

BITS F464: Machine Learning

34 Sequence Modeling in Neural Network



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ONLINE (Campus @ BITS-Pilani Jan-May 2021)

<http://ktiwari.in/ml>

Application of Sequence Data

There are various places we encounter Sequence Data

Sequence Prediction

- Weather Forecasting
- Stock Market Prediction
- Product Recommendation

Sequence Classification

- DNA Sequence Classification
- Anomaly Detection
- Sentiment Analysis

Sequence Generation

- Multi-Step Time Series Forecasting
- Text Summarization
- Language Translation



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Modeling Sequences

There are some ideas to fix the issue (difficulty in using ML models)

- Consider only fixed length.
(Unable to model long term dependencies)
- Bag of Words: use a vector of length equal to dictionary, and mark/count which words are present
(since order is not preserved; following lines becomes same)
David is good at math but is bad in science
David is bad at math but is good in science

To model sequences we need

- To deal with variable size input
- Maintain sequence order
- Keep track of long term dependencies
- Share parameters across the sequences

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Whether I should go to see a movie?
Suppose you have a **system**, whom you can ask whether should you go to see a movie or NOT



- The system need to consider many factors such as 1) who are the actors 2) what is IMDB rating of movie 3) your interests in type of movie 4) do you have money to purchase tickets etc.

- Everytime the System would give same answer.** How many times you can see the same movie?

Basic ML models considers only the current input (sometime it is useful to consider previous input/output as well)

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Sequences

Data is essentially a set of examples (every row represents one)

- Mostly we have fixed number of attributes in an example.
- However, **some interesting applications** (such as **text, voice, video etc**) have variable number of points
- These points could depend on each other in complicated way
- We want to do something like
 - Given a **text** we want to predict sentiment or next word
 - Given a **place**, one should go there and visit _____
 - Given a **voice** we want to recognize the speaker
 - Given a **video** we want to determine the activity
 - Given a **series** (say **stock values**) predict next one

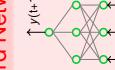
ISSUE: Basic ML models do **NOT** handle variable number of inputs

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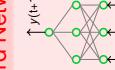
Recurrent Networks (RNN)

Feedforward network cannot capture the dependence of $y(t+1)$ on earlier values of x such as $x(t-1)$

Feedforward Network

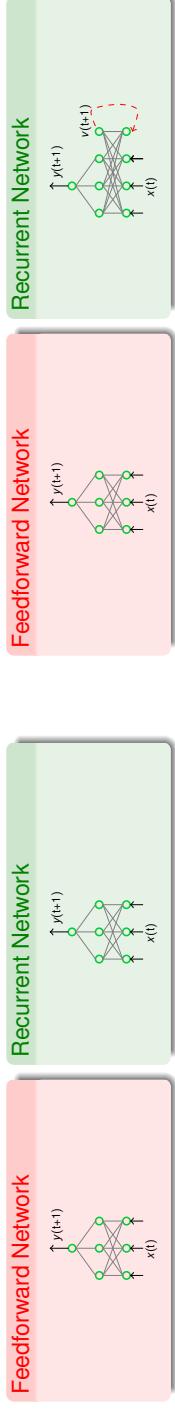


Recurrent Network



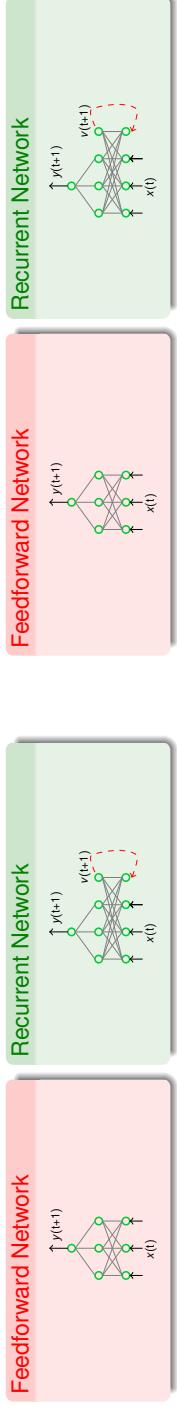
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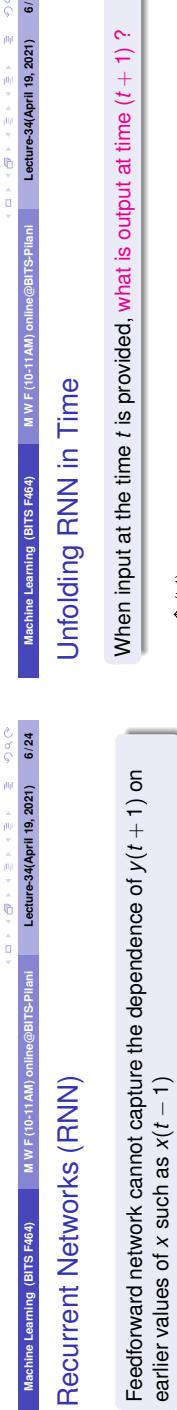


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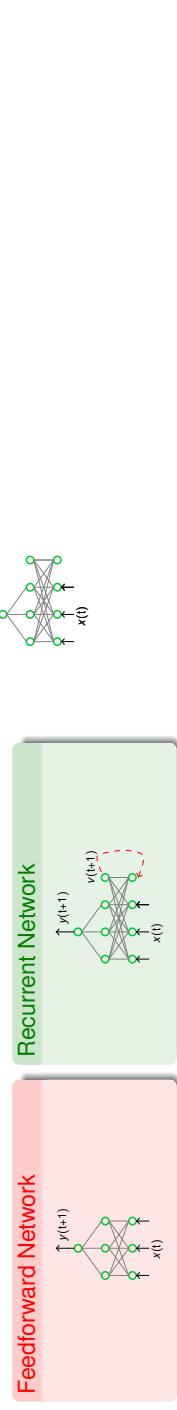


- RNN uses **states** (called self-state) of the **network units** available at time t as an input to the other units at time $t+1$



Recurrent Networks (RNN)

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- RNN uses **states** (called self-state) of the **network units** available at time t as an input to the other units at time $t+1$
- RNN is suitable for temporal data (like time series)

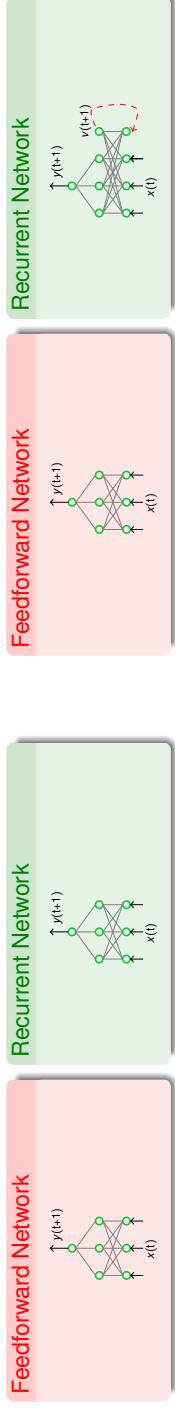
• Training may involve unfolding and averaging.



Unfolding RNN in Time

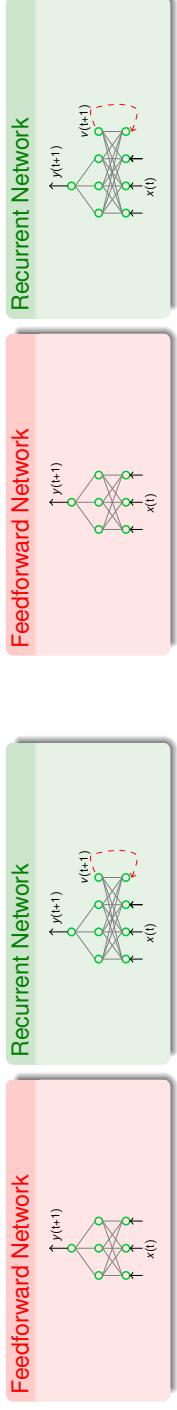
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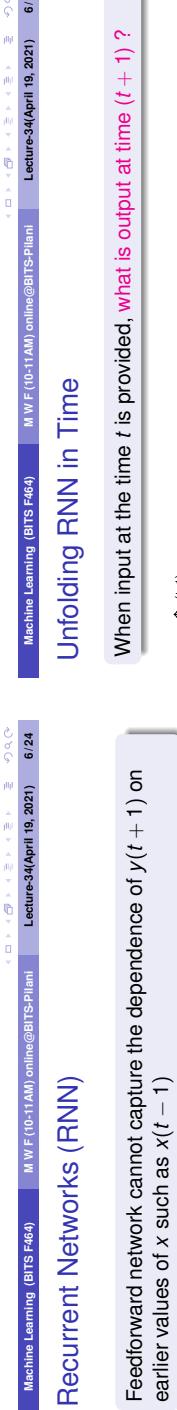


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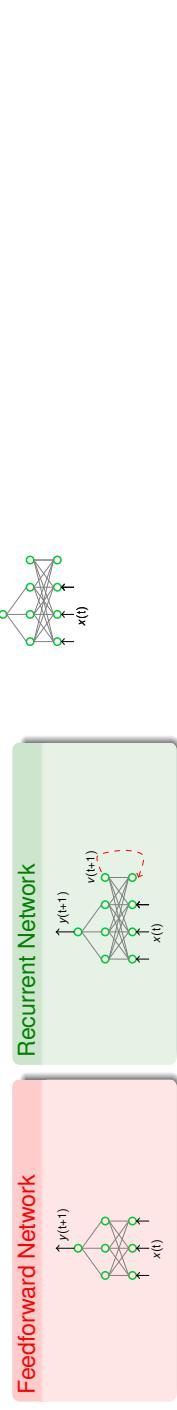


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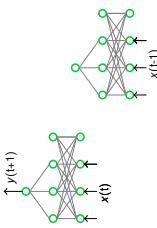
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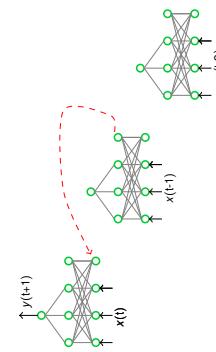
Unfolding RNN in Time

When input at the time t is provided, what is output at time ($t + 1$) ?



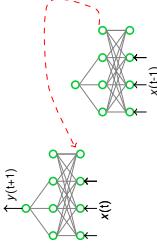
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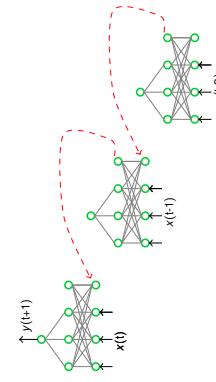
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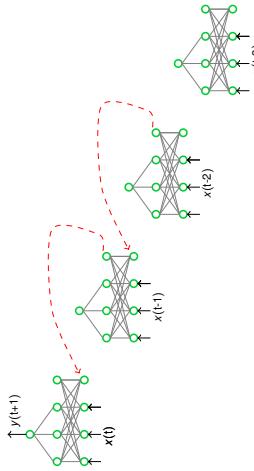
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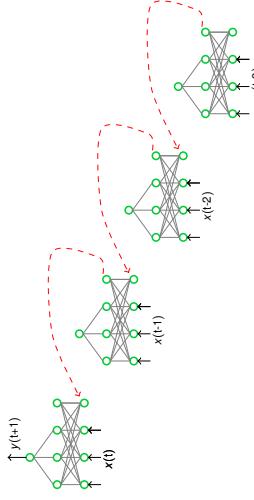
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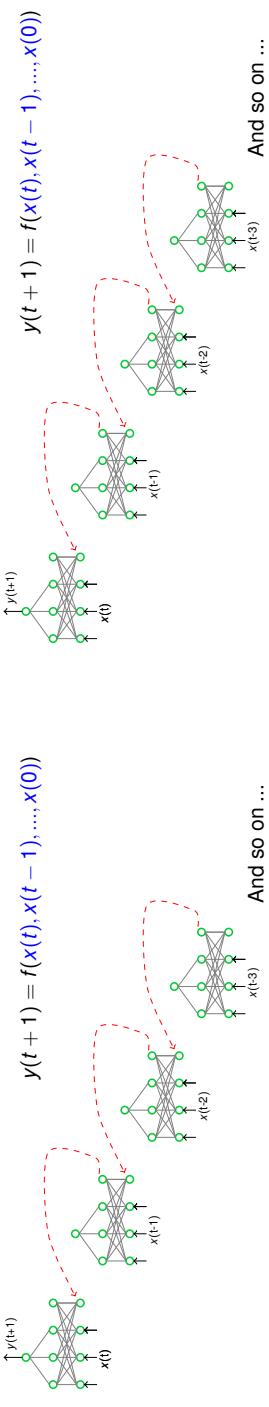
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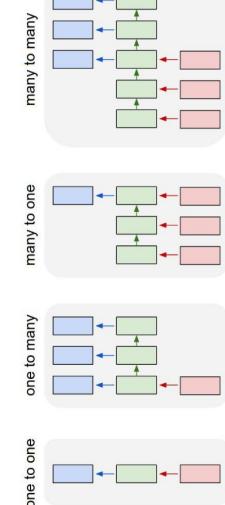
Unfolding RNN in Time

When input at the time t is provided, what is output at time $(t + 1)$?



Various arrangements are possible based on need

- What should be the next word? **One-to-One**
- Caption the given image? **One-to-Many**
- Segmentation or classification **Many-to-One**
- Translate from one language to other **Many-to-Many**

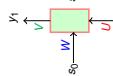


Output may be different for same input

We are optimizing over programs not on functions

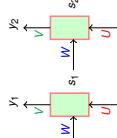
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Training: A Simplified Version of RNN



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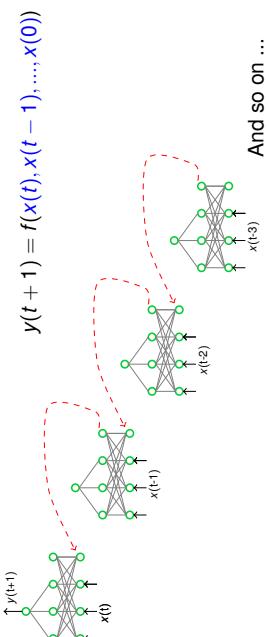
Character-Level Language Models

- Given a character what is the next character
- Characters are encoded using one-hot encoding
- Weights need to be adjusted

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Unfolding RNN in Time

When input at the time t is provided, what is output at time $(t + 1)$?



By this way RNN incorporates history of the network in output

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Model and an application of RNN 1

```
rmn = RNN()
y = rmn.step()
class RNN:
    def __init__(self, x):
        self.s = np.tanh(np.dot(self.W, self.s) + np.dot(self.U, x))
        y = np.dot(self.V, self.s)
        return y
```

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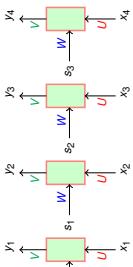
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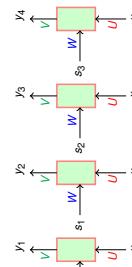
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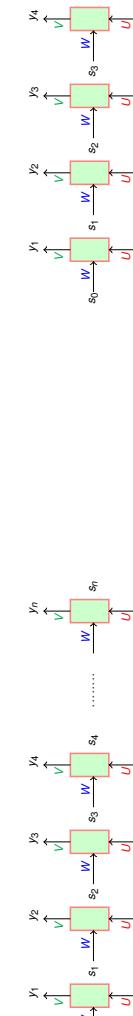
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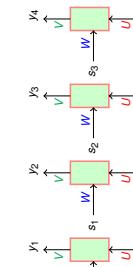
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Training: A Simplified Version of RNN



If loss at time t be J_t

Then total loss is $J = \sum_t J_t$

J_t could be something like $-\log(\text{probability of true output})$

How to train RNN?

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Training RNN

Backpropagation is used to train a RNN

- Total loss is the summation of J_t at every time step $J = \sum_t J_t$
- To train a **parameter** we need to find its gradient with respect to loss and shift the parameter in its opposite direction

$$W = W - \alpha \frac{\partial J}{\partial W} = W - \alpha \frac{\partial}{\partial W} \sum_t J_t = W - \alpha \sum_t \frac{\partial J_t}{\partial W}$$

- Consider a single summation term

$$\frac{\partial J_t}{\partial W} = \frac{\partial J_t}{\partial s_i} \times \frac{\partial s_i}{\partial W}$$

- Term $\frac{\partial s_i}{\partial W}$ is complicated. It depends on $s_{i-1}, s_{i-2}, \dots, s_1$

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Exploding and Vanishing Gradient

Consider $\frac{\partial s_i}{\partial s_k}$ that is $\frac{\partial s_i}{\partial s_{i-1}} \frac{\partial s_{i-1}}{\partial s_{i-2}} \dots \frac{\partial s_{k+2}}{\partial s_{k+1}} \frac{\partial s_{k+1}}{\partial s_k} = \prod_{j=i}^{k+1} \frac{\partial s_j}{\partial s_{j-1}}$

Focus on a single term $\frac{\partial s_i}{\partial s_{i-1}}$

it can be shown that it is upper-bounded by some constant (which depends on W) let's call that value c

Since $\frac{\partial s_i}{\partial s_k}$ is a multiplication of $i - k$ such terms (and we expect $i - k$ to be large to address long term dependency) therefore the value

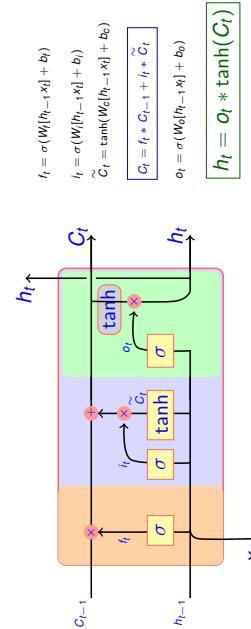
$$\frac{\partial s_i}{\partial s_k} \rightarrow \begin{cases} \text{Vanish} & \text{if } c < 1 \\ \text{Explode} & \text{if } c > 1 \end{cases}$$

(0.90 -> 0.81 -> 0.73 -> 0.66 -> 0.59 -> 0.53 -> 0.48 -> 0.43 -> 0.39) (1.50 -> 2.25 -> 3.38 -> 5.06 -> 7.59 -> 11.39 -> 17.09 -> 25.63)

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LSTM: Long Short Term Memory 2

LSTM are RNN with 4 special NN circuits for **forget**, **store** and **output**



²Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." Neural computation 9.8 (1997): 1735-1780. Lecture-34(April 19, 2021) 15/24

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Training RNN (contd..)

- As $s_i = \sigma(U^T x_i + W^T s_{i-1})$ where s_i also depends on W and other previous states s_{i-2}, \dots, s_1
- Its derivative has **explicit** and **implicit** parts. Explicit part considers other things as constant (we represent as ∂^+)

$$\begin{aligned} \frac{\partial s_i}{\partial W} &= \frac{\partial^+ s_i}{\partial W} + \frac{\partial s_i}{\partial s_{i-1}} \frac{\partial s_{i-1}}{\partial W} \\ &= \frac{\partial^+ s_i}{\partial W} + \frac{\partial s_i}{\partial s_{i-1}} \left[\frac{\partial^+ s_{i-1}}{\partial W} + \frac{\partial s_{i-1}}{\partial s_{i-2}} \frac{\partial s_{i-2}}{\partial W} \right] \\ &= \frac{\partial^+ s_i}{\partial W} + \frac{\partial s_i}{\partial s_{i-1}} \frac{\partial^+ s_{i-1}}{\partial W} + \frac{\partial s_i}{\partial s_{i-1}} \frac{\partial s_{i-1}}{\partial s_{i-2}} \frac{\partial s_{i-2}}{\partial W} + \frac{\partial s_i}{\partial s_{i-1}} \frac{\partial s_{i-1}}{\partial s_{i-3}} \frac{\partial s_{i-3}}{\partial W} \\ &= \sum_{k=1}^i \frac{\partial s_i}{\partial s_k} \frac{\partial s_k}{\partial W} \end{aligned}$$

where we use $\frac{\partial s_i}{\partial s_k}$ as a short form for $\frac{\partial s_i}{\partial s_{i-1}} \frac{\partial s_{i-1}}{\partial s_{i-2}} \dots \frac{\partial s_{k+2}}{\partial s_{k+1}} \frac{\partial s_{k+1}}{\partial s_k}$

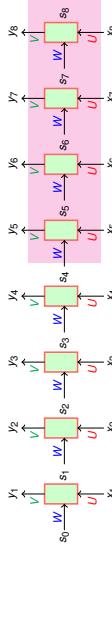
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How to Avoid Exploding and Vanishing Gradient

1 Clipping

Try normalizing value of c keeping it some range $T_l \leq c \leq T_h$
At any step look for only for last k timestamps

2 Truncated Backpropagation



③ **LSTM**
Special circuits for handling long term dependencies

from random import randint
from numpy import array
from numpy import argmax
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers import Dense

def generate_sequence(length, n_features):
 return [randint(0, n_features - 1) for _ in range(length)]

def one_hot_encode(sequence, n_features):
 encoding = [1] * n_features
 for value in sequence:
 encoding[value] = 1
 return array(encoding)

def one_hot_decode(encoded_seq):
 return [argmax(vector) for vector in encoded_seq]

def generate_example(length, n_features, out_index):
 encoding = one_hot_encode(sequence, n_features)
 X = encoded.reshape(1, length, n_features)
 Y = encoded[out_index:, reshape(1, n_features)]
 return X, y

Example-01 [1/2]

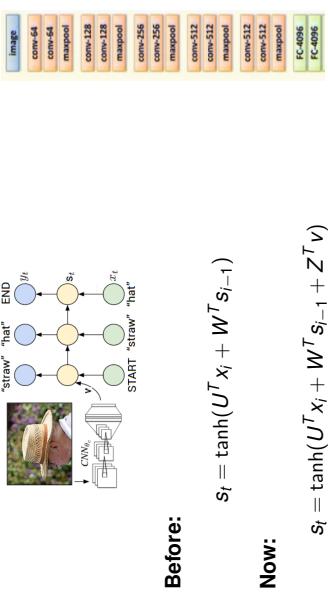
Five numbers are fed and we want the 2nd one as output.

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Example-05: Image Captioning 7

Thank You!



⁷Kemathy Andrei and Li Fei-Fei, "Deep visual-semantic alignments for generating image descriptions," Proceedings of the IEEE conference on computer vision and pattern recognition, 2015.