LCS2
LABORATORY FOR COMPUTATIONAL SOCIAL SYSTEMS

Convolutional and Recurrent Neural Networks

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Outline

- Deep Learning
- AutoEncoder
- Convolutional Neural Network (CNN)
- Recurrent Neural Network (RNN)
- Long Short Term Memory (LSTM)
- Gated Recurrent Unit (GRU)
- Attention Mechanism
- Few NLP Applications

Few key terms to start with

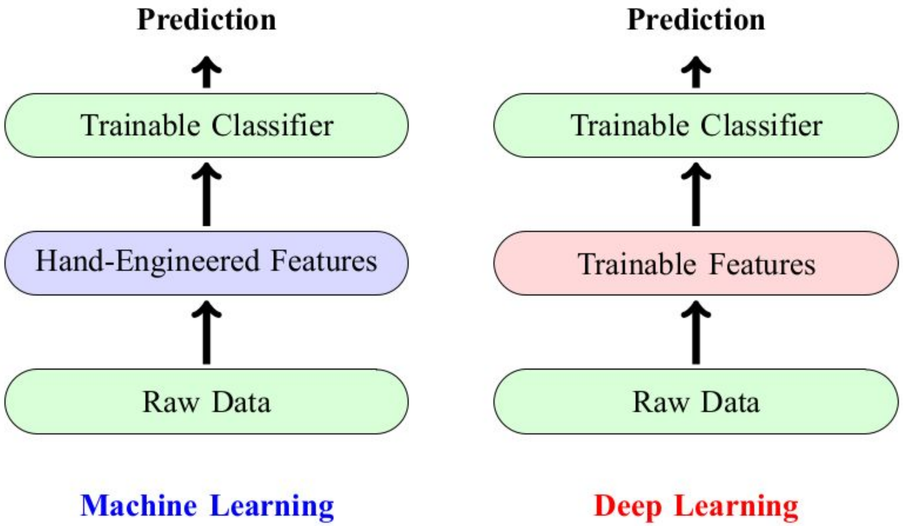
- Neurons
- Layers
  - *Input, Output and Hidden*
- Activation functions
  - *Sigmoid, Tanh, Relu*
- Softmax
- Weight matrices
  - *Input → Hidden, Hidden → Hidden, Hidden → Output*
- Backpropagation
  - Optimizers
    - Gradient Descent (GD), Stochastic Gradient Descent (SGD), Adam etc.
  - Error (Loss) functions
    - Mean-Squared Error, Cross-Entropy etc.
  - Gradient of error
  - Passes: Forward pass and Backward pass

History of Neural Network and Deep learning

- Neural Network and Perceptron learning algorithm: [McCulloch and Pitts (1943), Rosenblatt (1957)]
- Backpropagation: Rumelhart, Hinton and Williams, 1986
  - Theoretically, a neural network can have any number of hidden layers.
  - But, in practice, it rarely had more than one layer hidden layers.
    - Computational issue: Limited computing power
    - Algorithmical issues: Vanishing gradient and Exploding gradient.
- Beginning of Deep learning: Late 1990's and early 2000's
  - **Solutions:**
    - Computational issue: Advance computing powers such as GPUs, TPUs
    - Algorithmical issues
      - Pre-training (e.g., AutoEncoder, RBM)
      - Better architectures (e.g., LSTM)
      - Better activation functions (e.g., Relu)

Deep Learning vs Machine Learning Paradigm

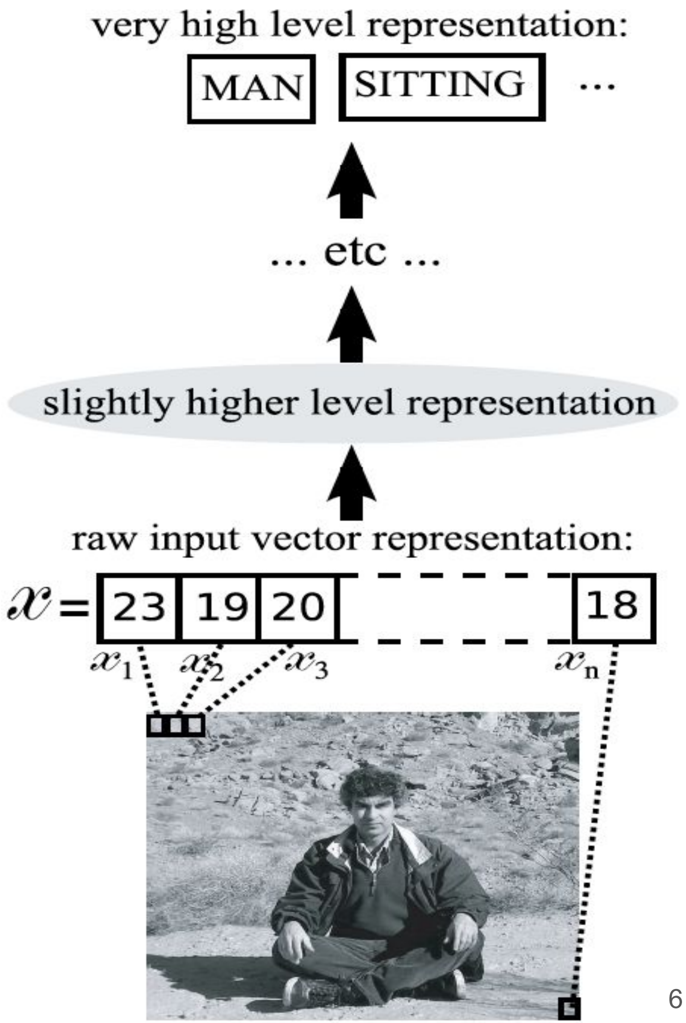
- The main advantage of deep learning based approaches is the trainable features, i.e., it extracts relevant features, on its own, during training.
- Requires minimal human intervention.



Why Deep Learning?

- Recall, artificial neural network tries to mimic the functionality of a brain.
- In brain, computations happen in layers.

- View of representation
  - As we go up in the network, we get high-level representations ⇒ Assists in performing more complex tasks.



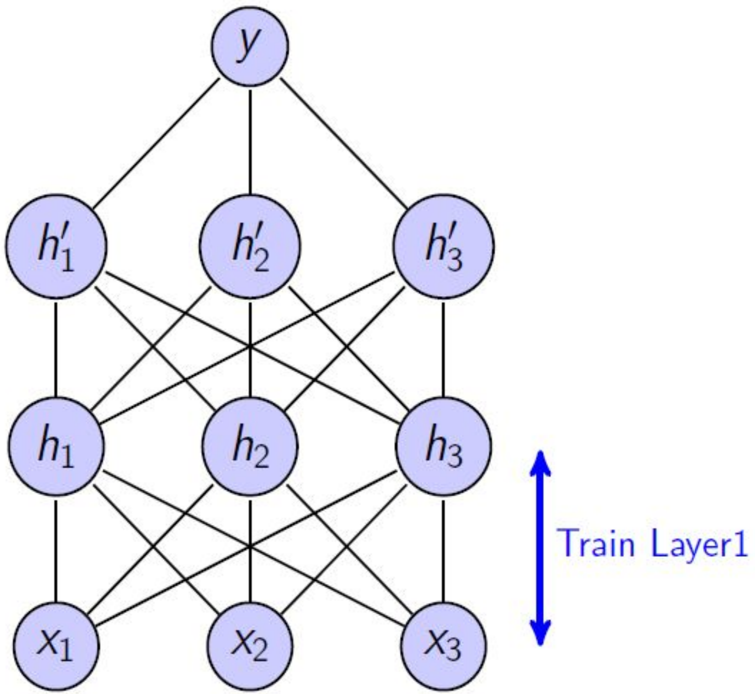
Why Deep Architectures were hard to train?

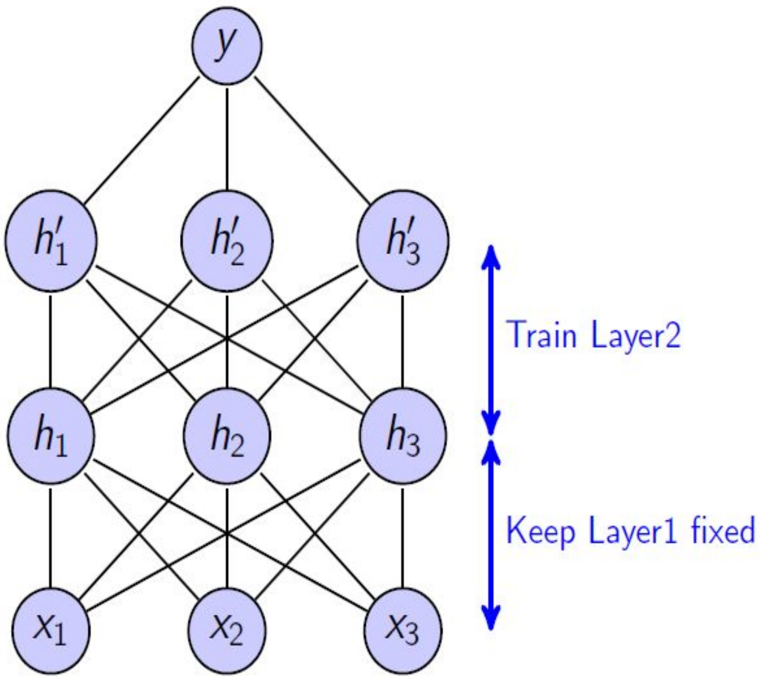
- General weight-updation rule

$$
\begin{aligned}
w_{ij} &= w_{ij} + \Delta w_{ij} \\
\Delta w_{ij} &= -\eta \frac{\partial E}{\partial w_{ij}} \\
&= -\eta \delta_j o_i \\
\delta_j &= \delta_k w_{jk} \sigma'
\end{aligned}
$$

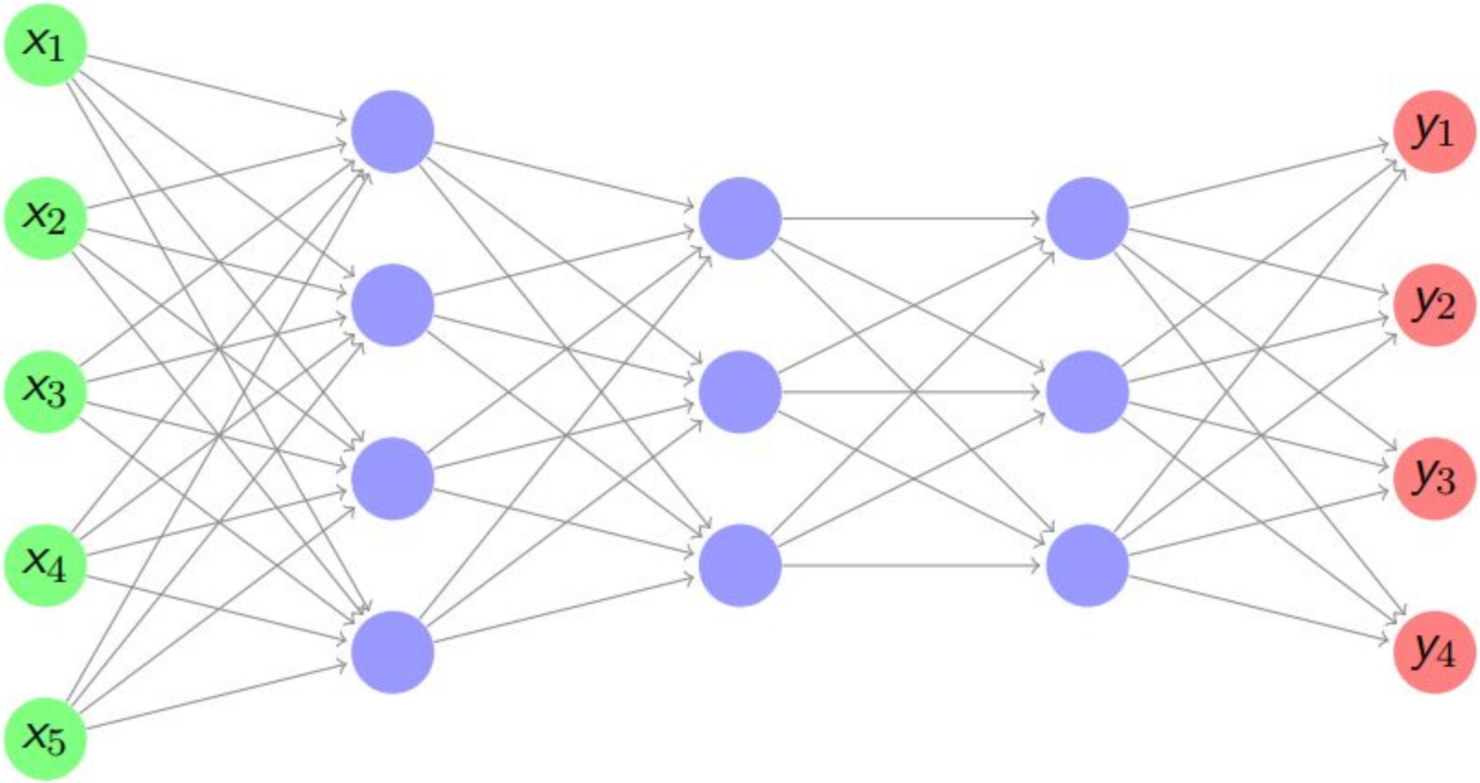
- For lower-layers in deep architecture
  - δ_j will vanish, if it is less than 1
  - δ_j will explode, if it is more than 1

Layer-wise pre-training

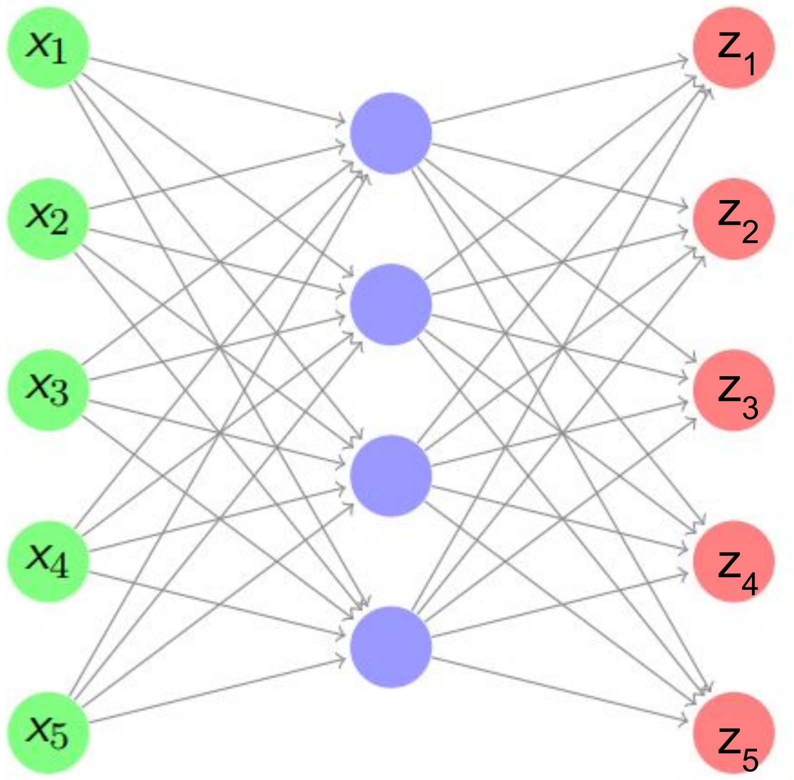




AutoEncoder

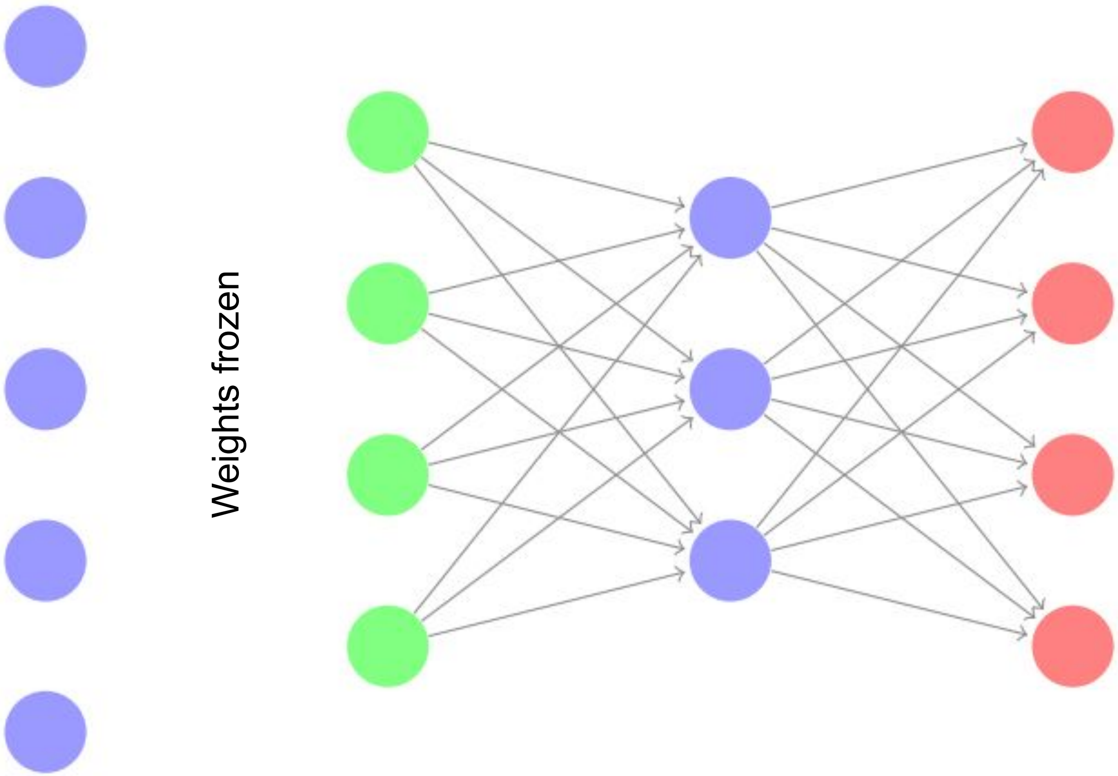


AutoEncoder: Layer 1

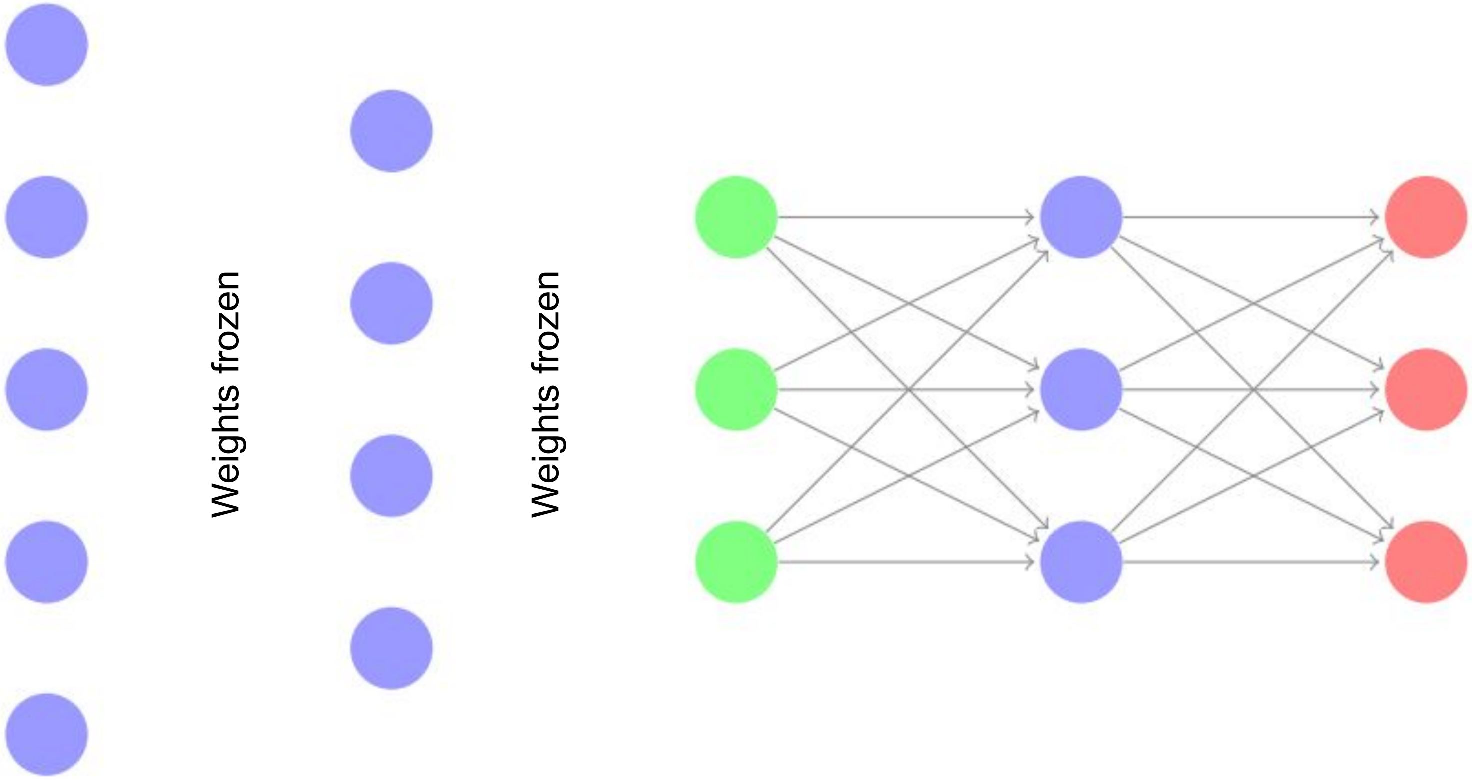


$z = f(x)$,
where $z \approx x$

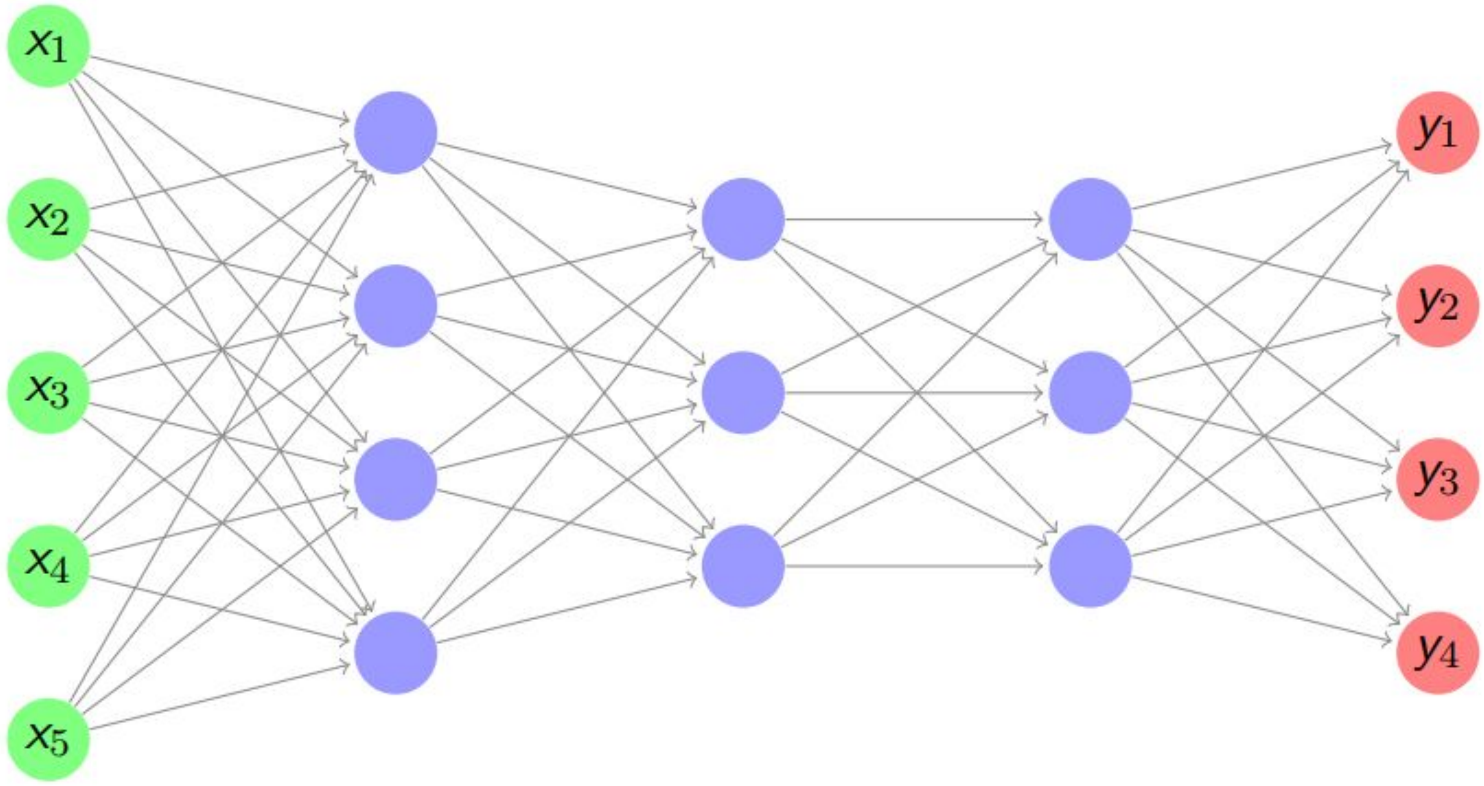
AutoEncoder: Layer 2



AutoEncoder: Layer 3



AutoEncoder: Pre-trained network



Deep Learning Architectures

- Convolutional neural network (CNN)
  - Aims to extract the local spatial features
- Recurrent neural network (RNN)
  - Exploits the sequential information of a sentence (sentence is a sequence of words).

Convolutional Neural Network

LeCunn and Bengio (1995)

Convolutional Neural Networks (CNN)

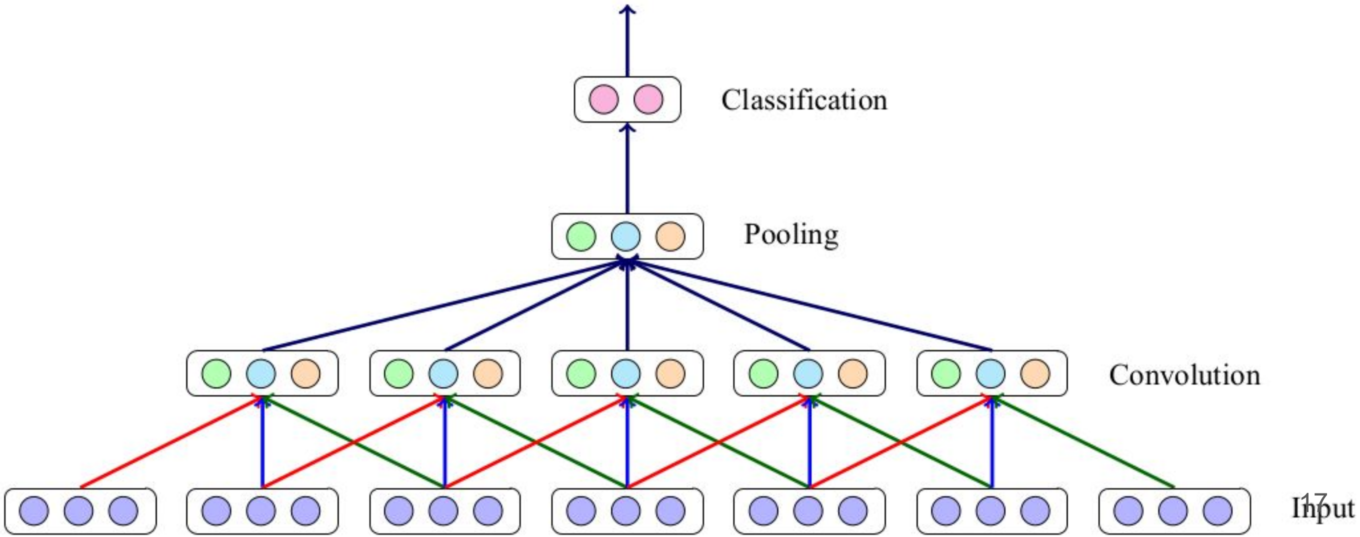
- A CNN consists of a series (≥ 1) of convolution layer and pooling layer.
- Convolutional operation extracts the feature representations from the input data.
  - Shares the convolution filters over different spatial locations, in a quest of extracting location-invariant features in the input.
  - Shape and weights of the convolution filter determine the features to be extracted from the input data.
  - In general, multiple filters of different shapes are used to ensure the diversity in the extracted features.
- Pooling operation extracts the most relevant features from the convoluted features. Similar to downsampling in image-processing.

CNN

For an input $X \in \mathbb{R}^{n \times d}$ and filter $F \in \mathbb{R}^{m \times d}$,

$$conv(x_i) = \sum_{j=1}^{m} \overrightarrow{f_j} \cdot \overrightarrow{x}_{i+j-1} \qquad \forall i \in [1, 2, ..., n-m+1]$$

$$Conv(X) = [conv(x_1), conv(x_2), ..., conv(x_{n-m+1})]$$

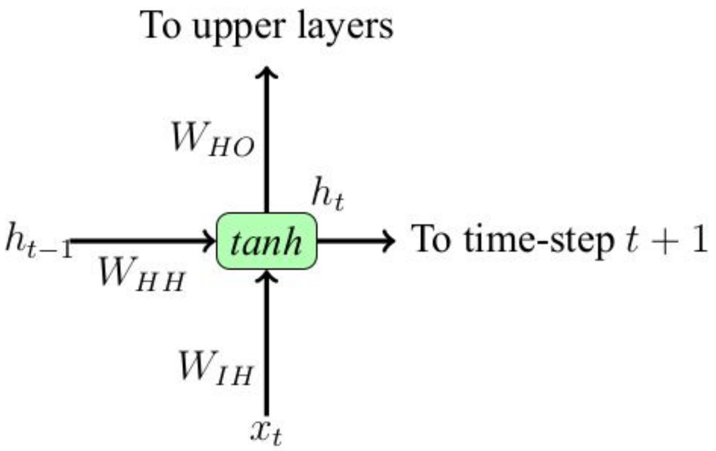


Recurrent Neural Network (RNN)

Recurrent Neural Network (RNN)

- A neural network with feedback connections
- Enable networks to do temporal processing
- Good at learning sequences
- Acts as memory unit

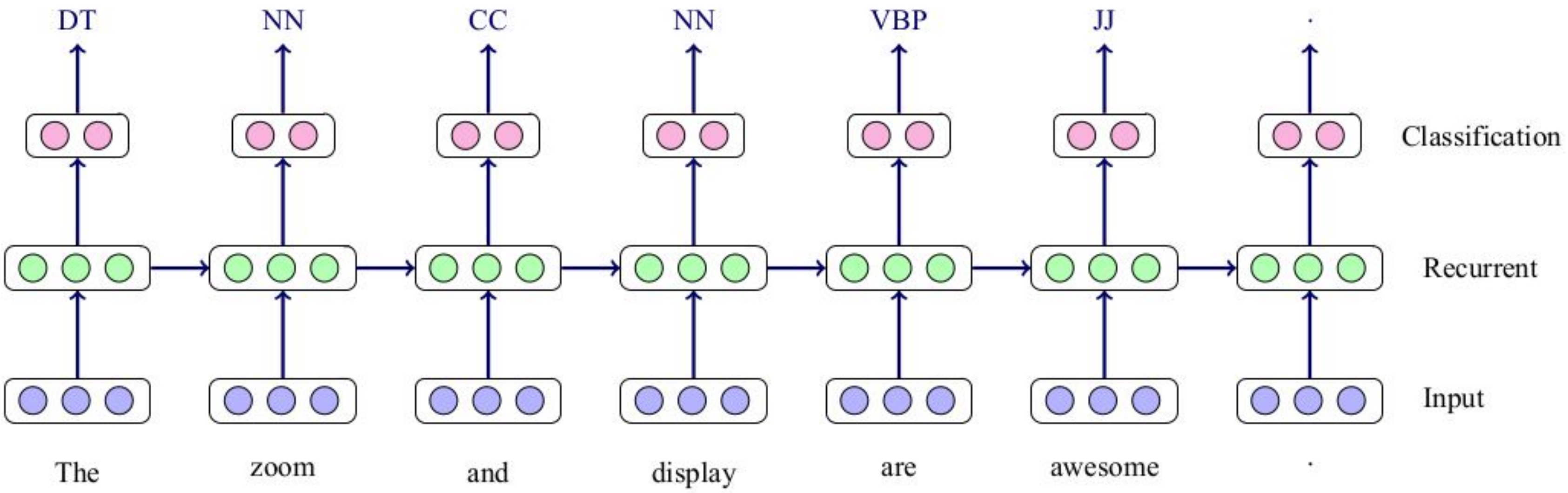
$$
\begin{aligned}
h_t &= tanh(W_{IH} \cdot x_t + W_{HH} \cdot h_{t-1} + b) \\
&= tanh([W_{IH}, W_{HH}] \cdot [x_t, h_{t-1}] + b)
\end{aligned}
$$



RNN - Example 1

Part-of-speech tagging:

- Given a sentence X, tag each word its corresponding grammatical class.



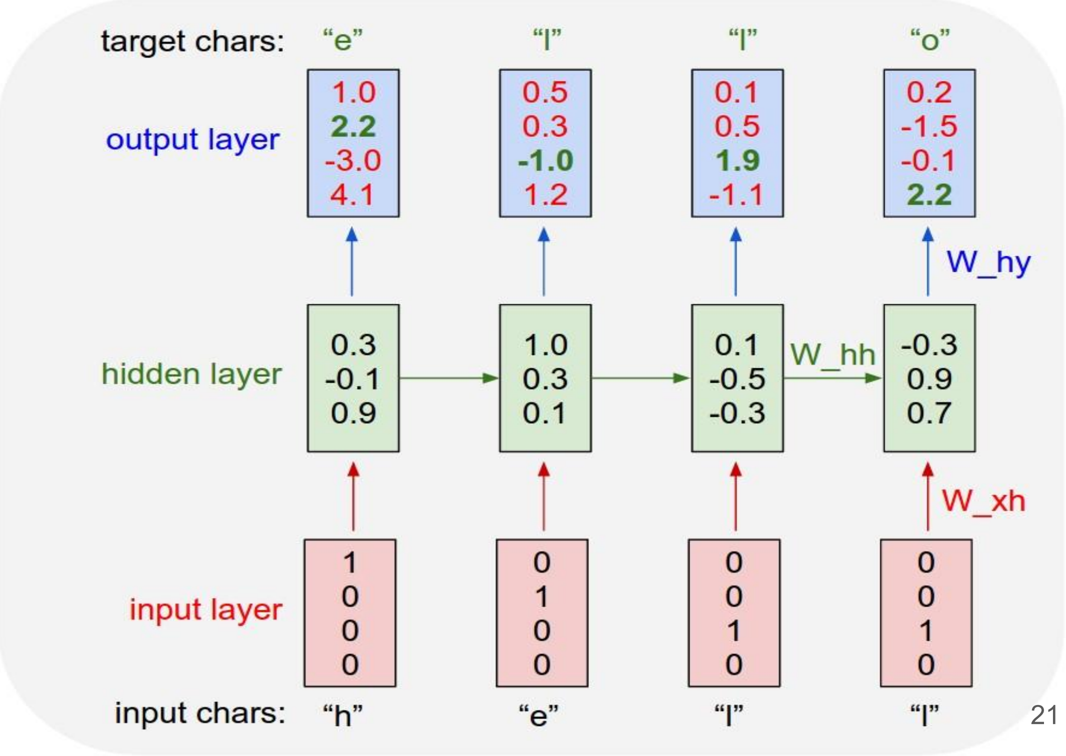
RNN - Example 2

Character level language model:

- Given previous and current characters, predict the next character in the sequence.

Let

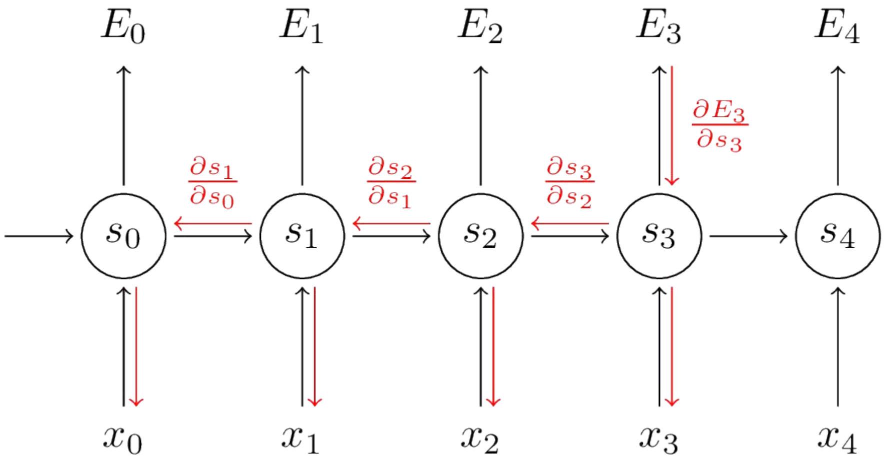
- **Vocabulary: [h,e,l,o]**
- **One-hot representations**
  - **h = [1 0 0 0]**
  - **e = [0 1 0 0]**
  - **l = [0 0 1 0]**
  - **o = [0 0 0 1]**



Training of RNNs

How to train RNNs?

- Typical FFN
  - Backpropagation algorithm
- RNNs
  - A variant of backpropagation algorithm namely **Back-Propagation Through Time (BPTT)**.

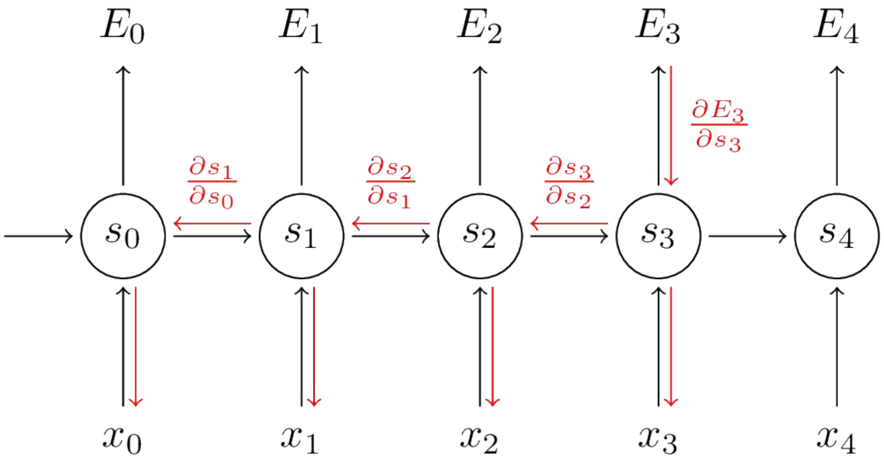


BackPropagation Through Time (BPTT)

Error for an instance = Sum of errors at each time step of the instance

Gradient of error

$$\frac{\partial E}{\partial W} = \sum_t \frac{\partial E_t}{\partial W}$$



BackPropagation Through Time (BPTT)

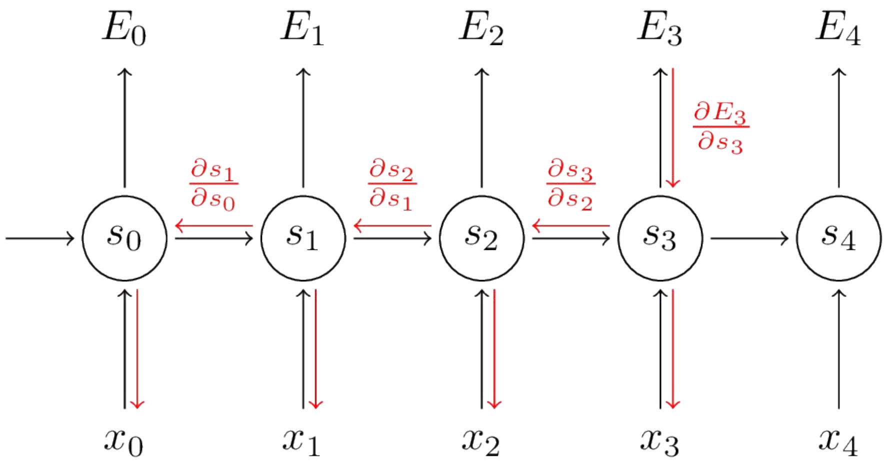
For *V*

$$\frac{\partial E_3}{\partial V} = \frac{\partial E_3}{\partial \hat{y}_3}\frac{\partial \hat{y}_3}{\partial V}$$

For *W* (Similarly for U)

$$\frac{\partial E_3}{\partial W} = \frac{\partial E_3}{\partial \hat{y}_3}\frac{\partial \hat{y}_3}{\partial s_3}\frac{\partial s_3}{\partial W}$$

$$\frac{\partial E_3}{\partial W} = \sum_{k=0}^{3}\frac{\partial E_3}{\partial \hat{y}_3}\frac{\partial \hat{y}_3}{\partial s_3}\frac{\partial s_3}{\partial s_k}\frac{\partial s_k}{\partial W}$$



Visualization of RNN through Feed-Forward Neural Network

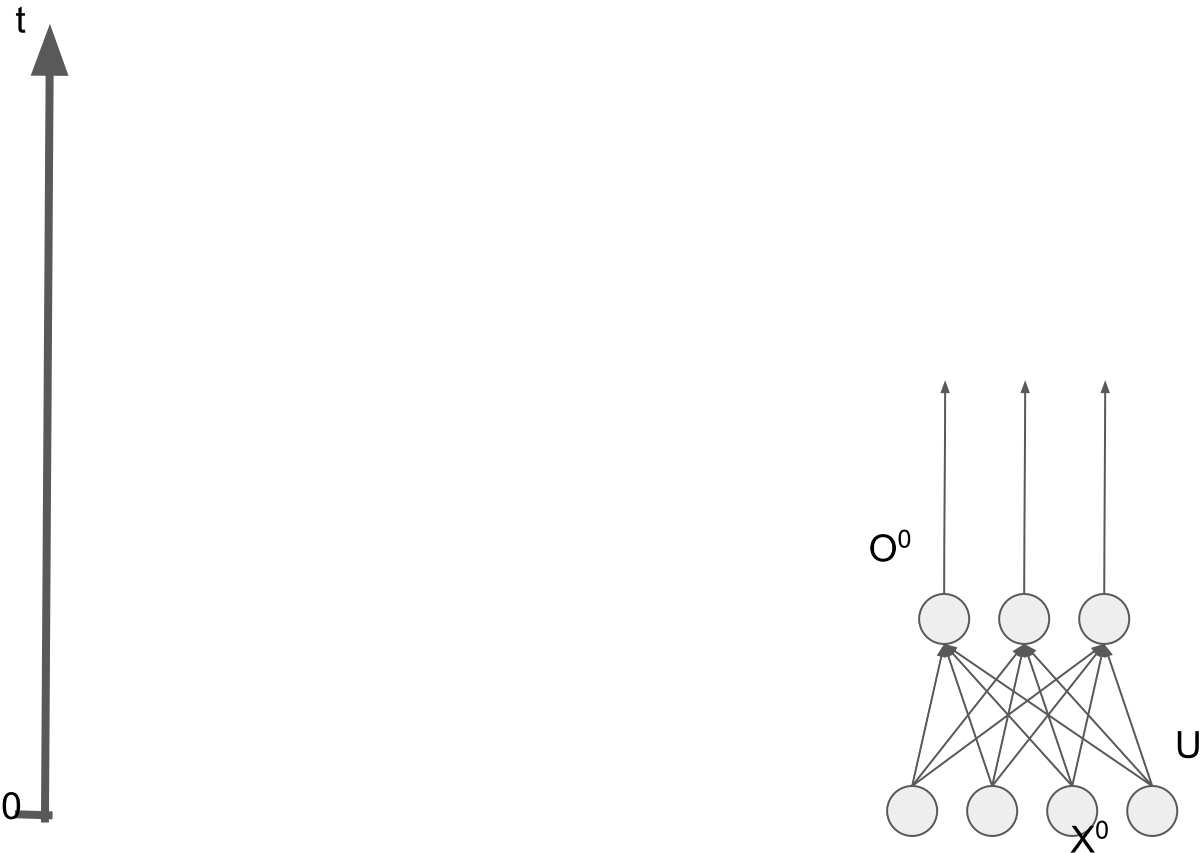
Problem, Data and Network Architecture

- Problem:
  - I/p sequence (X) : $X^0, X^1, \ldots, X^T$
  - O/p sequence (O) : $O^0, O^1, \ldots, O^T$

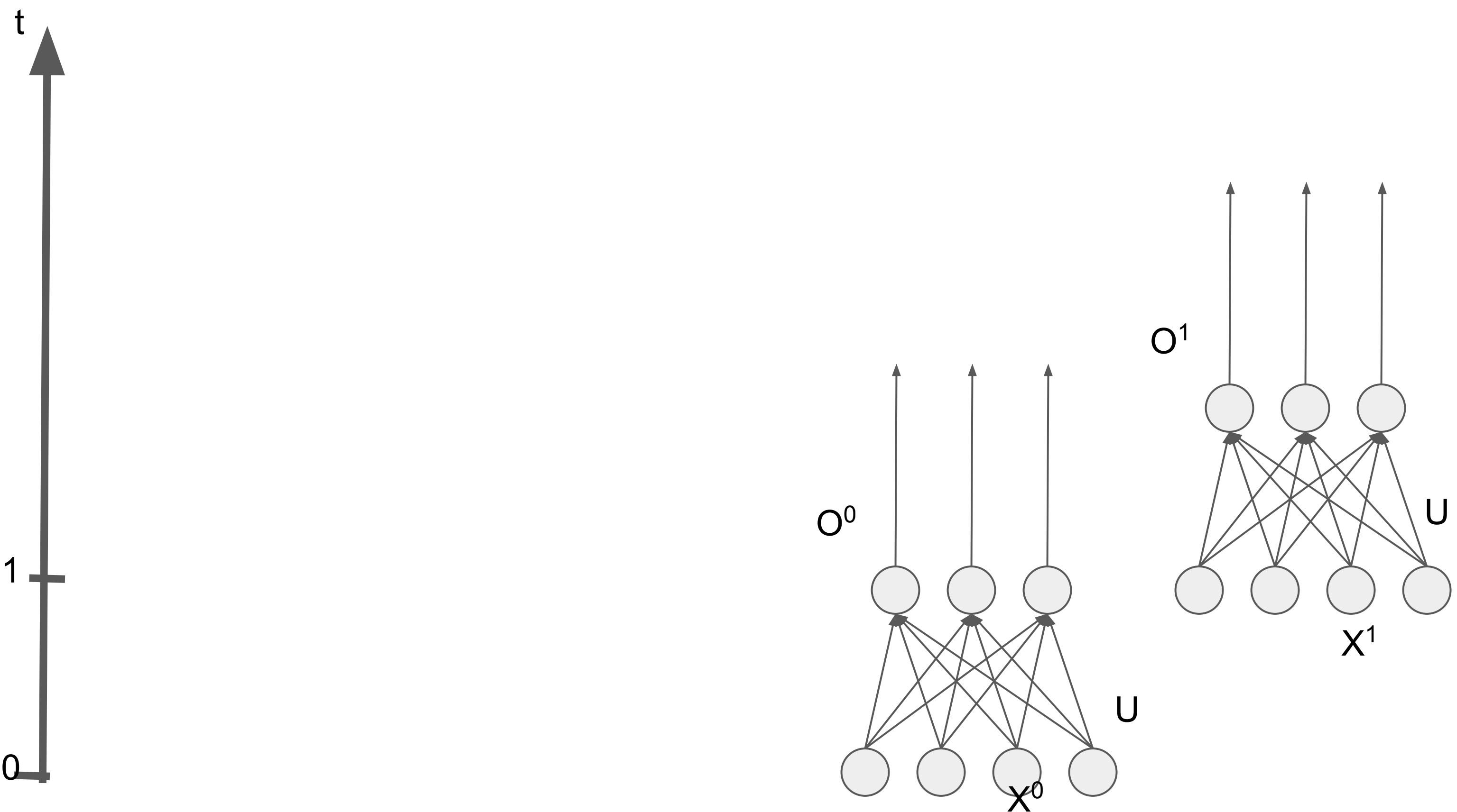
- Representation of data:
  - I/p dimension : 4
    - $X^0 \rightarrow 0\ 1\ 1\ 0$
  - O/p dimension : 3
    - $O^0 \rightarrow 0\ 0\ 1$

- Network Architecture
  - Number of neurons at I/p layer : 4
  - Number of neurons at O/p layer : 3
  - Do we need hidden layers?
    - If yes, number of neurons at each hidden layers

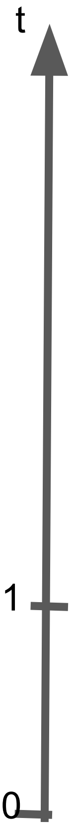
Network @ $t = 0$

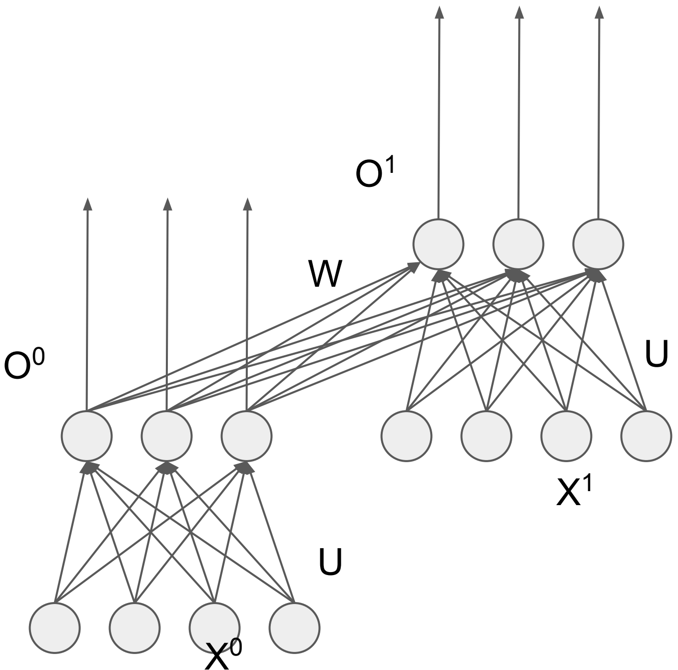


Network @ $t = 1$

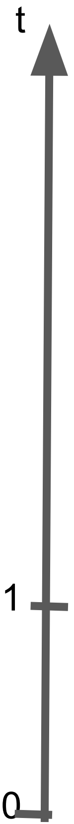


Network @ $t = 1$

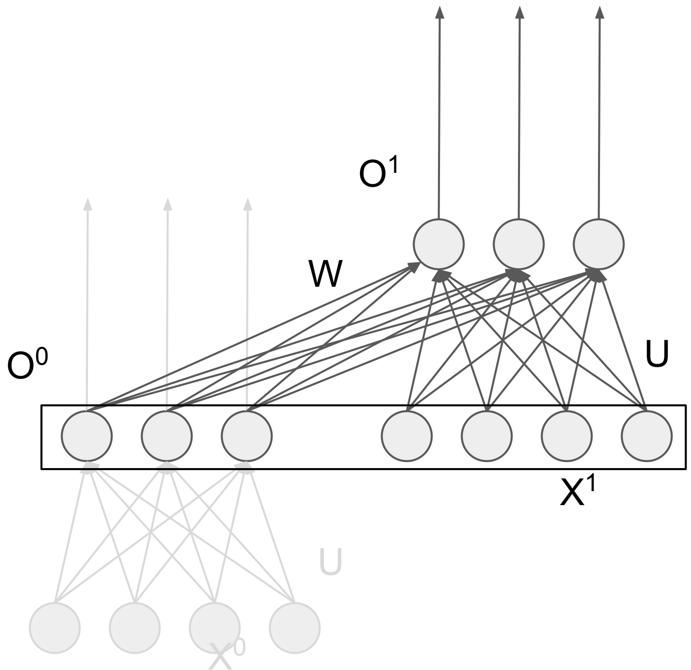




Network @ t = 1

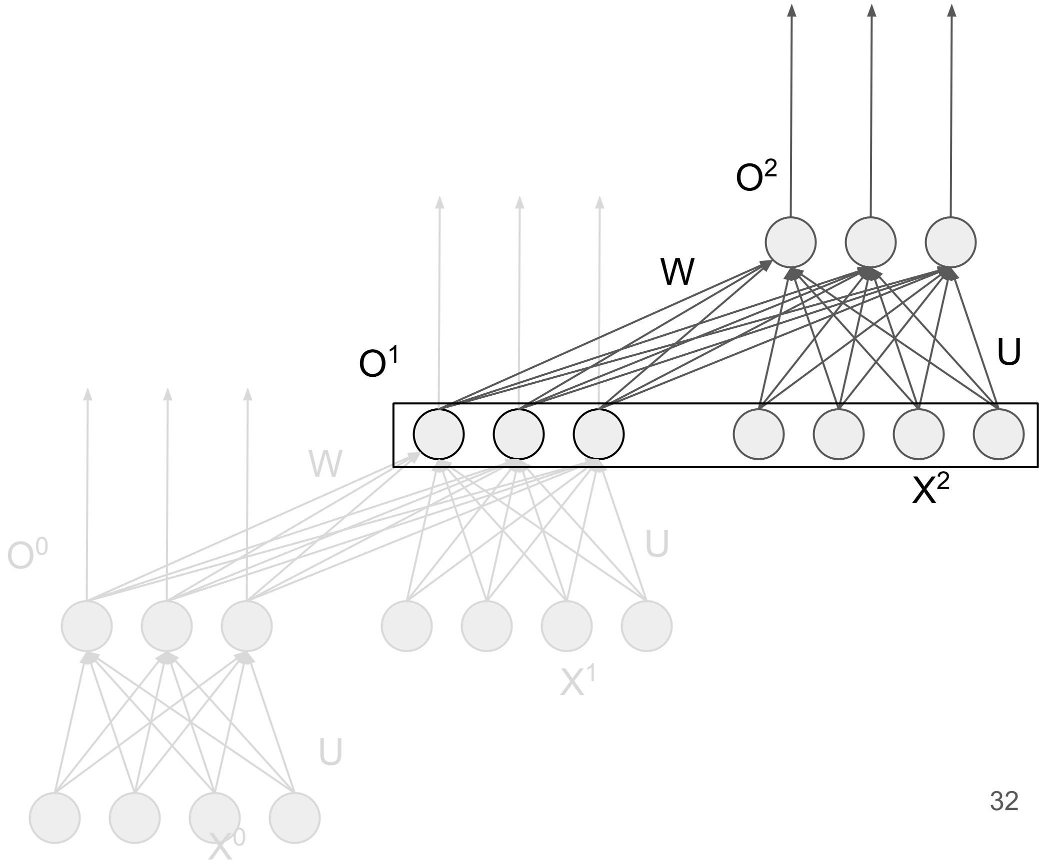


$$O^1 = f(W.O^0 + U.X^1)$$
$$= f([W, U] . [O^0, x^1])$$

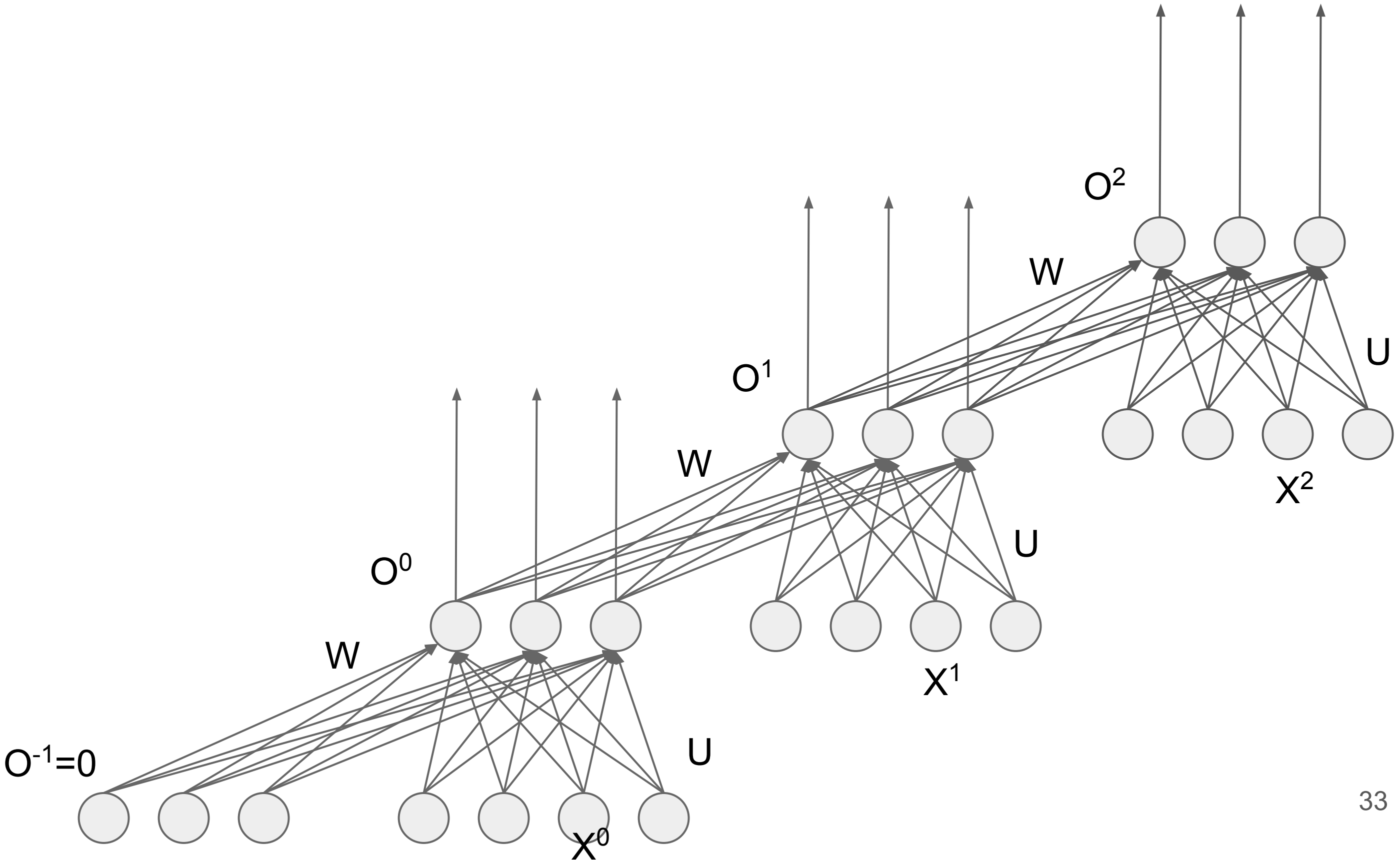


Network @ $t = 2$

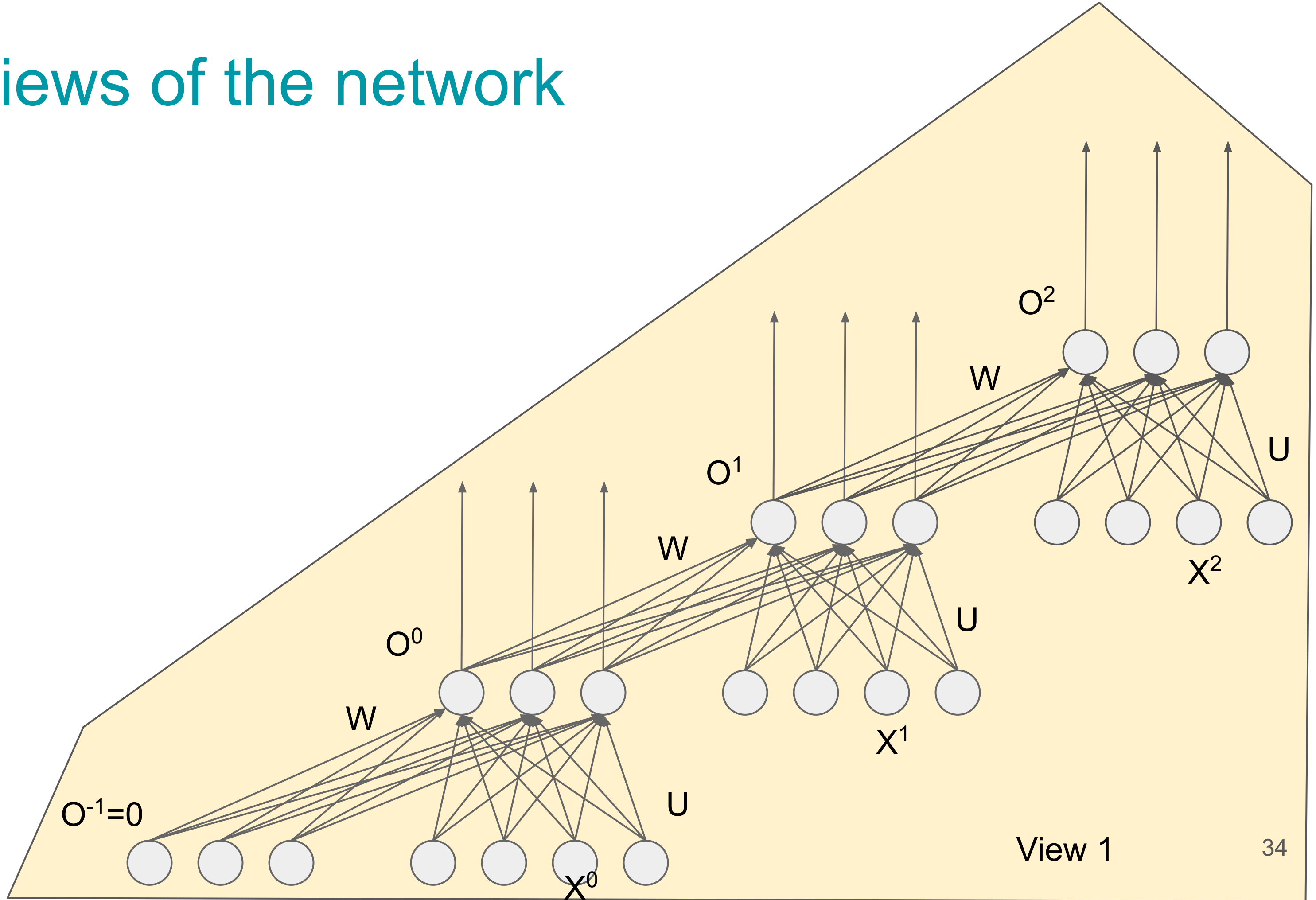
$$O^2 = f(W.O^1 + U.X^2)$$
$$= f([W, U] . [O^1, x^2])$$



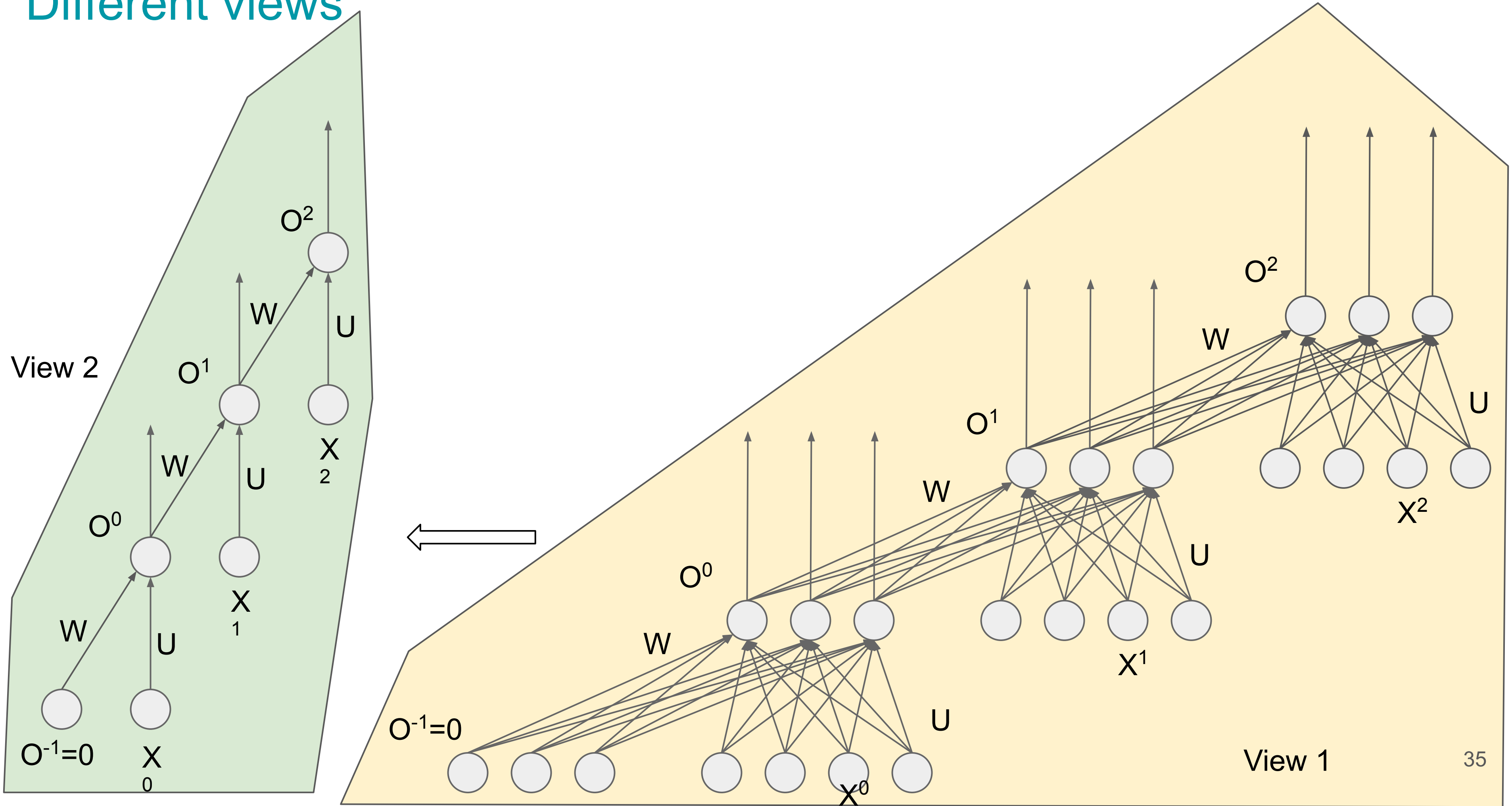
Complete Network



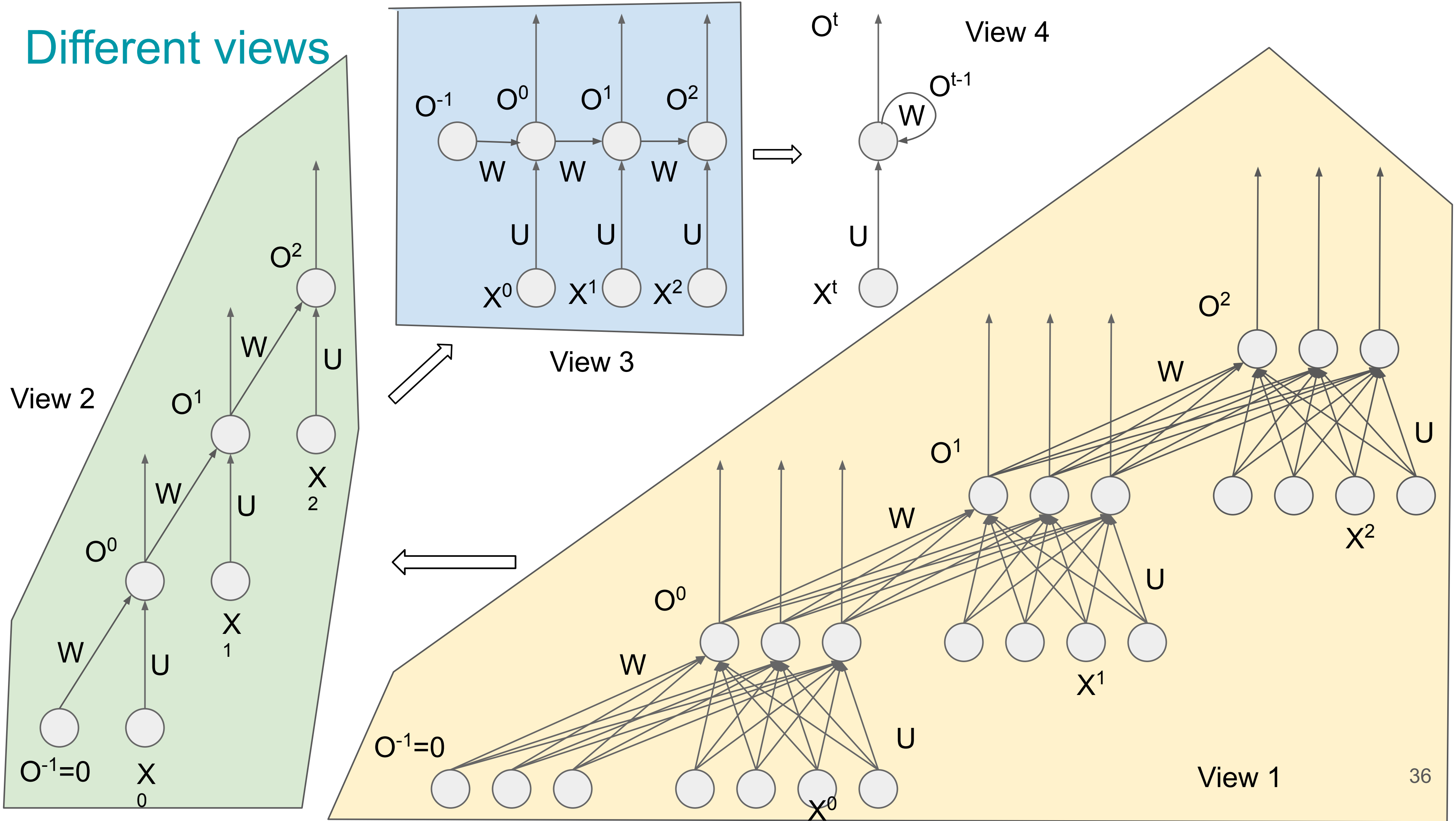
Different views of the network



Different views



Different views



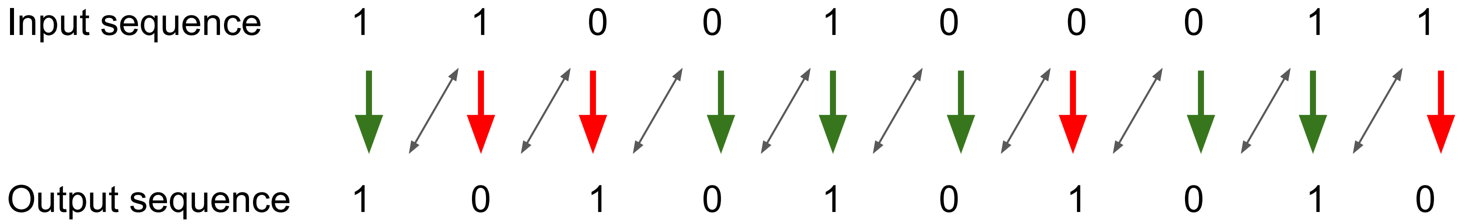
When to use RNNs

Usage

- Depends on the problems that we aim to solve.
- Typically good for sequence processings.
- Some sort of memorization is required.

Bit reverse problem

- Problem definition:
  - **Problem 1:** Reverse a binary digit.
    - 0 → 1   and   1 → 0
  - **Problem 2:** Reverse a sequence of binary digits.
    - 0 1 0 1 0 0 1   →   1 0 1 0 1 1 0
    - Sequence: Fixed or Variable length
  - **Problem 3:** Reverse a sequence of bits over time.
    - 0 1 0 1 0 0 1   →   1 0 1 0 1 1 0
  - **Problem 4:** Reverse a bit if the current i/p and previous o/p are same.



Data

Let

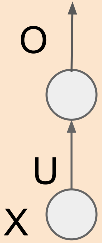
- **Problem 1**
  - I/p dimension: **1 bit** O/p dimension: **1 bit**
- **Problem 2**
  - Fixed
    - I/p dimension: **10 bit** O/p dimension: **10 bit**
  - Variable: Pad each sequence upto max sequence length: **10**
    - Padding value: **-1**
    - I/p dimension: **10 bit** O/p dimension: **10 bit**
- **Problem 3 & 4**
  - Dimension of each element of I/p (X) : **1 bit**
  - Dimension of each element of O/p (O) : **1 bit**
  - Sequence length : **10**

No. of I/p neurons = I/p dimension

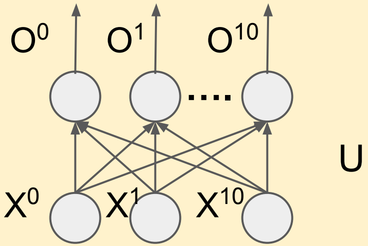
No. of O/p neurons = O/p dimension

Network Architecture

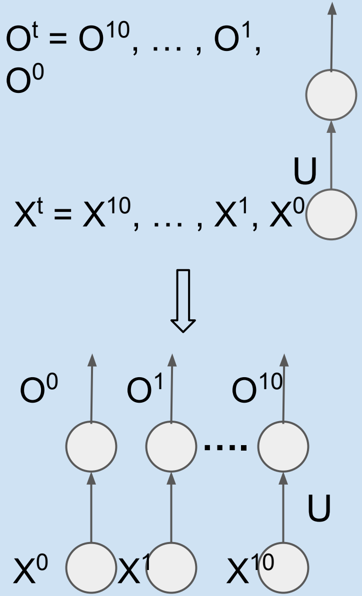
Problem 1:
- I/p neurons = 1
- O/p neurons = 1



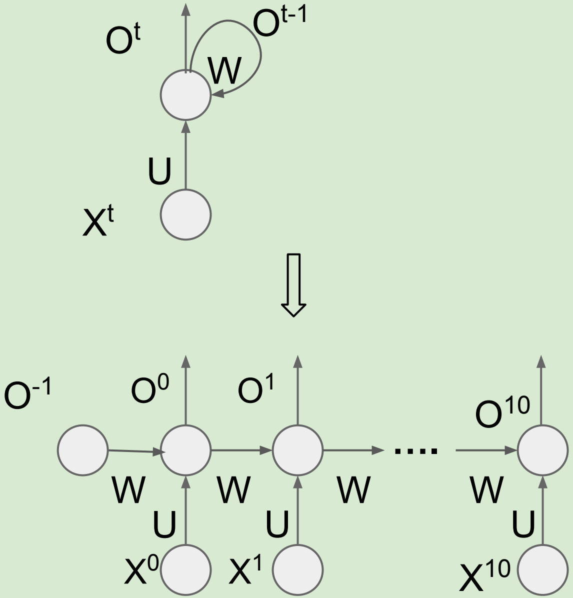
Problem 2: Fixed & Variable
- I/p neurons = 10
- O/p neurons = 10



Problem 3:
- I/p neurons = 1
- O/p neurons = 1
- Seq len = 10



Problem 4:
- I/p neurons = 1
- O/p neurons = 1
- Seq len = 10



Different configurations of RNNs

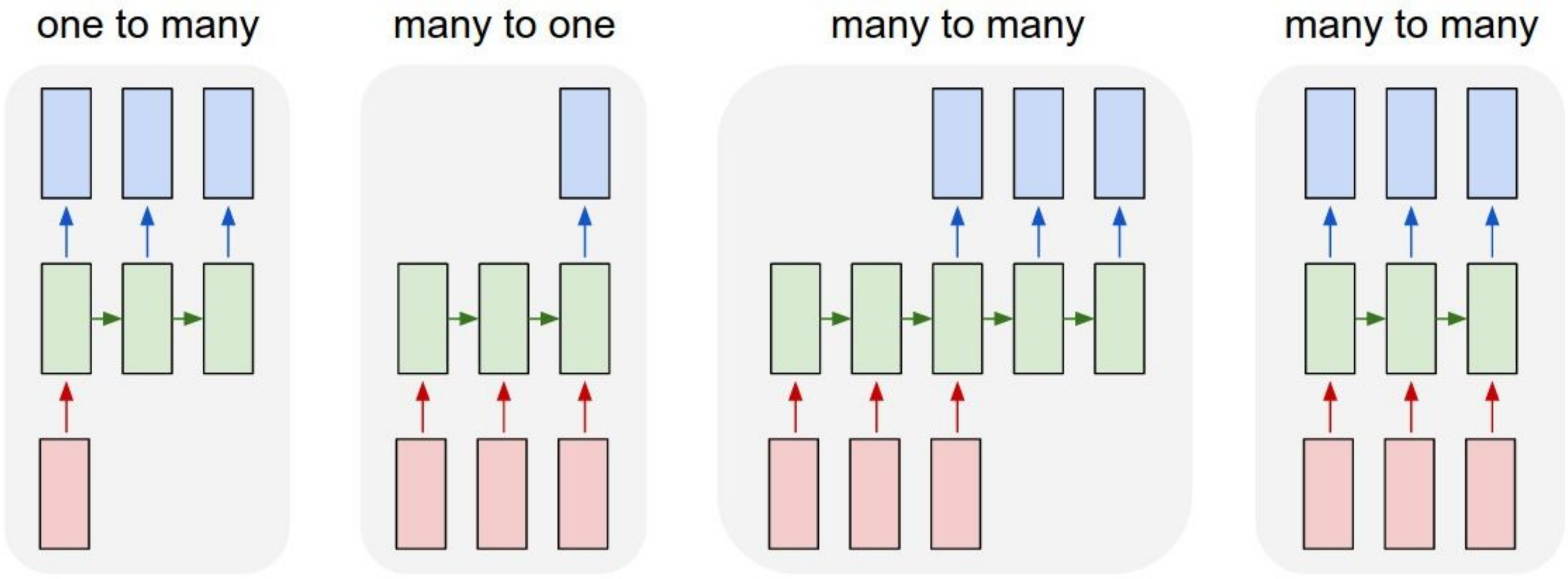


Image Captioning

Sentiment Analysis

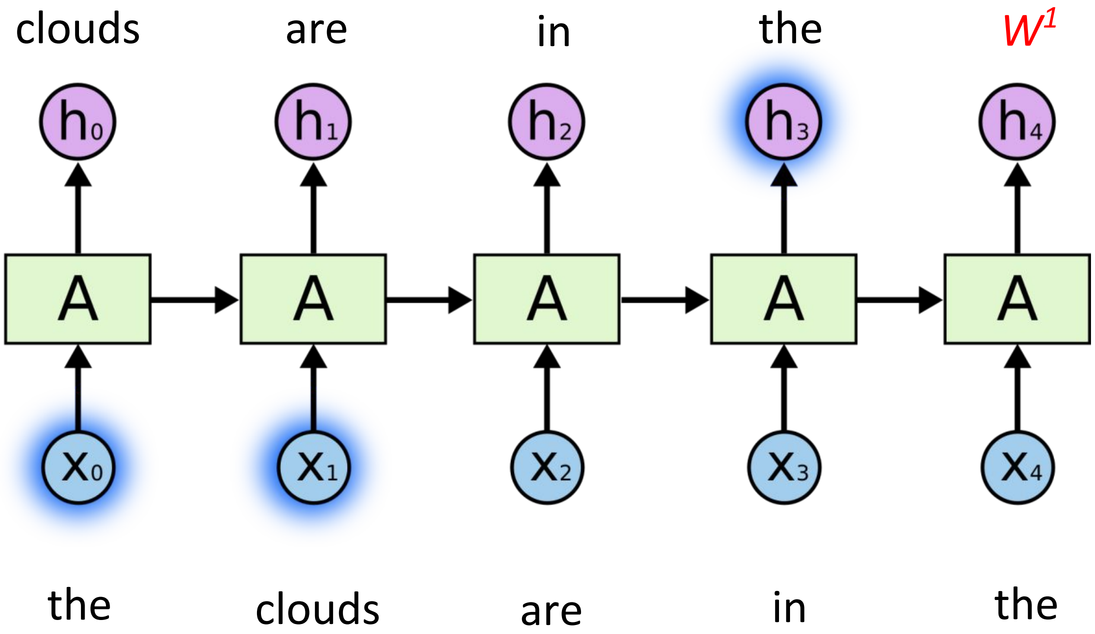
Machine Translation

Language modelling

Problems with RNNs

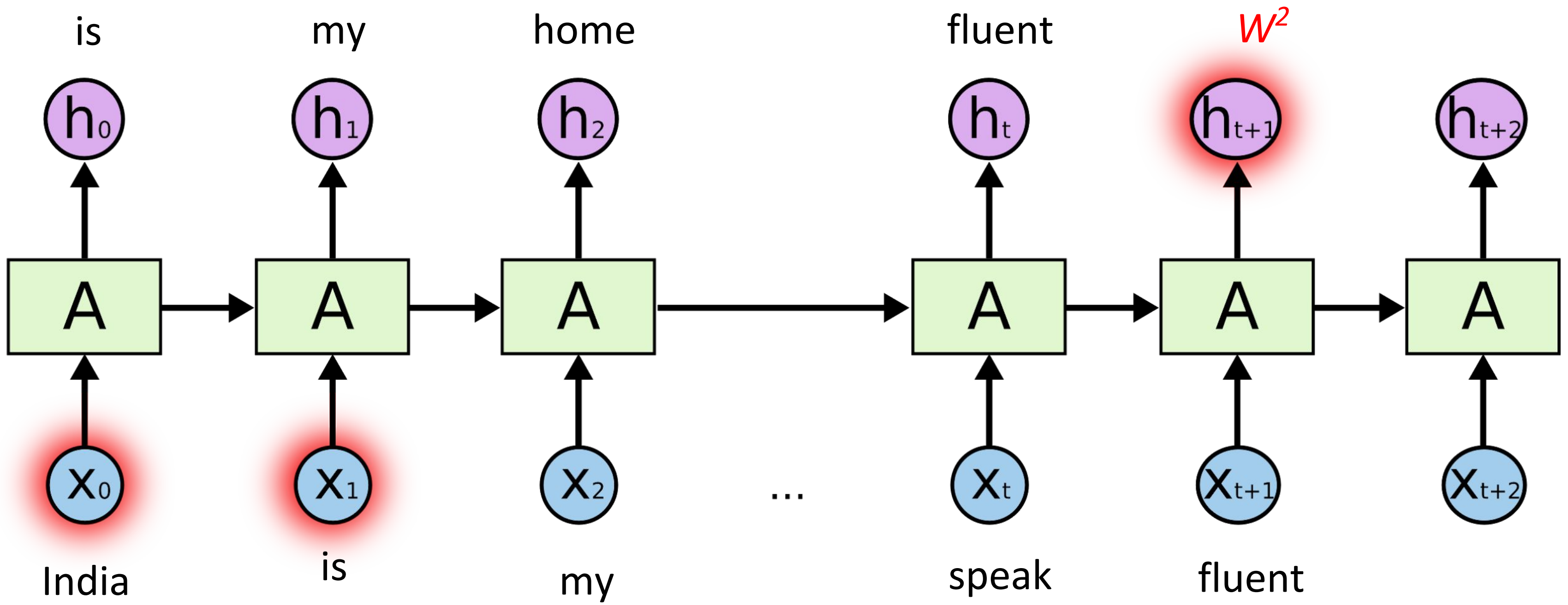
Language modelling: Example - 1

- “the clouds are in the *sky*”



Language modelling: Example - 2

- "India is my home country. I can speak fluent *Hindi*."



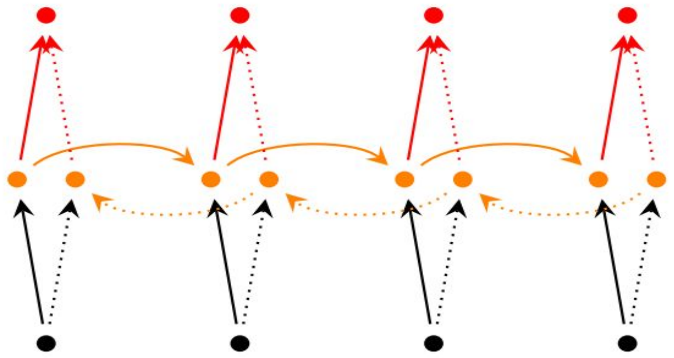
Vanishing/Exploding gradients

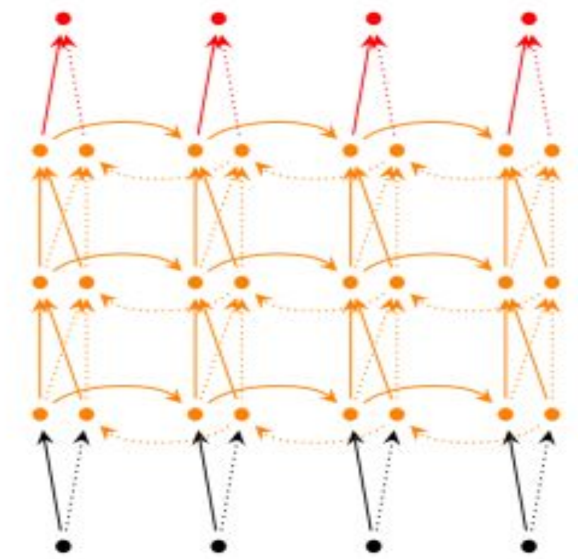
- Cue word for the prediction
  - Example 1: ***sky*** → ***clouds*** [3 units apart]
  - Example 2: ***hindi*** → ***India*** [9 units apart]

- As the sequence length increases, it becomes hard for RNNs to learn "long-term dependencies."
  - **Vanishing gradients:** If weights are small, gradient shrinks exponentially. Network stops learning.
  - **Exploding gradients:** If weights are large, gradient grows exponentially. Weights fluctuate and become unstable.

RNN extensions

- Bi-directional RNN
- Deep (Bi-directional) RNN





Long Short Term Memory (LSTM)

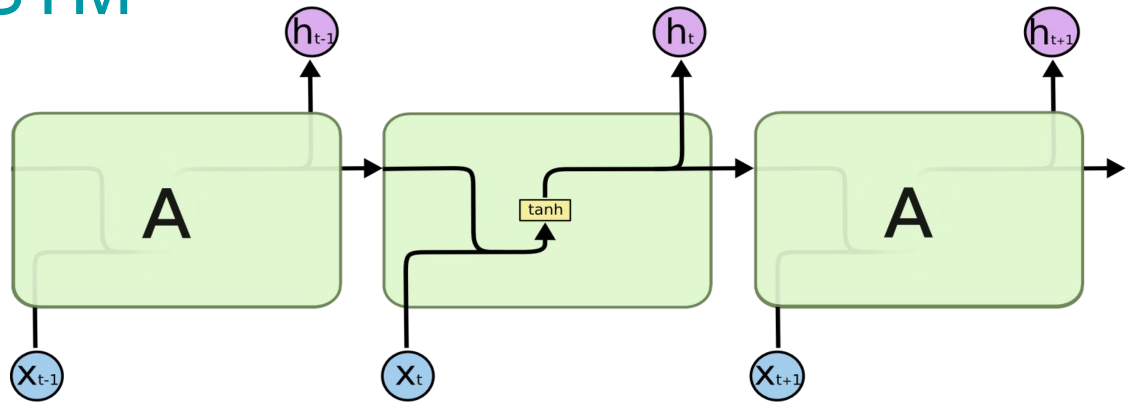
Hochreiter & Schmidhuber (1997)

LSTM

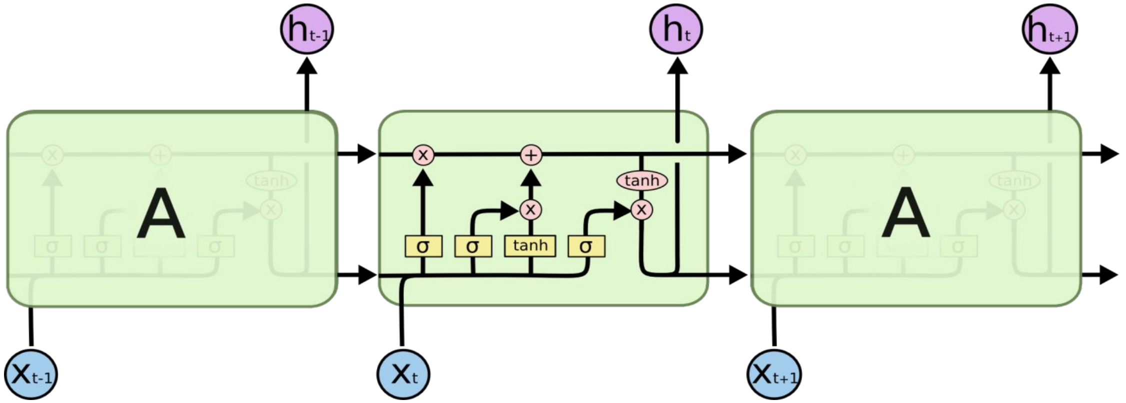
- A variant of simple RNN (Vanilla RNN)
- Capable of learning long dependencies.
- Regulates information flow from recurrent units.

Vanilla RNN vs LSTM

Vanilla RNN cell



LSTM cell



An LSTM cell

- Cell state c_t (blue arrow), hidden state h_t (green arrow) and input x_t (red arrow)
- Three gates
  - Forget (Red-dotted box)

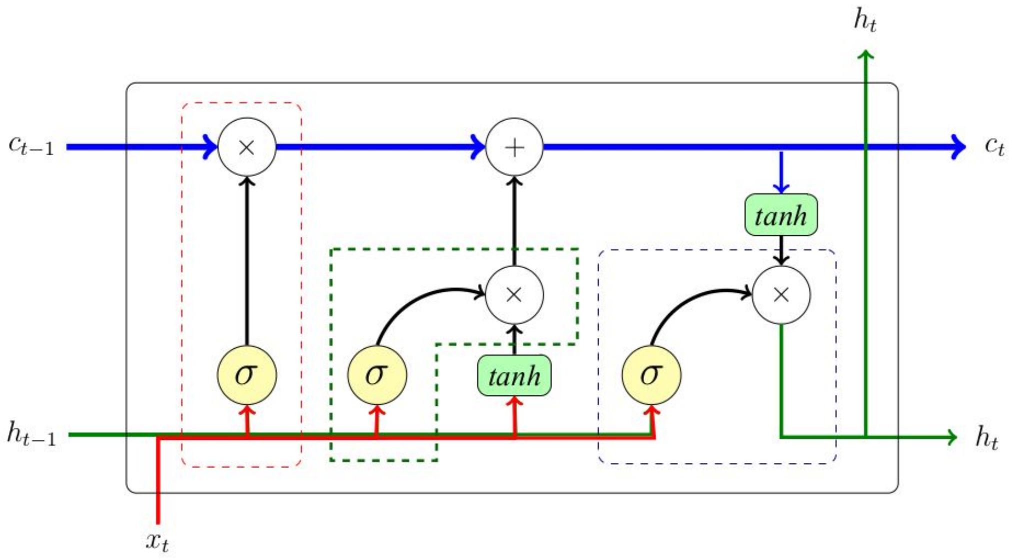
$$\begin{aligned} f_t &= \sigma(W_f \cdot [h_{t-1}, x_t]) \\ c_t &= f_t \otimes c_{t-1} \end{aligned}$$

  - Input (Green-dotted box)

$$\begin{aligned} z_t &= tanh(W_z \cdot [h_{t-1}, x_t]) \\ i_t &= \sigma(W_i \cdot [h_{t-1}, x_t]) \\ c_t &= c_t + (i_t \otimes z_t) \end{aligned}$$

  - Output (Blue-dotted box)

$$\begin{aligned} o_t &= \sigma(W_o \cdot [h_{t-1}, x_t]) \\ h_t &= o_t \otimes tanh(c_t) \end{aligned}$$



Gated Recurrent Units (GRU)

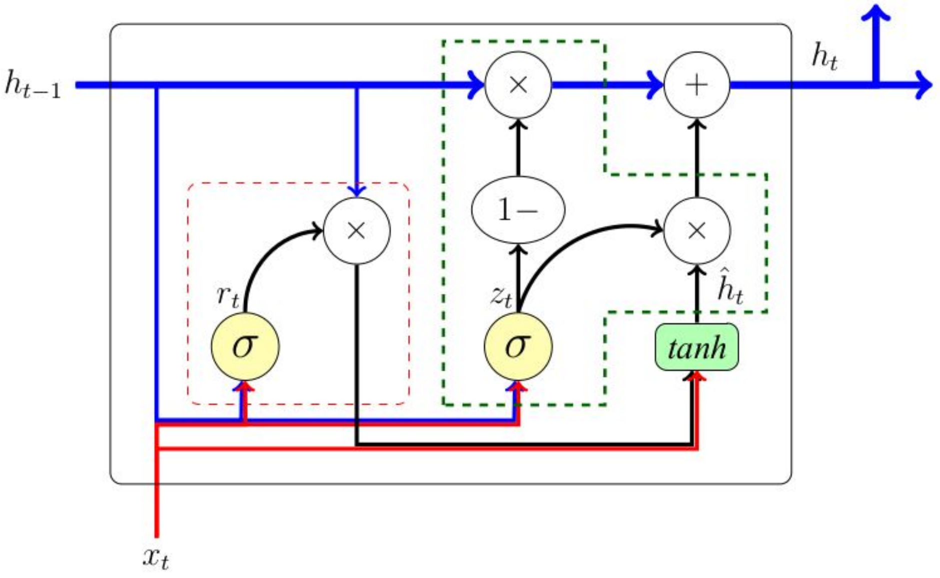
Kyunghyun Cho, Bart van Merrienboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, Yoshua Bengio (2014)

Gated Recurrent Unit (GRU) [Cho et al. (2014)]

- A variant of simple RNN (Vanilla RNN)
- Similar to LSTM
  - Whatever LSTM can do GRU can also do.
- Differences
  - Cell state and hidden are merged together
  - Two gates
    - Reset gate - similar to forget
    - Update gate - similar to input gate
  - No output gate
  - Cell/Hidden state is completely exposed to subsequent units.
- GRU needs fewer parameters to learn and is relatively efficient *w.r.t.* computation.

A GRU cell

$$
\begin{aligned}
z_t &= \sigma(W_z \cdot [h_{t-1}, x_t]) \\
r_t &= \sigma(W_r \cdot [h_{t-1}, x_t]) \\
\hat{h}_t &= tanh(W \cdot [r_t \otimes h_{t-1}, x_t]) \\
h_t &= (1 - z_t) \otimes h_{t-1} + z_t \otimes \hat{h}_t
\end{aligned}
$$



Application of DL methods for NLP tasks

NLP hierarchy

- Like deep learning, NLP happens in layers!
- Each task receives features from its previous (lower-level) task, and process them to produce its own output and so on.

Pragmatics & Discourse	*Study of semantics in context.*
Semantics	*Meaning of the sentence.*
Parsing	*Syntactic structure of the sentence.*
Chunking	*Grouping of meaningful phrases.*
Part of speech tagging	*Grammatical classes.*
Morphology	*Study of word structure.*

↑ Increasing Complexity Of Processing

NLP problems

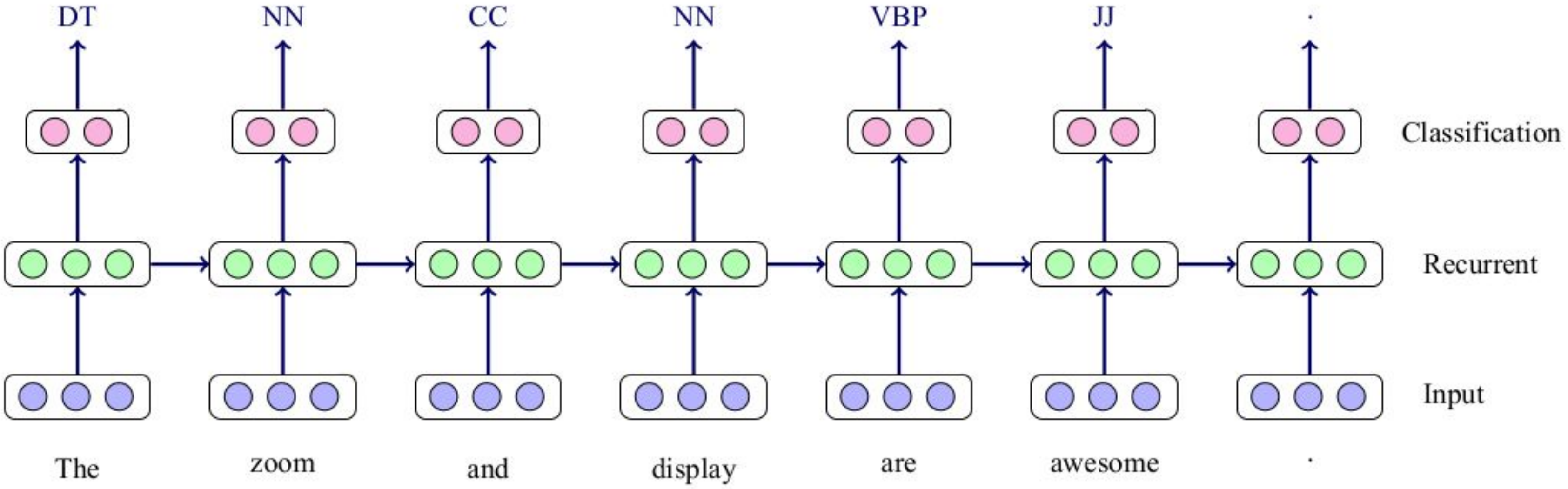
Problems	**Paradigm**
POS Tagging	Sequence Labelling
Named Entity Recognition	
Sentiment Analysis	Classification
Machine Translation	Sequence Transformation
Question Answering	
Summarization	

Sequence Labelling

RNN/LSTM/GRU for Sequence Labelling

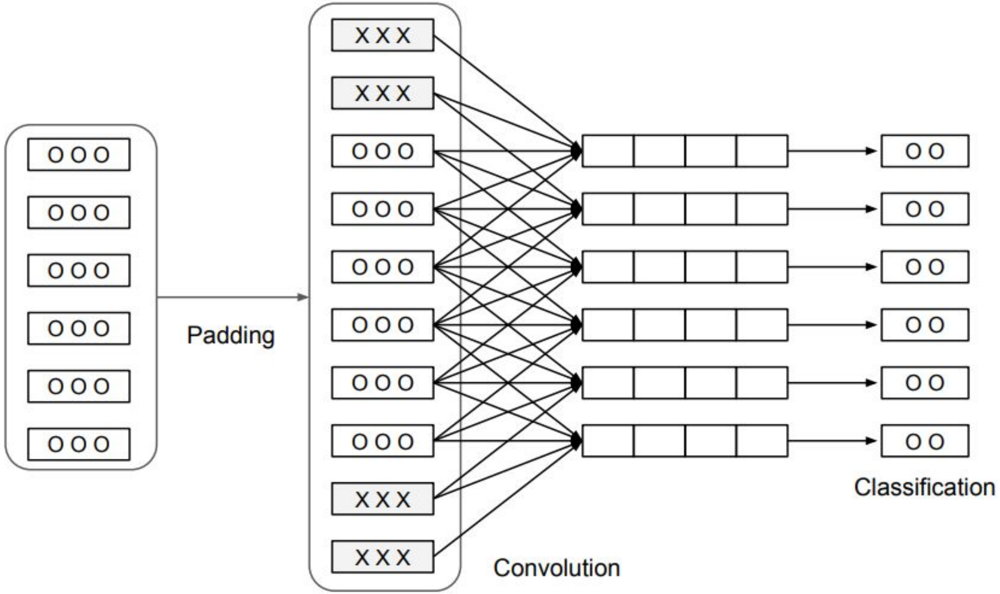
Part-of-speech tagging:

- Given a sentence X, tag each word its corresponding grammatical class.



CNN for Sequence Labelling

- Sentence matrix
- Pad sentence to ensure the sequence length
  - Pad length = filter_size - 1
  - Evenly distribute padding at the start and end of the sequence.
- Apply Convolution filters
- Classification

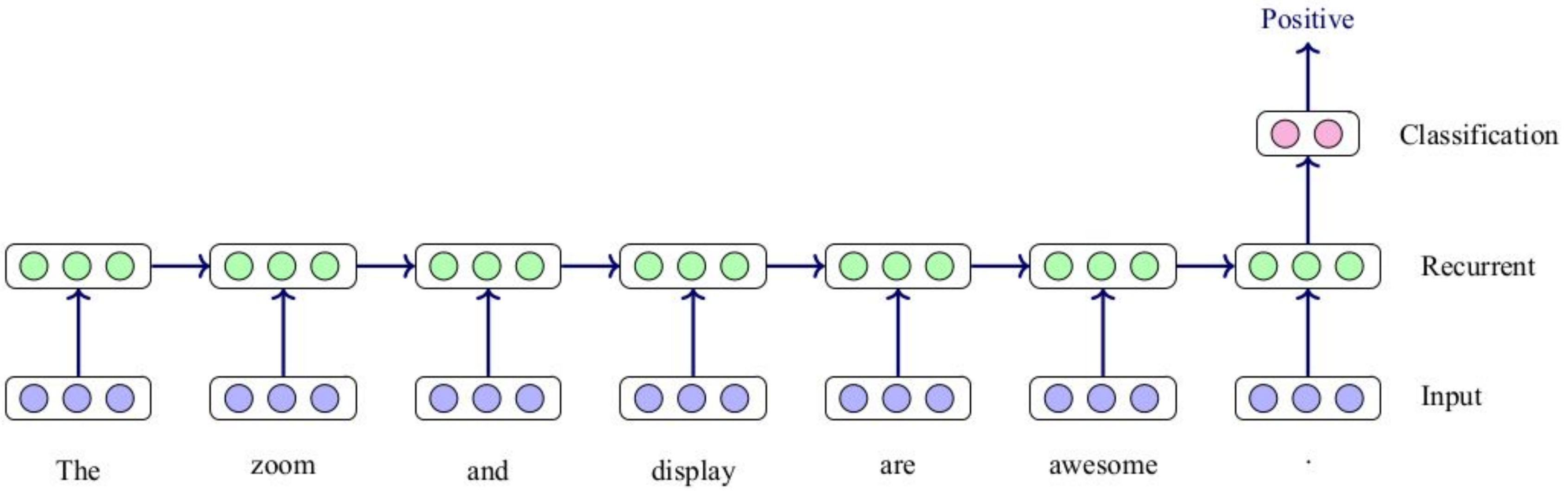


Classification

RNN/LSTM/GRU for Sentence Classification

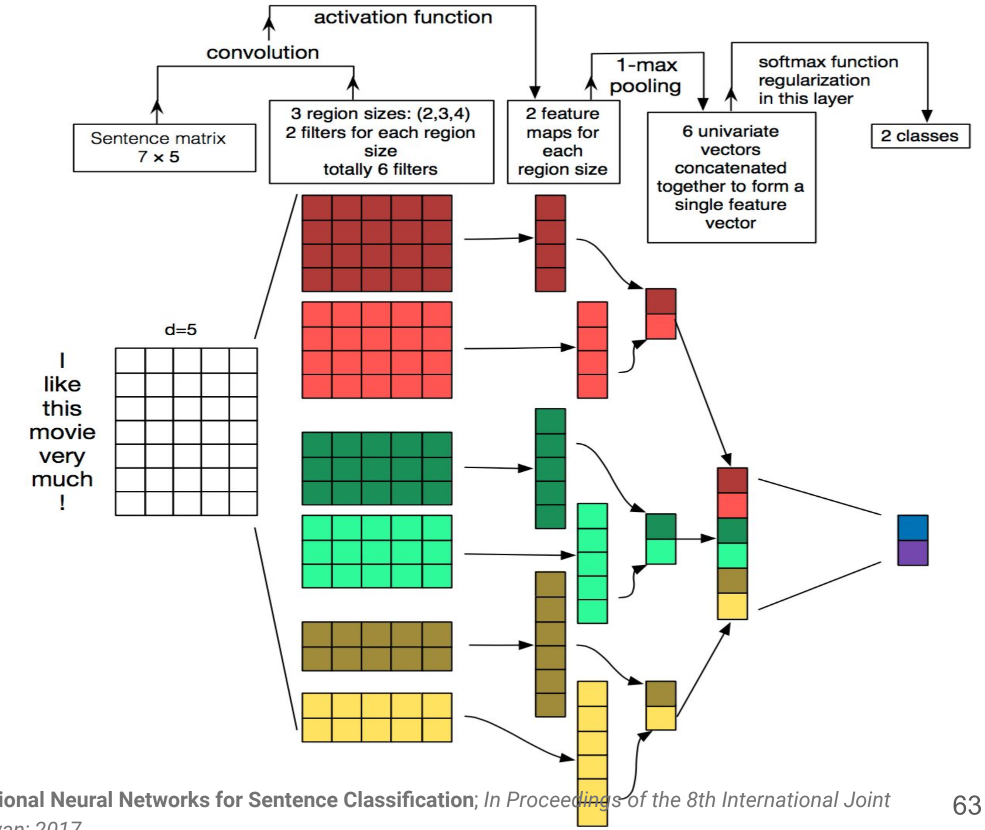
Sentiment Classification:

- Given a sentence X, identify the expressed sentiment.



CNN for Sentence Classification

1. Sentence matrix
   a. embeddings of words
2. Convolution filters
   a. Total 6 filters; Two each of size 2, 3 & 4.
   b. 1 feature maps for each filter
3. Pooling
   a. 1-max pooling
4. Concatenate the max-pooled vector
5. Classification
   a. Softmax

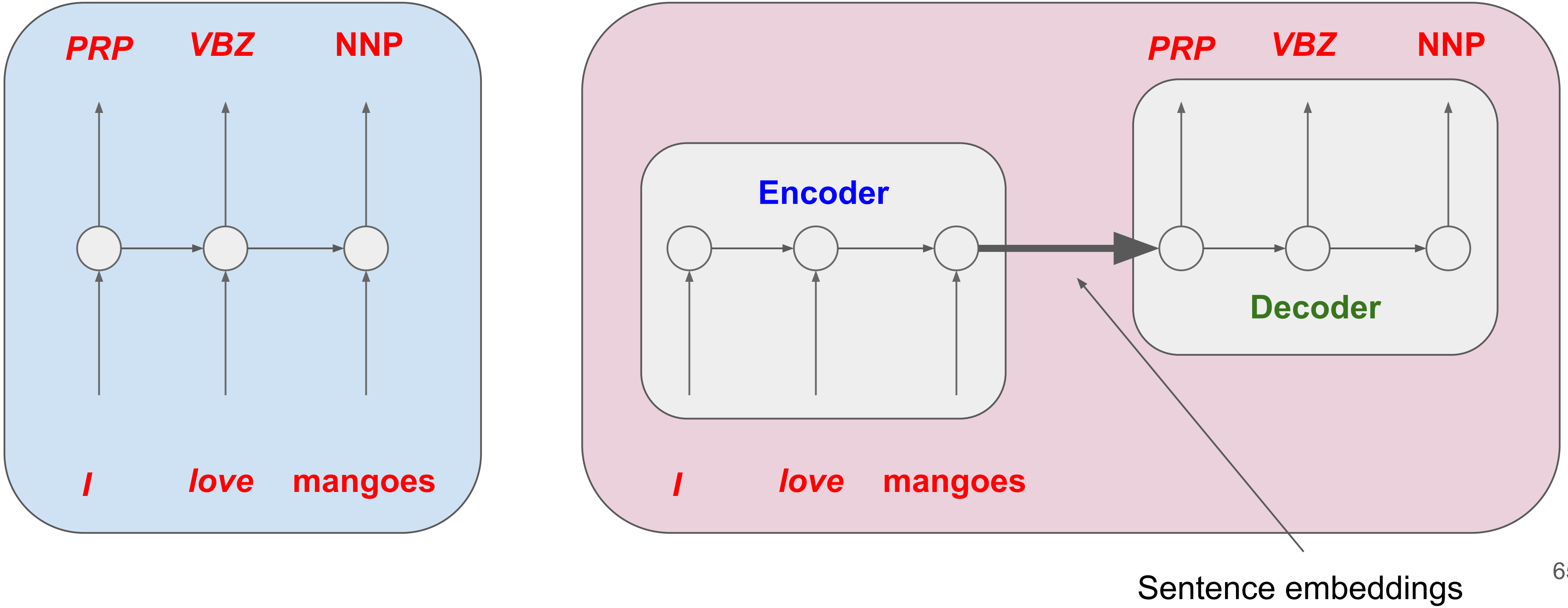


Zhang, Y., Wallace, B. ; **A Sensitivity Analysis of (and Practitioners' Guide to) Convolutional Neural Networks for Sentence Classification**; *In Proceedings of the 8th International Joint Conference on Natural Language Processing (IJCNLP-2017); pages 253-263; Taipie, Taiwan; 2017.*

Sequence to sequence transformation with Attention Mechanism

Sequence labeling v/s Sequence transformation

- PoS Tagging

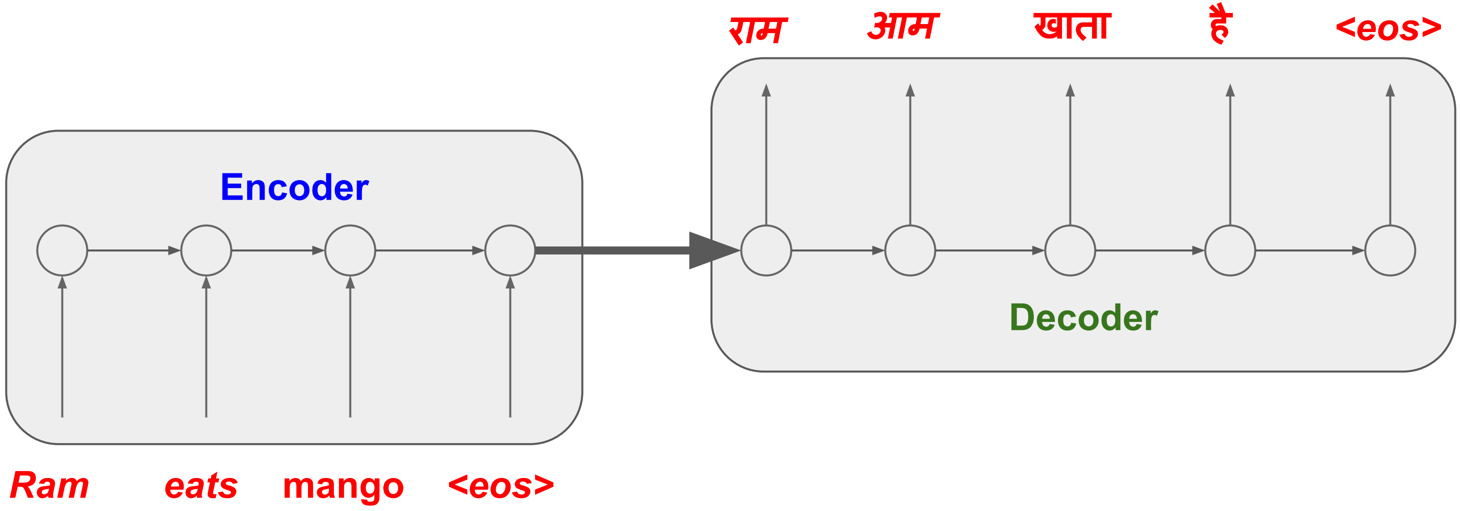


Why sequence transformation is required?

- For many application length of I/p and O/p are not necessarily same. E.g. Machine Translation, Summarization, Question Answering etc.
- For many application length of O/p is not known.
- Non-monotone mapping: Reordering of words.
- Applications for which sequence transformation is not require
  - PoS tagging,
  - Named Entity Recognition
  - ....

Encode-Decode paradigm

- English-Hindi Machine Translation
  - Source sentence: 3 words
  - Target sentence: 4 words
  - Second word of the source sentence maps to 3rd & 4th words of the target sentence.
  - Third word of the source sentence maps to 2nd word of the target sentence



Problems with Encode-Decode paradigm

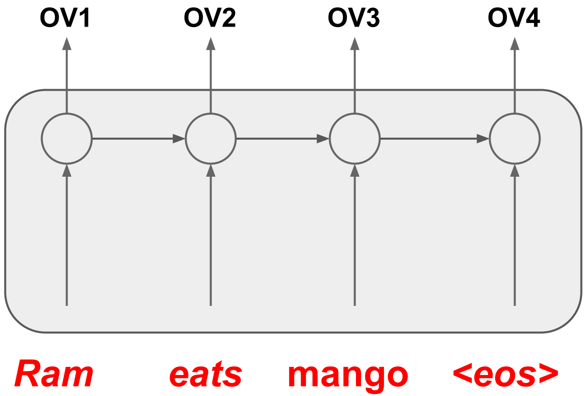
- Encoding transforms the entire sentence into a single vector.
- Decoding process uses this sentence representation for predicting the output.
  - Quality of prediction depends upon the quality of sentence embeddings.
- After few time steps decoding process may not properly use the sentence representation due to long-term dependency.

Solutions

- To improve the quality of predictions we can
  - Improve the quality of sentence embeddings **‘OR’**
  - Present the source sentence representation for prediction at each time step. **‘OR’**
  - Present the RELEVANT source sentence representation for prediction at each time step.
    - *Encode* - *Attend* - *Decode* (Attention mechanism)

Attention Mechanism

- Represent the source sentence by the set of **output vectors** from the encoder.
- Each **output vector** (OV) at time *t* is a contextual representation of the input at time *t*.



Attention Mechanism

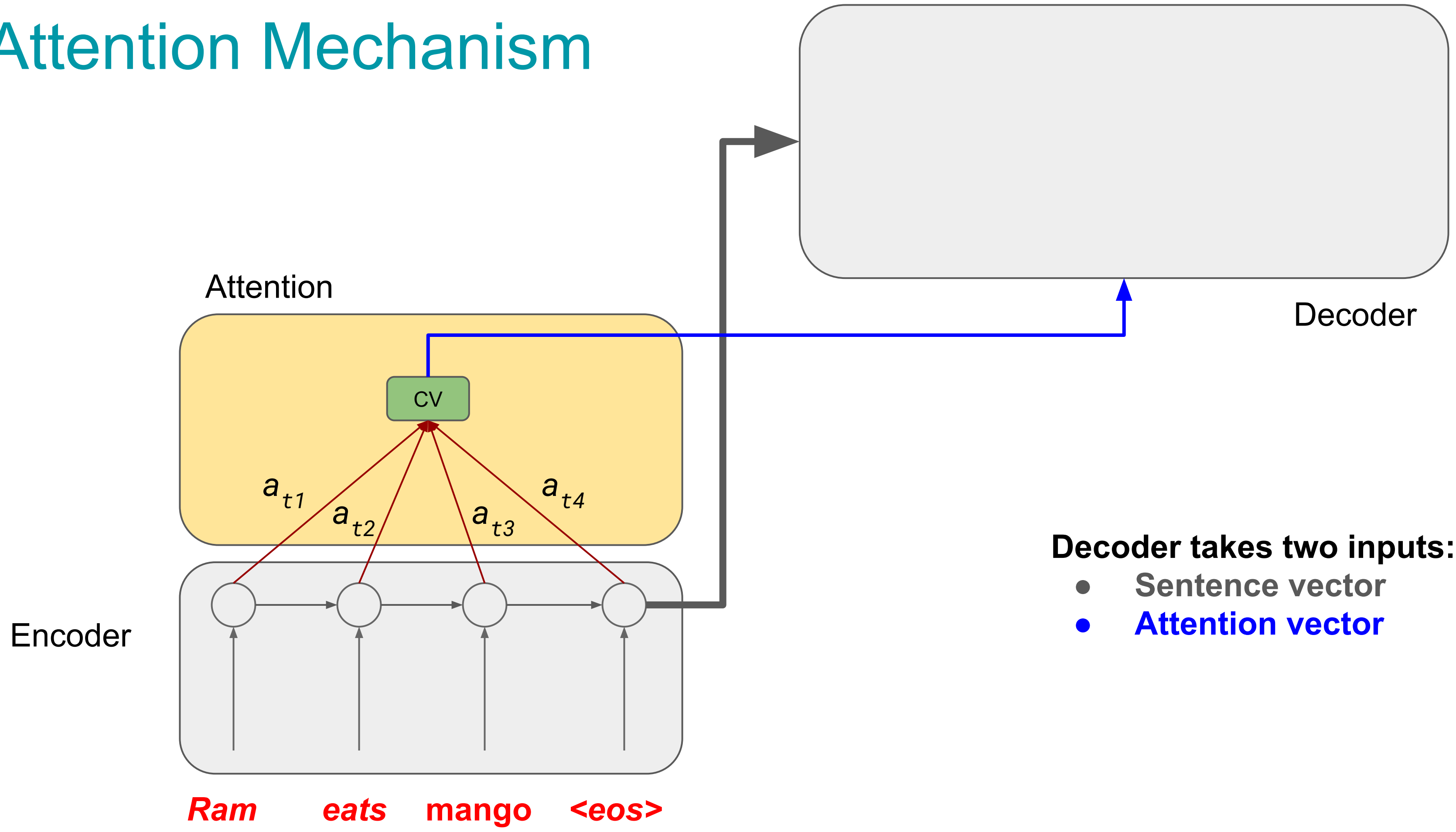
- Each of these output vectors (OVs) may not be equally relevant during decoding process at time *t*.
- Weighted average of the output vectors can resolve the relevancy.
  - Assign more weights to an output vector that needs more ***attention*** during decoding at time *t*.
- The weighted average ***context vector (CV)*** will be the input to decoder along with the sentence representation.
  - $CV_i = \sum_j a_{ij} \cdot OV_j$

$$a_{ij} = \frac{exp(e_{ij})}{\sum_k^T exp(e_{ik})}$$

where a_{ij} `is the attn-wt of the` j^{th} `OV`

$$e_{ij} = FeedForward(s_{i-1}, OV_j)$$

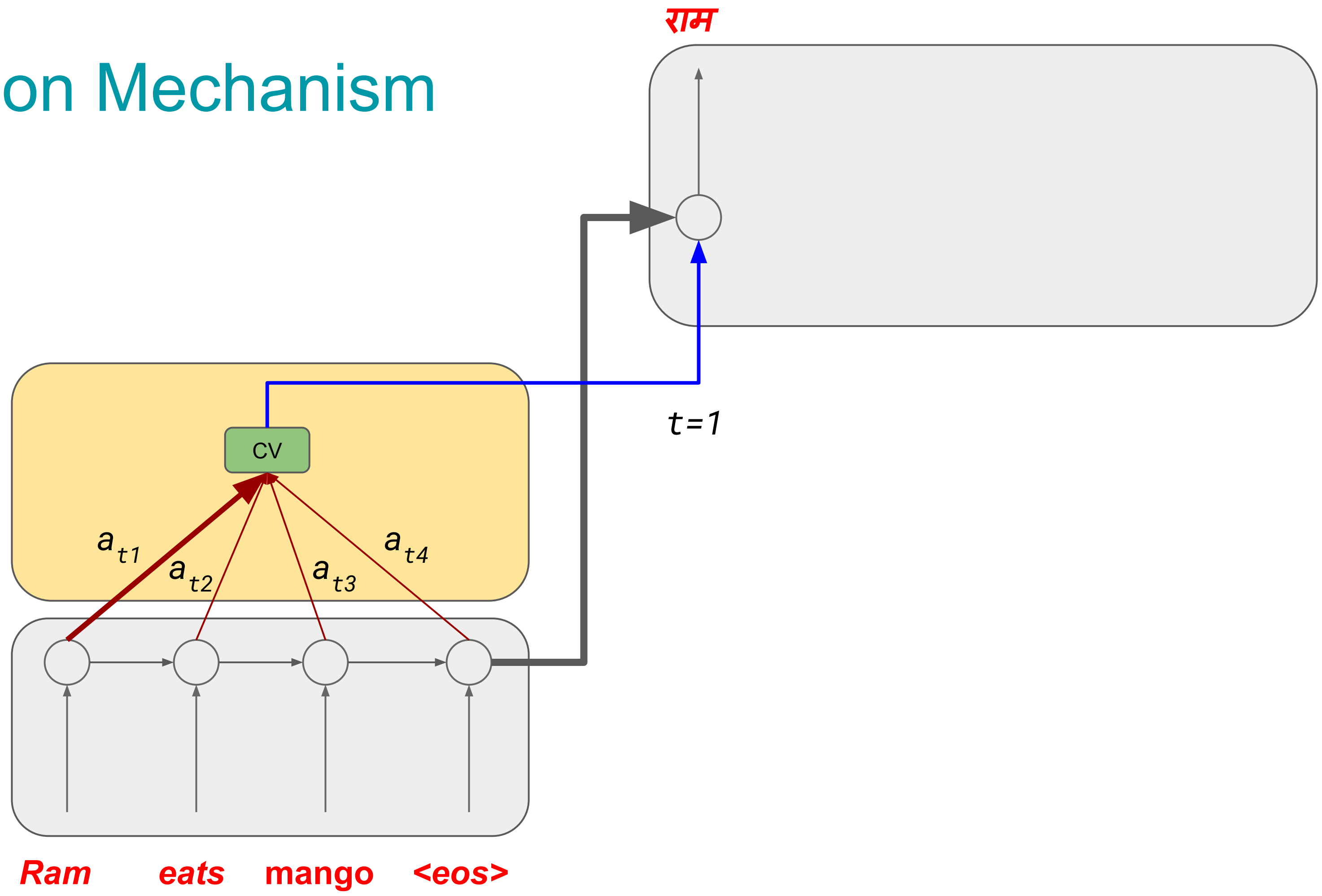
Attention Mechanism



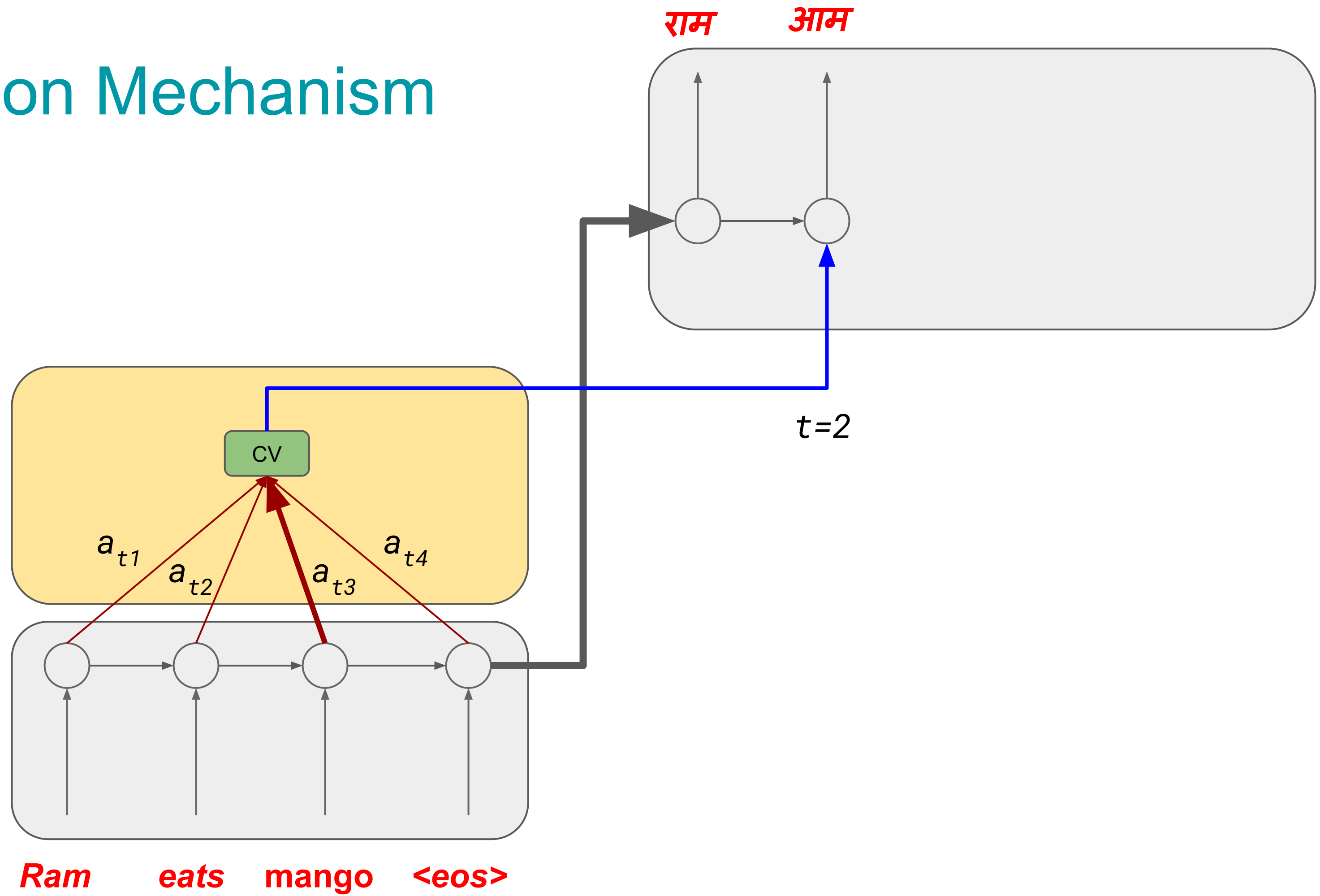
Decoder takes two inputs:

- **Sentence vector**
- **Attention vector**

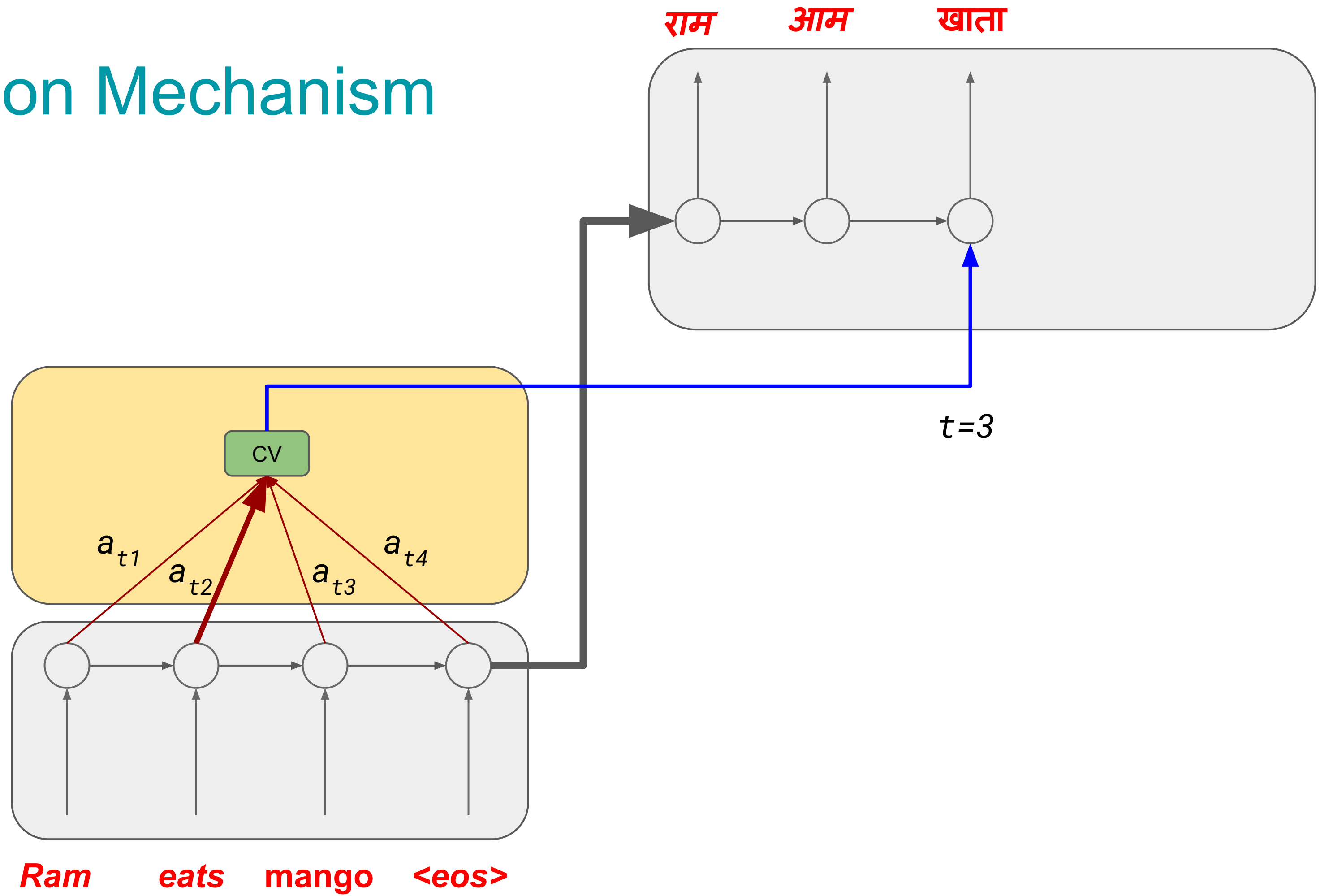
Attention Mechanism



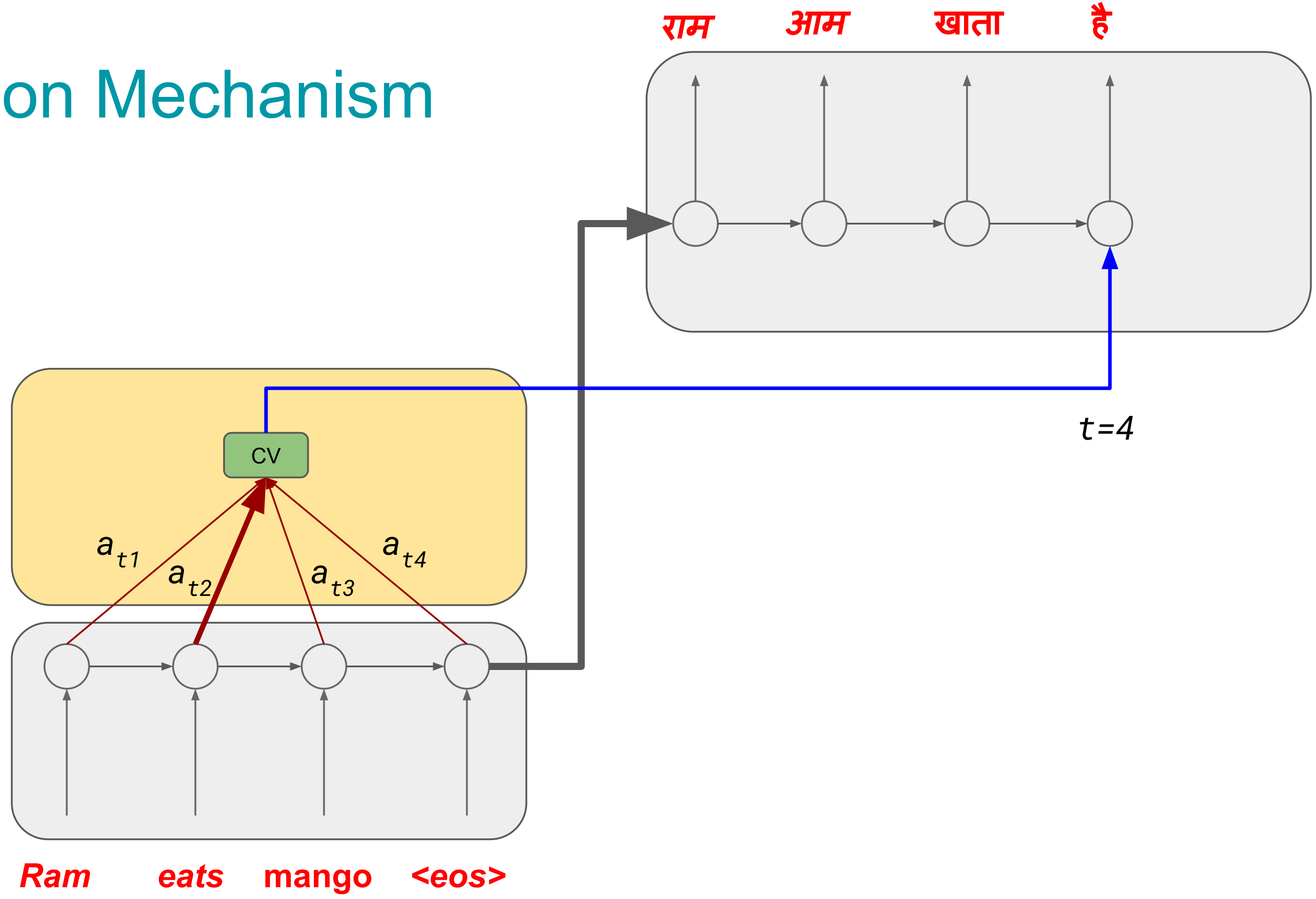
Attention Mechanism



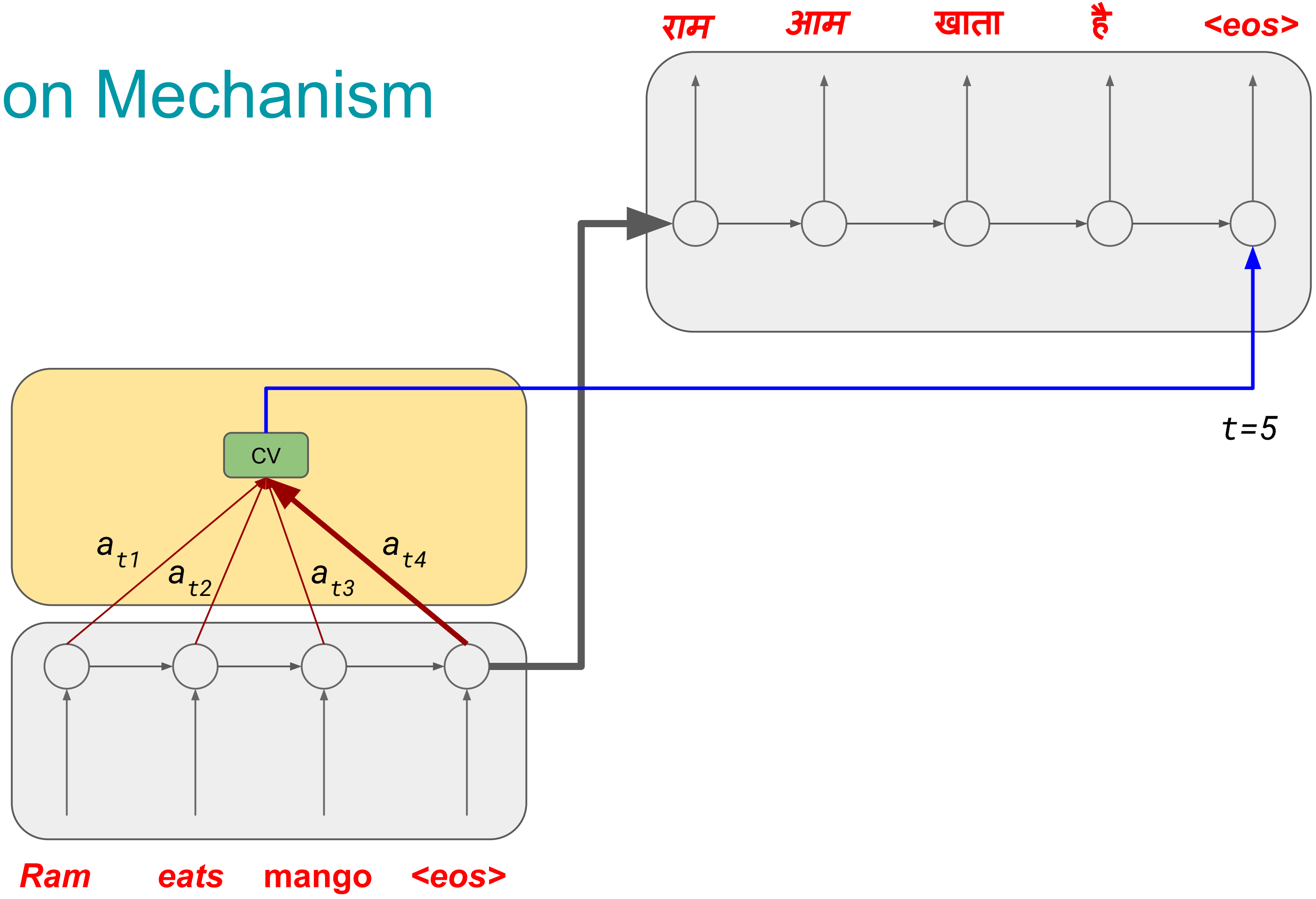
Attention Mechanism



Attention Mechanism

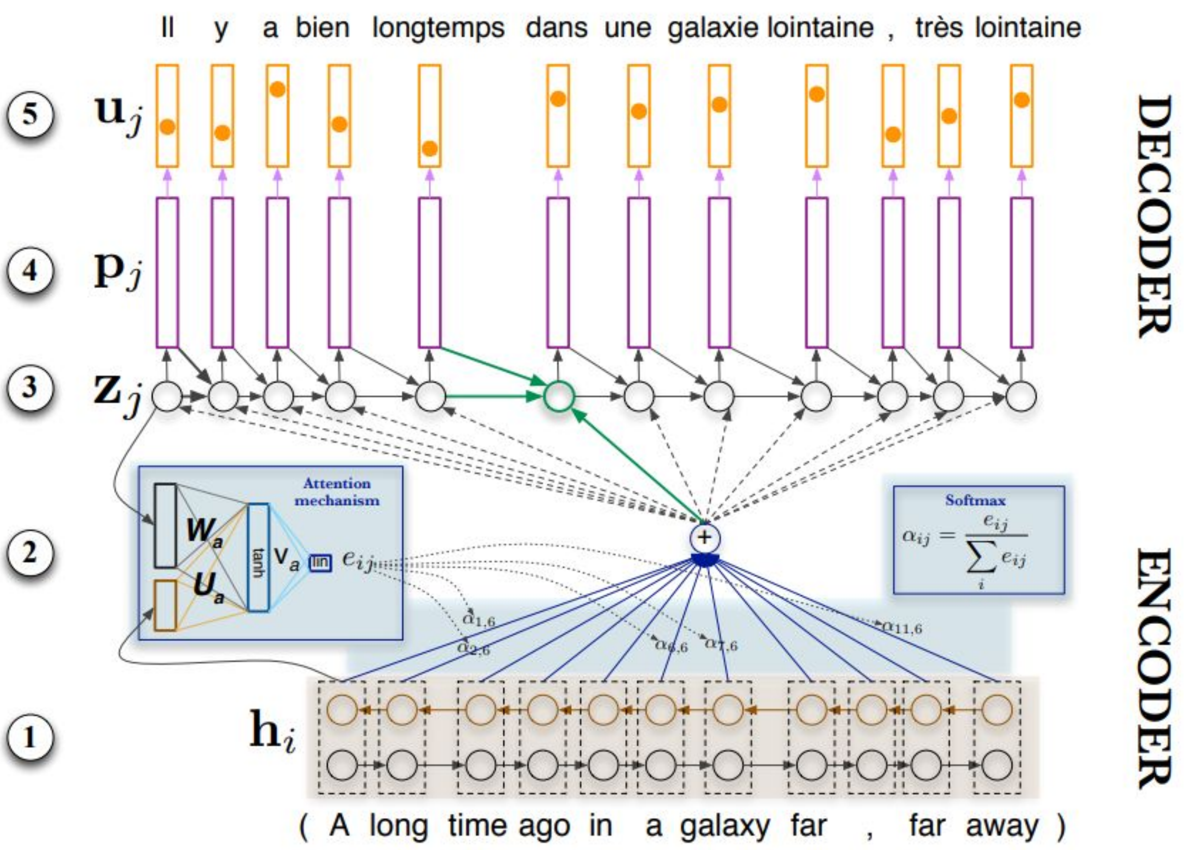


Attention Mechanism



Attention Mechanism

1. Bi-RNN Encoder
2. Attention
3. RNN Decoder
4. Output Embeddings
5. Output probabilities



[Garc´ıa-Mart´ınez et al., 2016]

Attention - Types

Given an input sequence $(x_1, x_2, \dots, x_N)$ and an output sequence $(y_1, y_2, \dots, y_M)$

- Encoder-Decoder Attention
  - $y_j \mid x_1, x_2, \dots, x_N$
- Decoder Attention
  - $y_j \mid y_1, y_2, \dots, y_{j-1}$
- Encoder Attention (Self)
  - $x_i \mid x_1, x_2, \dots, x_N$

Word Representation

Why do we need word representation?

- Many Machine Learning algorithms do not understand text data, they require input to be numeric. E.g. SVM, NN etc.
- Two types of representations
  - Local Representation
    - One hot
      - Cat = [0,0,0,0,1,0,0,0,0,0]
      - Sparse
      - No semantics
      - Curse of Dimensionality
  - Distributed Representation
    - Word embeddings
      - Cat = [2.4, 1.0,3.1,5.3]
      - Dense
      - Very good at capturing semantic relations.

Available word representation models

- Word2vec [Mikolov et al., 2013]
  - Contextual model
  - Two variants
    - Skip-gram
    - Continuous Bag-of-word
- GloVe [Pennington et al., 2014]
  - Co-occurrence matrix
  - Matrix Factorization
- FastText [Bojanowski et al., 2016]
  - Similar to word2vec
  - Works on sub-word level
- Bidirectional Encoder Representations from Transformers (BERT) [Devlin et al., 2018]
  - Based on Transformer model
- Embeddings from Language Models (ELMo) [Peters et al., 2018]
  - Contextual
    - The representation for each word depends on the entire context in which it is used.

Few good reads..

- Denny Britz; Recurrent Neural Networks Tutorial, Part 1-4
  http://www.wildml.com/2015/09/recurrent-neural-networks-tutorial-part-1-introduction-to-rnns/
- Andrej Karpathy; The Unreasonable Effectiveness of Recurrent Neural Networks
  http://karpathy.github.io/2015/05/21/rnn-effectiveness/
- Chris Olah; Understanding LSTM Networks
  http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Question!

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Thank You!