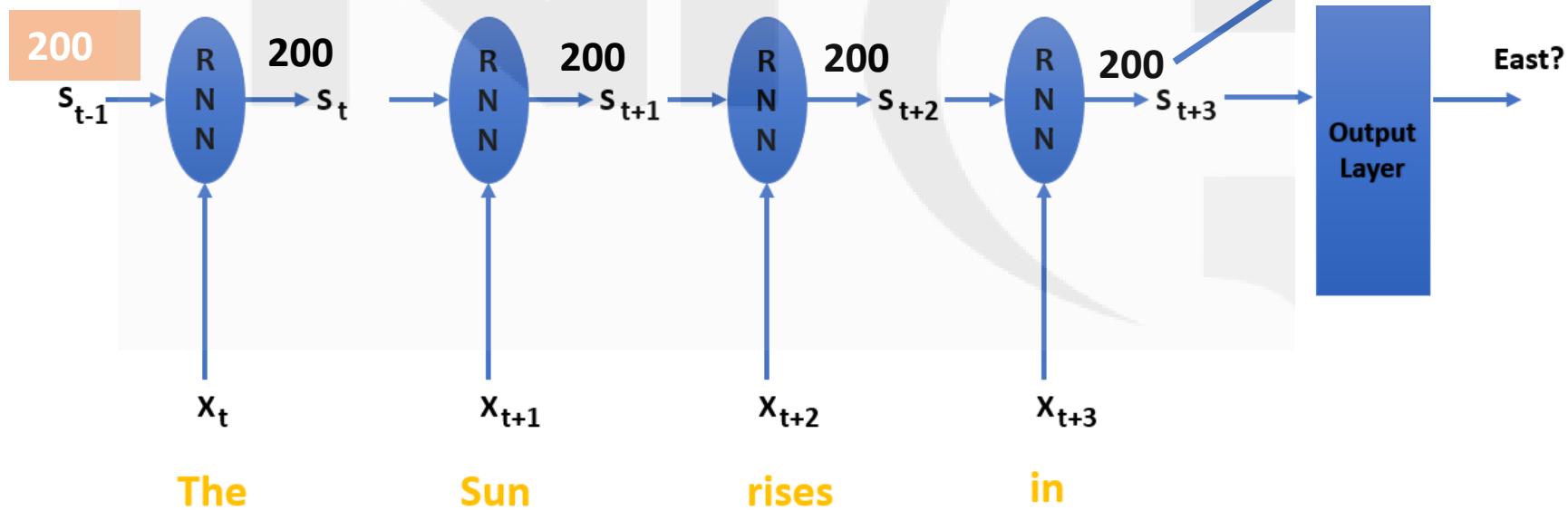
It's a hyperparameter (Size of RNN state or memory)

Let's say memory size is **200**

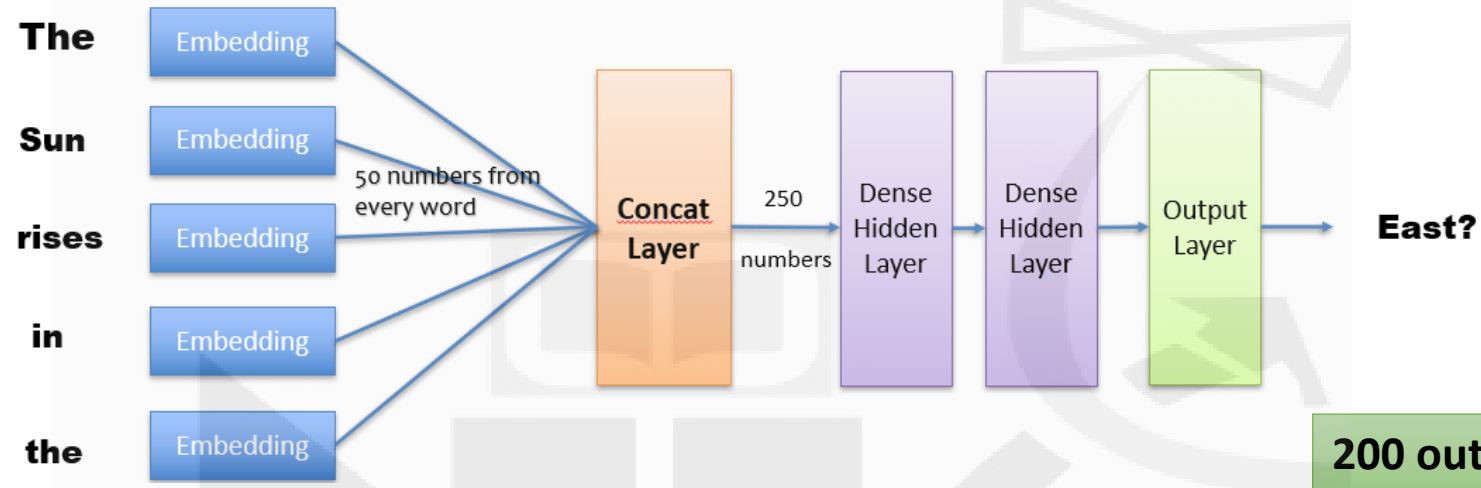
Dense Neural Network(DNN)



Recurrent Neural Network(RNN)

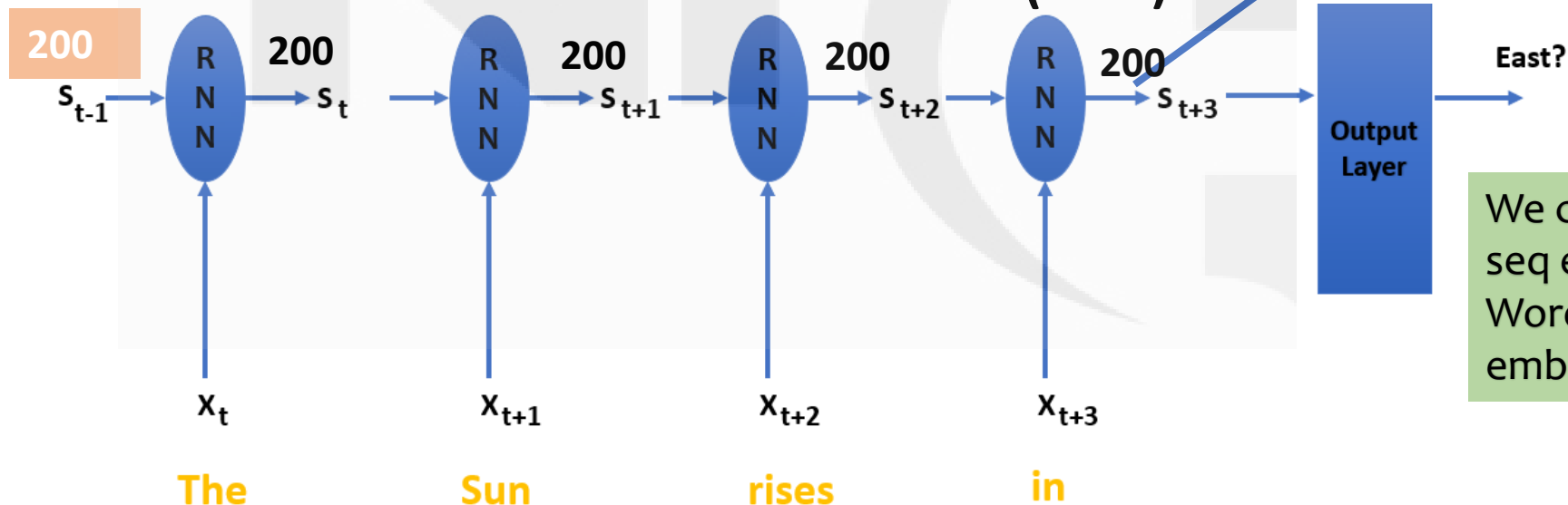


Dense Neural Network(DNN)



At every time step the memory size remains same (e.g. 200) in this case. The value in memory keeps Changing with new input

Recurrent Neural Network(RNN)



We can think of this output as seq embedding just like Word2Vec gives us word embeddings

Quick comparison of Dense vs Rnn approach

- As the seq size changes the output size change in dense
- RNN size remains same = memory size



How RNN builds its
memory?

RNN CELL

**Previous
memory**



At every time step RNN has
two inputs

x_t

**INPUT
word**

RNN CELL

Previous
Memory

s_{t-1}

Weights \rightarrow **W**

Dense

+

Tanh
(or ReLU)

Updated
Memory

s_t

Dense

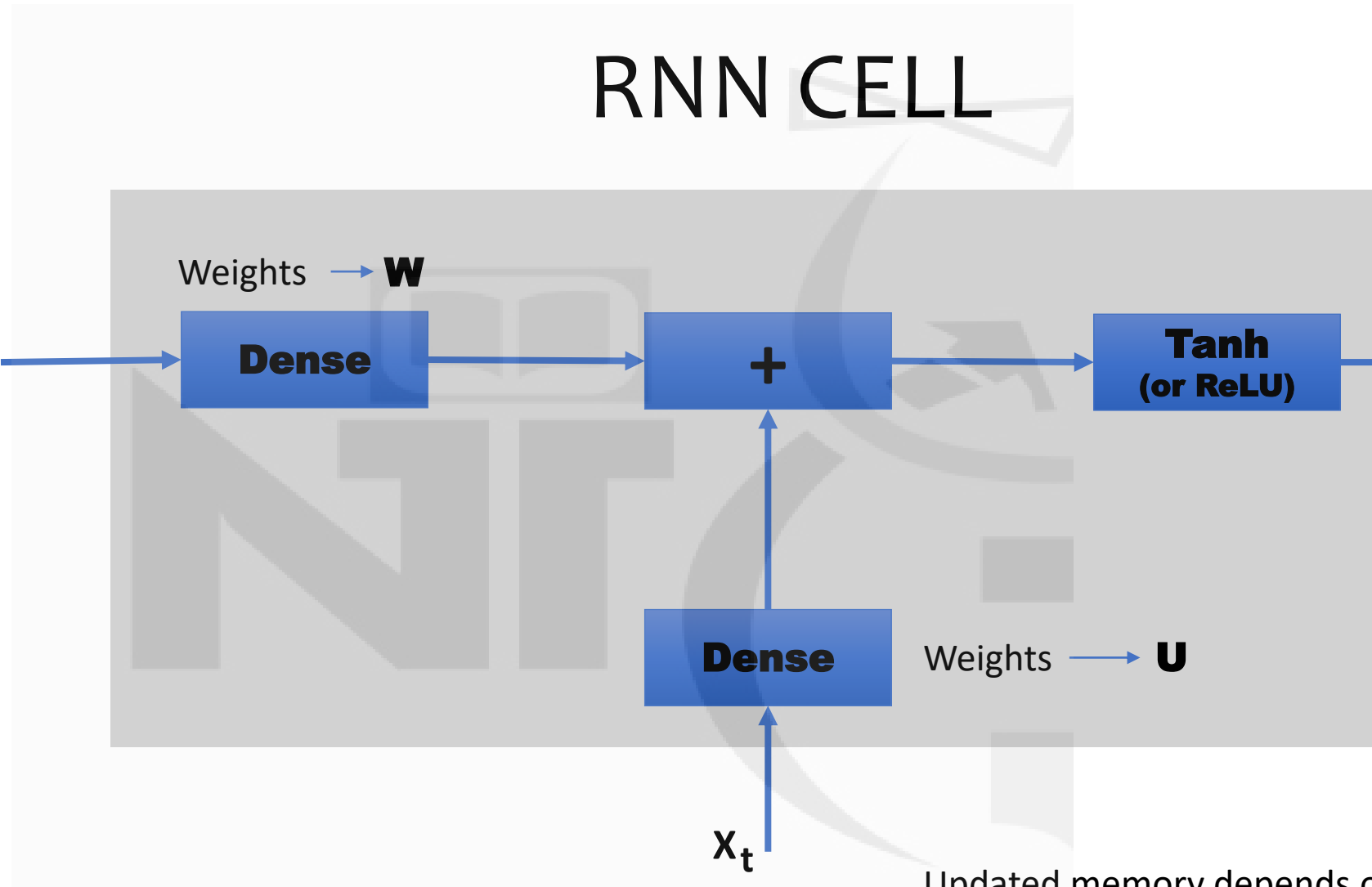
Weights \rightarrow **U**

x_t

INPUT

Eg: Word

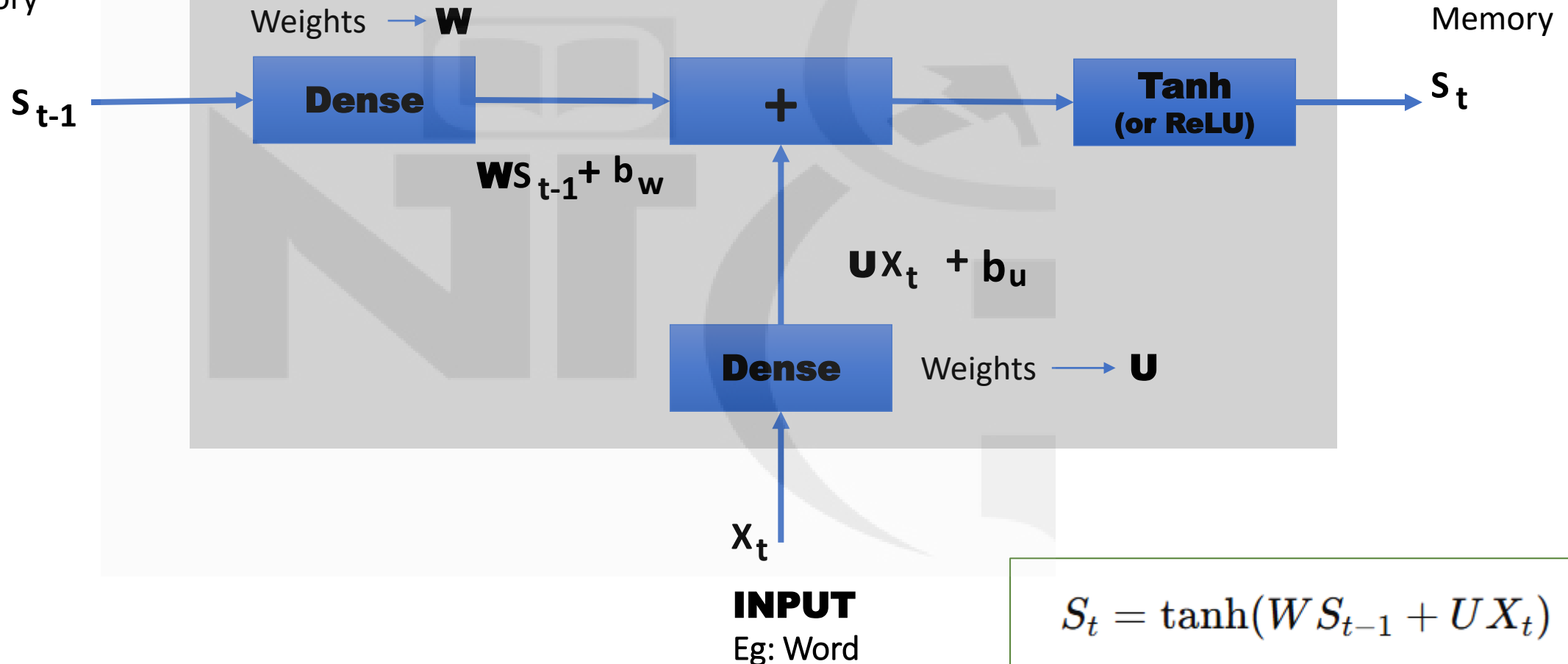
Updated memory depends on what
was there in memory earlier and
what we learnt just now



RNN CELL

Size of **U** & **W** ?

Previous
Memory



RNN CELL

Previous
Memory

s_{t-1}

Weights \rightarrow **W**

Dense

$$\mathbf{W} \mathbf{s}_{t-1} + \mathbf{b}_w$$

+

$$\mathbf{U} \mathbf{x}_t + \mathbf{b}_u$$

Dense

Weights \rightarrow **U**

x_t

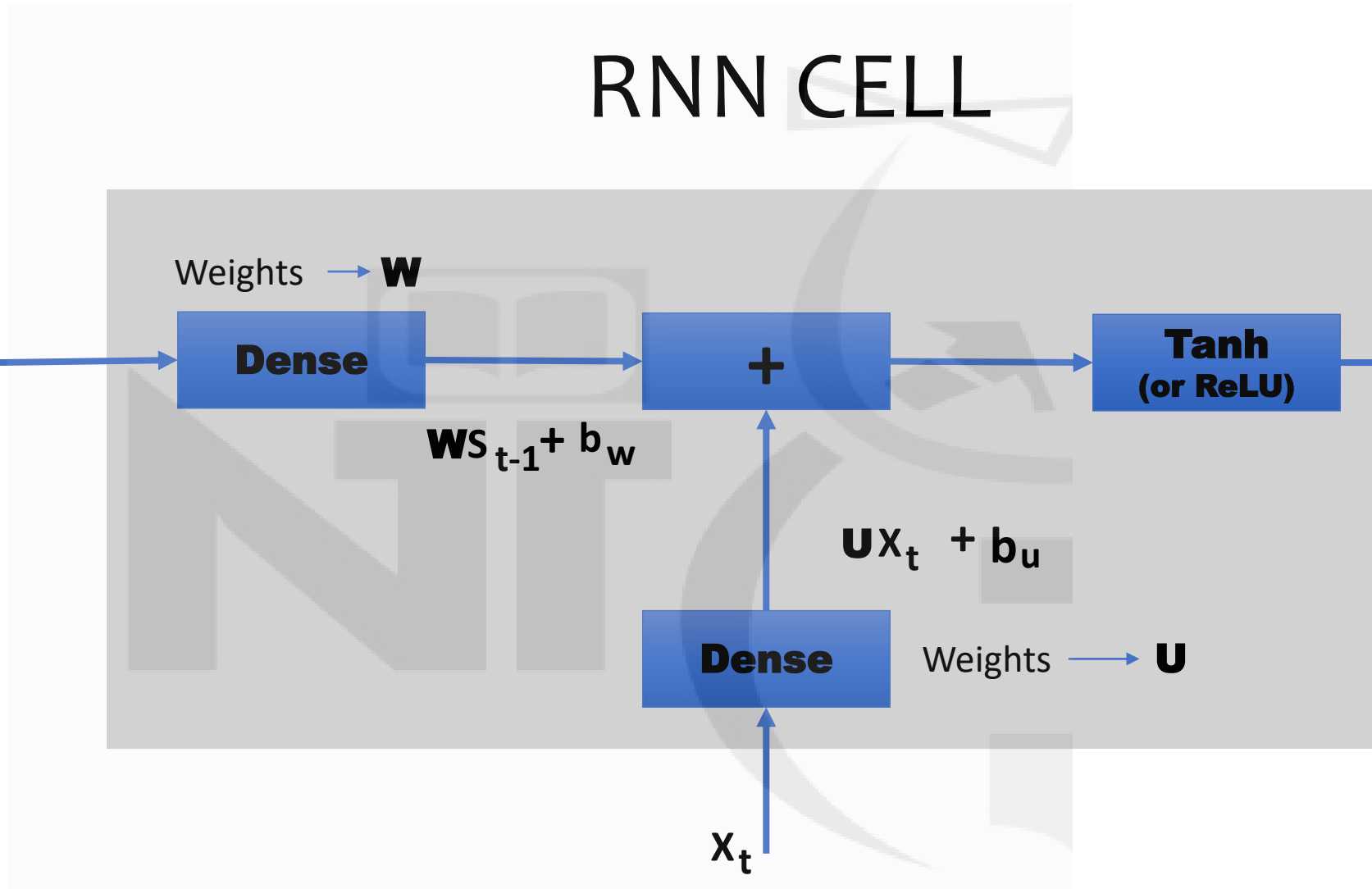
INPUT

Eg: Word

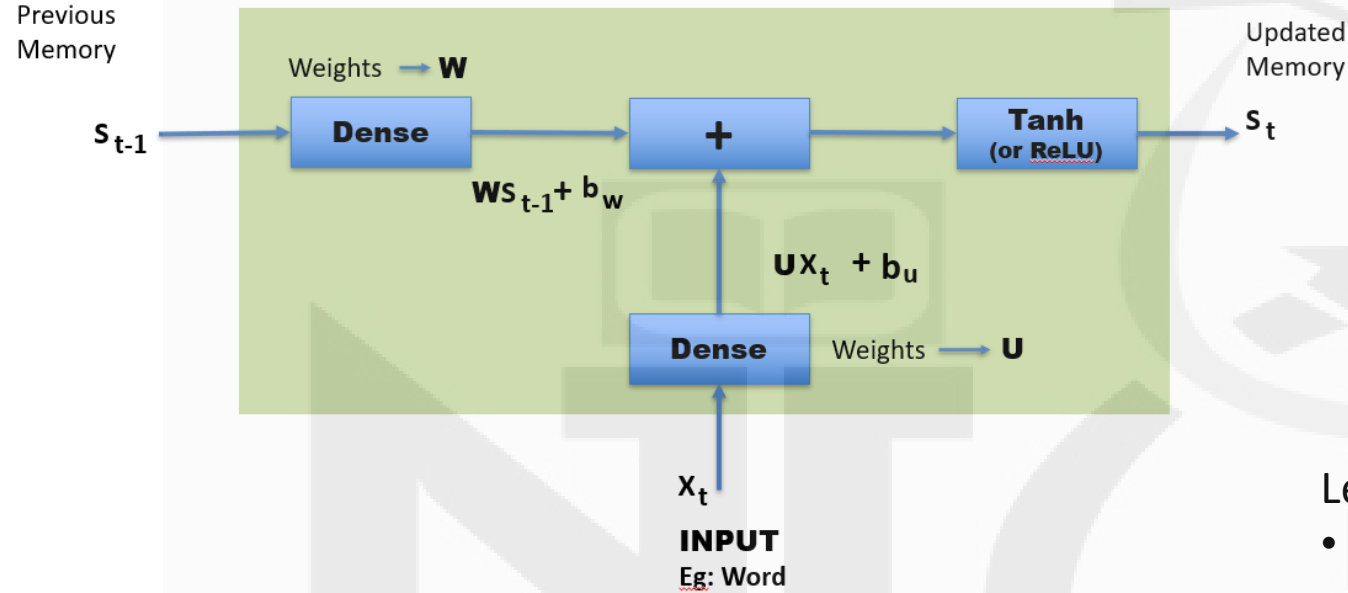
Tanh
(or ReLU)

Updated
Memory

s_t



RNN CELL



Size of U & W ?

Let's assume size of ...

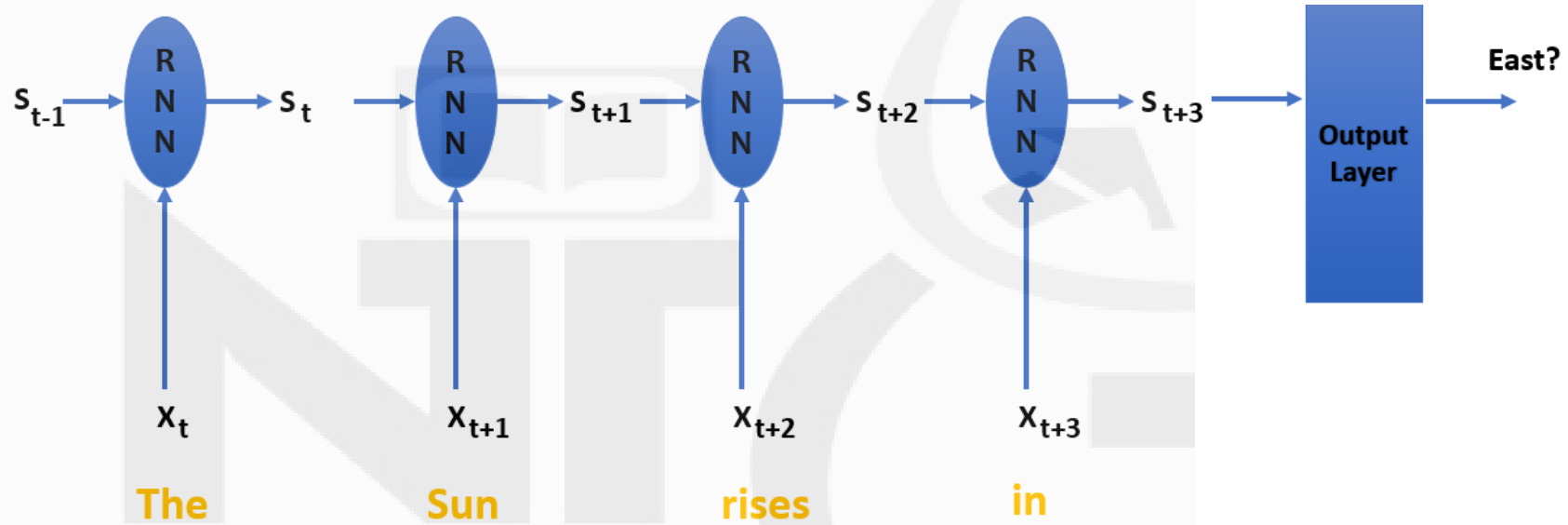
- RNN State (S) = [200,1]
- Input word embedding (X) = [50,1]

Use matrix multiplication rules to calculate the size of U and W

U = [200, 50]

W = [200, 200]

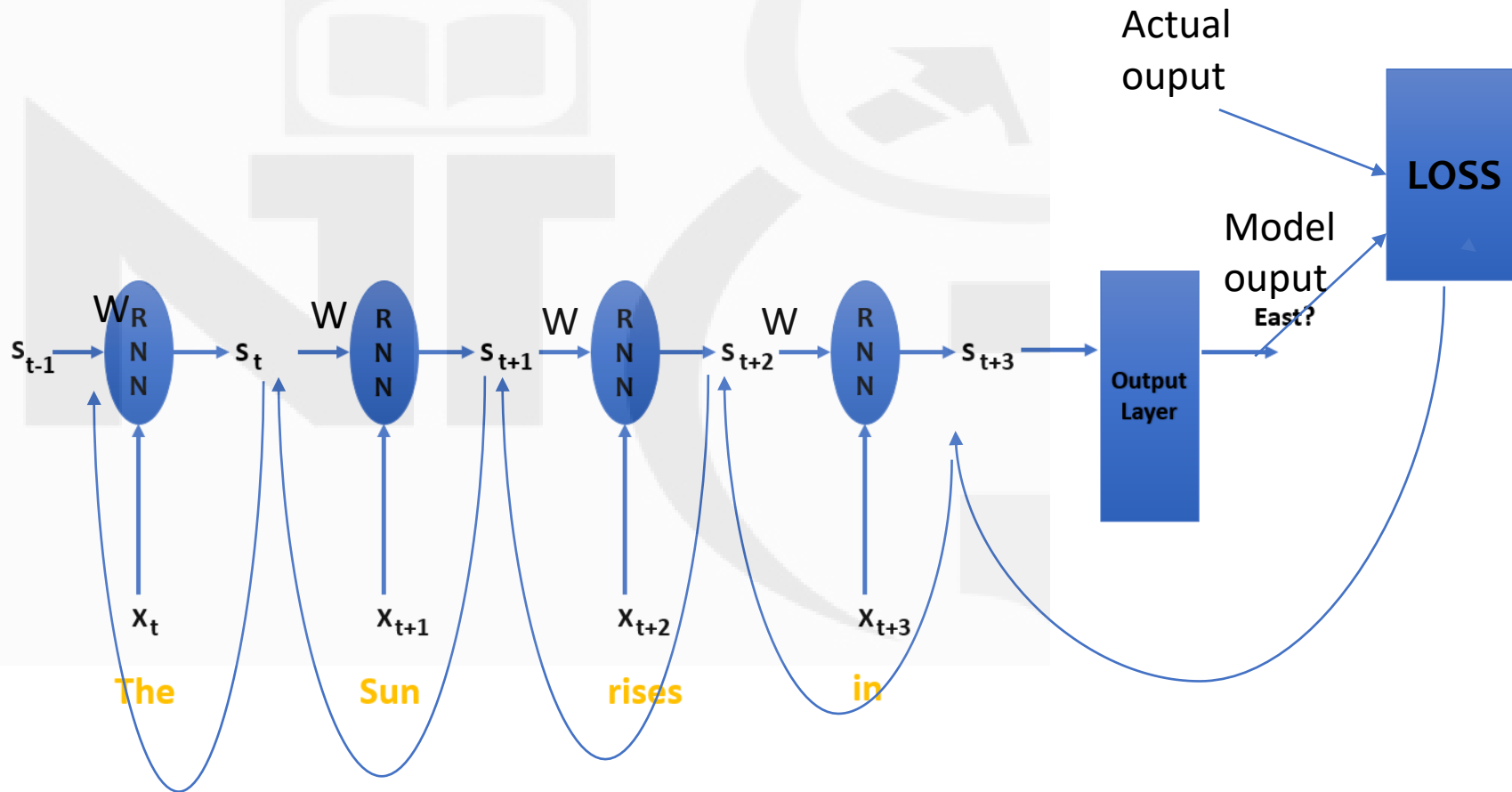
Recurrent Neural Network(RNN)



Weights of RNN (U, W) remain same at all time steps

"How is Loss related to W ?"

$\text{Loss} \rightarrow O_{t+3} \rightarrow S_{t+3} \rightarrow S_{t+2} \rightarrow S_{t+1} \rightarrow S_t \rightarrow W$



Gradient of Loss w.r.t W using Chain rule

Loss $\rightarrow O_{t+3} \rightarrow S_{t+3} \rightarrow S_{t+2} \rightarrow S_{t+1} \rightarrow S_t \rightarrow W$

$$\frac{d\text{Loss}}{dW} = \frac{d\text{Loss}}{dO_{t+3}} \cdot \frac{dO_{t+3}}{dS_{t+3}} \cdot \frac{dS_{t+3}}{dS_{t+2}} \cdot \frac{dS_{t+2}}{dS_{t+1}} \cdot \frac{dS_{t+1}}{dS_t} \cdot \frac{dS_t}{dW}$$

BackPropagation through Time (BPTT)

Gradient of S_{t+n} with respect to S_{t+n-1}

$$S_{t+n} = \tanh(W S_{t+n-1} + U X_{t+n})$$

$n \rightarrow$ relative time step

$$\frac{dS_{t+n}}{dS_{t+n-1}} = W$$

Gradient of Loss w.r.t W using Chain rule

$$Loss \rightarrow O_{t+3} \rightarrow S_{t+3} \rightarrow S_{t+2} \rightarrow S_{t+1} \rightarrow S_t \rightarrow W$$

$$\frac{dLoss}{dW} = \frac{dLoss}{dO_{t+3}} * \frac{dO_{t+3}}{dS_{t+3}} * \frac{dS_{t+3}}{dS_{t+2}} * \frac{dS_{t+2}}{dS_{t+1}} * \frac{dS_{t+1}}{dS_t} * \frac{dS_t}{dW}$$

$$\frac{dLoss}{dW} = \frac{dLoss}{dO_{t+3}} * \frac{dO_{t+3}}{dS_{t+3}} * W * W * W * \frac{dS_t}{dW}$$

Gradient calculation requires repeated multiplication by 'W'

Vanishing or Exploding Gradient

(If W is small or large)

Cannot remember for long

(very short memory)



Hence, we do not use RNN in real-time applications