Deep Learning

13. Recurrent Neural Networks

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So far...

1. Perceptron, MLP, Gradient Descent (Backpropagation)

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2. CNNs (visualizing and understanding)

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3. 'Feedforward Neural networks'

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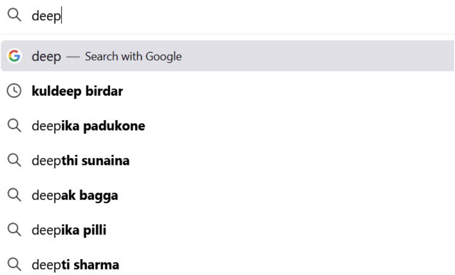
2. Successive i/p are i.i.d.
3. Processing of successive i/p is independent of each other

Consider ‘auto-completion’ task



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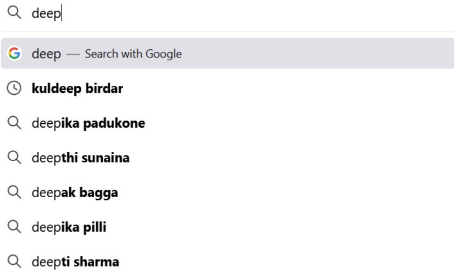

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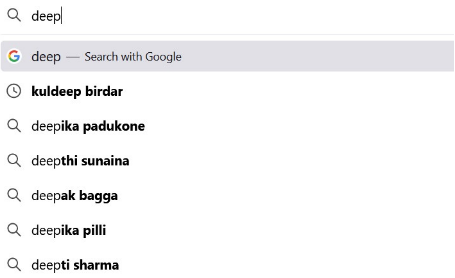

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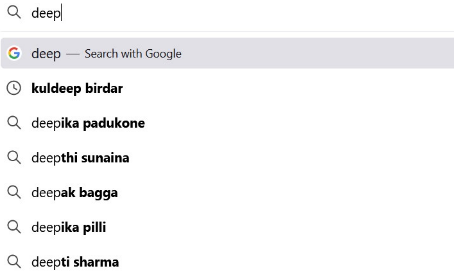

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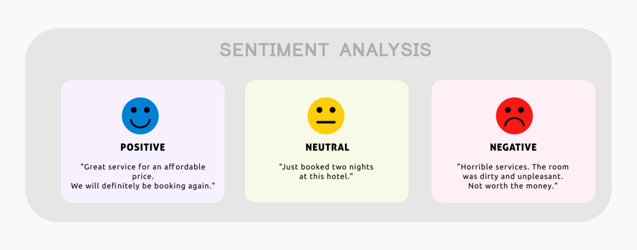
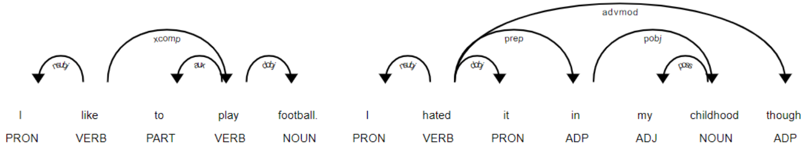
4. Sequence Learning Problems

Sequence Learning Tasks: Example



Sentiment Analysis (Source)

Sequence Learning Tasks: Example



POS-Tagging (Source:Kaggle)

Sequence Learning Tasks: Example

Action Recognition (Source)

Sequence Learning Tasks: Example

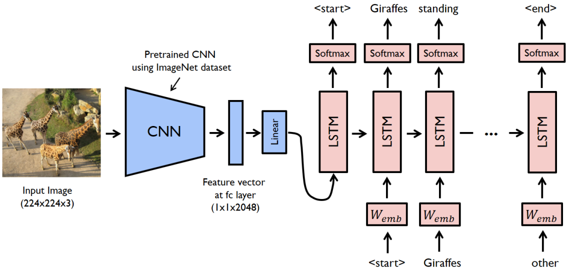
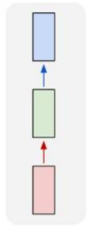


Image Captioning(Source)

Sequence Learning Tasks: Variations



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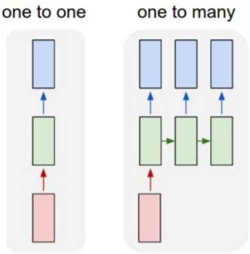

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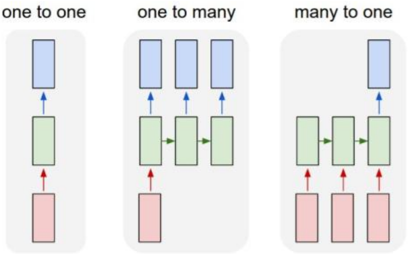

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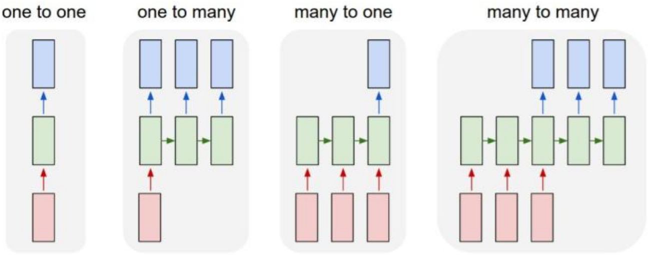

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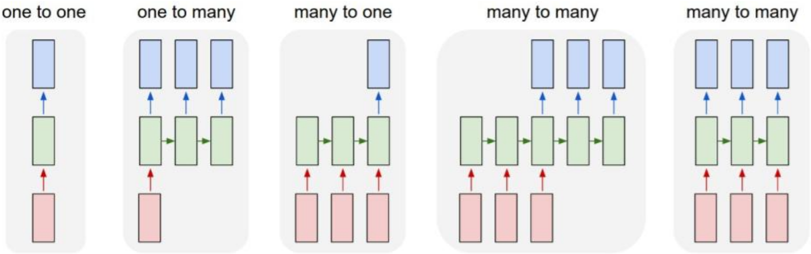

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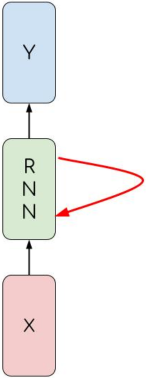
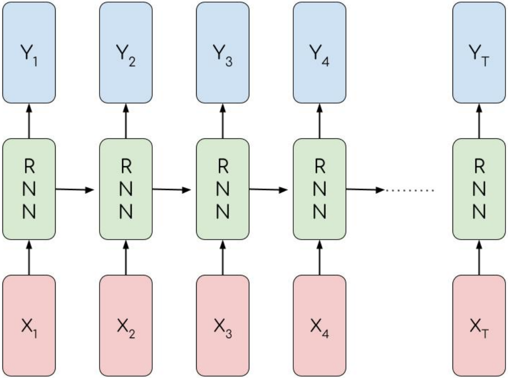
2. Characteristics
    1. Model the dependence among the i/p
    2. Handle variable length of i/p
    3. Same function applied at all time instances

RNNs: internal state



RNNs have internal state (or, memory) that gets updated with input

RNNs: unfolding



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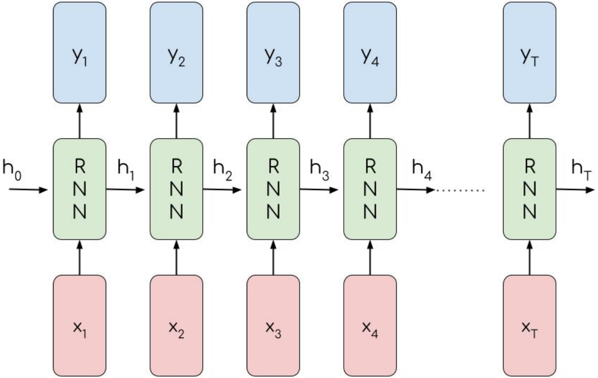
2. i/p sequence $x_t \in \mathbb{R}^{\mathbb{D}}$
3. Initial recurrent state $h_0 \in \mathbb{R}^{\mathbb{Q}}$
4. RNN model computes sequence of recurrent states iteratively
   $h_t = \phi(x_t, h_{t-1}; w)$

RNNs



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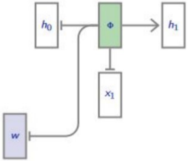
2. $h_t = tanh(W_{xh}.x_t + W_{hh}.h_{t-1} + b_h)$
3. $y_t = softmax(W_{hy}.y_t + b_y)$

RNNs as computational graph

1. Use the same set of parameters at each time step



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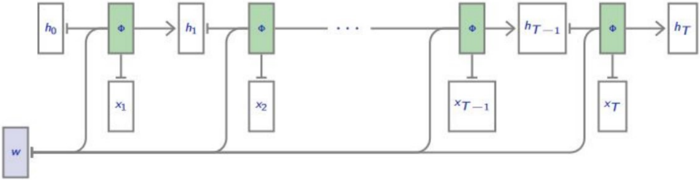

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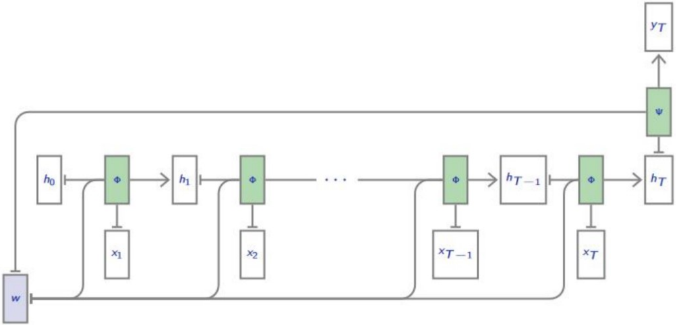
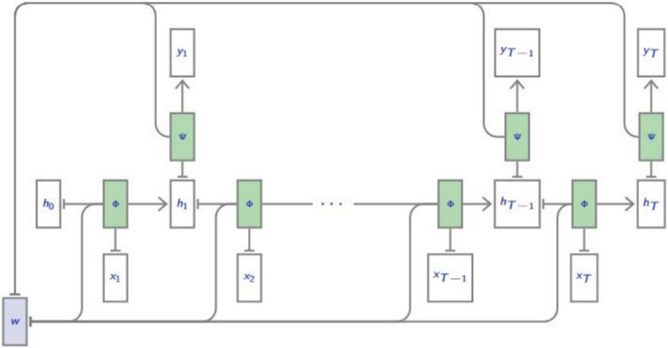


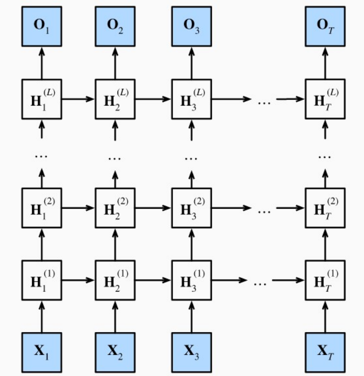
RNNs as computational graph

1. Use the same set of parameters at each time step
2. Flexible to realize different variants (with some tricks!)



Multi-layered RNNs

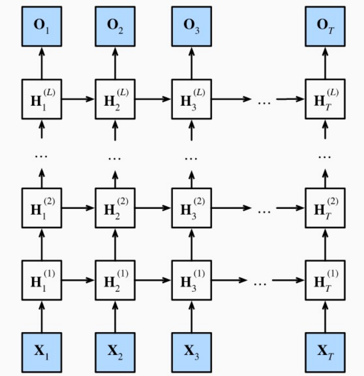
1. Stack multiple RNNs between i/p and o/p layers



Source

Multi-layered RNNs

1. Stack multiple RNNs between i/p and o/p layers
2. $H_t^{(l)} = W_{xh}^{(l)} \cdot H_t^{(l-1)} + W_{hh}^{(l)} \cdot H_{t-1}^{(l)} + b_h^{(l)}$



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Backpropagation Through Time (BPTT)

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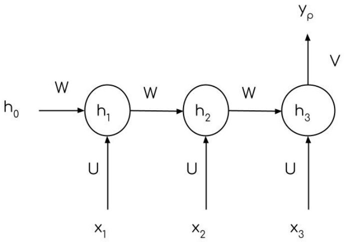

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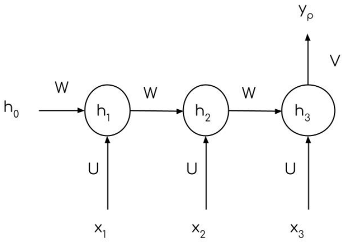

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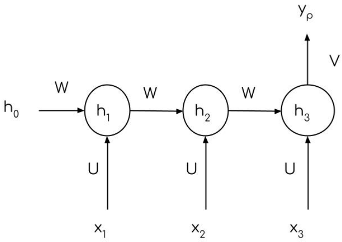
1. Let's now perform SGD (assume loss L is formulated on y_p)



Backpropagation Through Time (BPTT)

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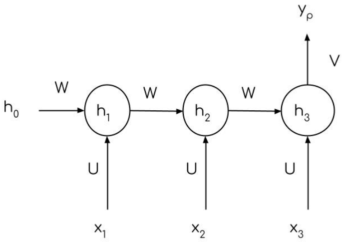
Indian Institute of Technology Hyderabad

1. Let's now perform SGD (assume loss L is formulated on y_p)
2. $\rightarrow$ we need to compute $\frac{\partial L}{\partial V}$, $\frac{\partial L}{\partial W}$, and $\frac{\partial L}{\partial U}$



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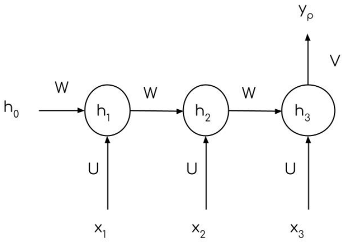
1. $\frac{\partial L}{\partial V} = \frac{\partial L}{\partial y_p} \frac{\partial y_p}{\partial V} = \frac{\partial L}{\partial y_p} \cdot \frac{\partial y_p}{\partial z_3} \cdot \frac{\partial z_3}{\partial V}$



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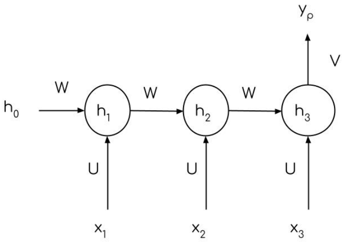
2. Since we know that $z_3 = V \cdot h_3 + b_y$ and h_3, b_y are independent of V, we can compute $\frac{\partial L}{\partial V}$ in a single step



Backpropagation Through Time (BPTT)

1. Let's now consider $\frac{\partial L}{\partial W}$