Deep Neural Network for NLP

Sequential NLP Data

Sequential Data

- Characters in words
- Words in sentences
- Sentences in paragraphs
- Paragraphs in documents

NLP is full of **sequential** data

Dependencies in Language

Dependencies: the relationship between two words (it can be semantic or syntax)

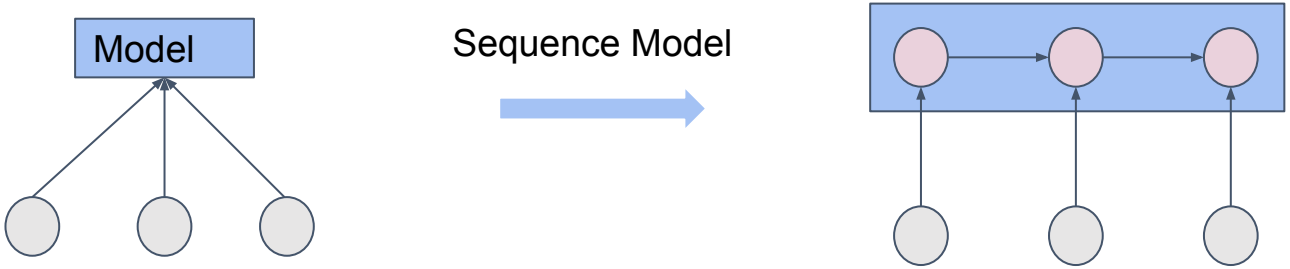
- It is equal to the sequential information contained in the sequence data.

Long-distance Dependencies in Languages

Examples

- He does not have very much confidence in himself
- The rain has lasted as long as the life of clouds
- The *trophy* would not fit in the brown *suitcase* because it was too small

Sequential NLP Data



Machine learning models should capture this kind of sequential information in NLP data.

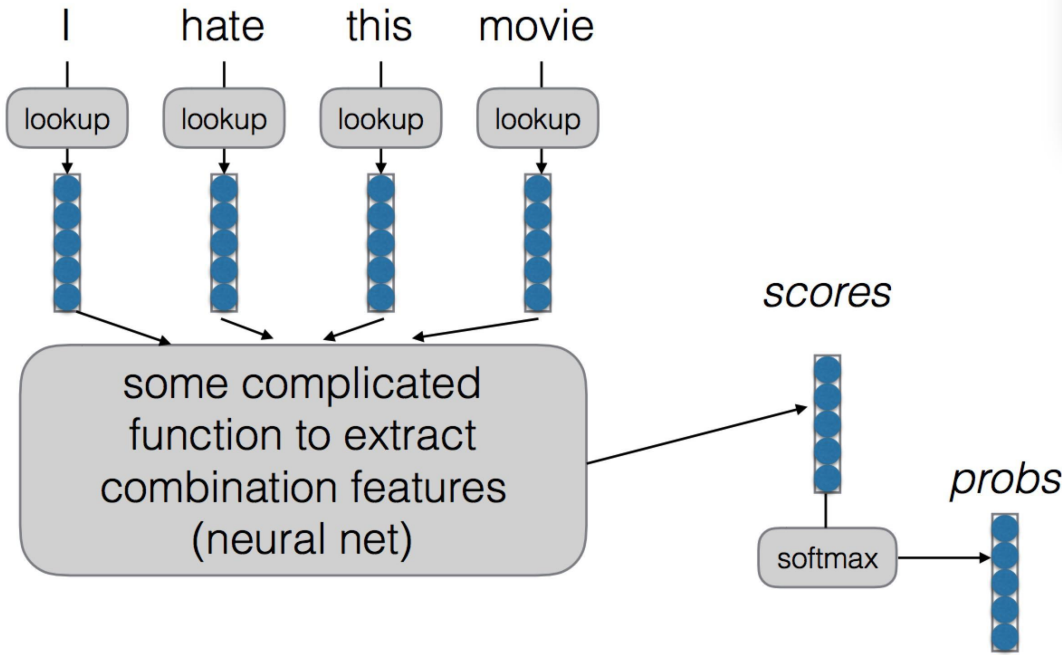
Complex Semantic

1. **Input Text:** a sequence of words;

2. **Through Word Embedding Look-up:** a sequence of word vectors;

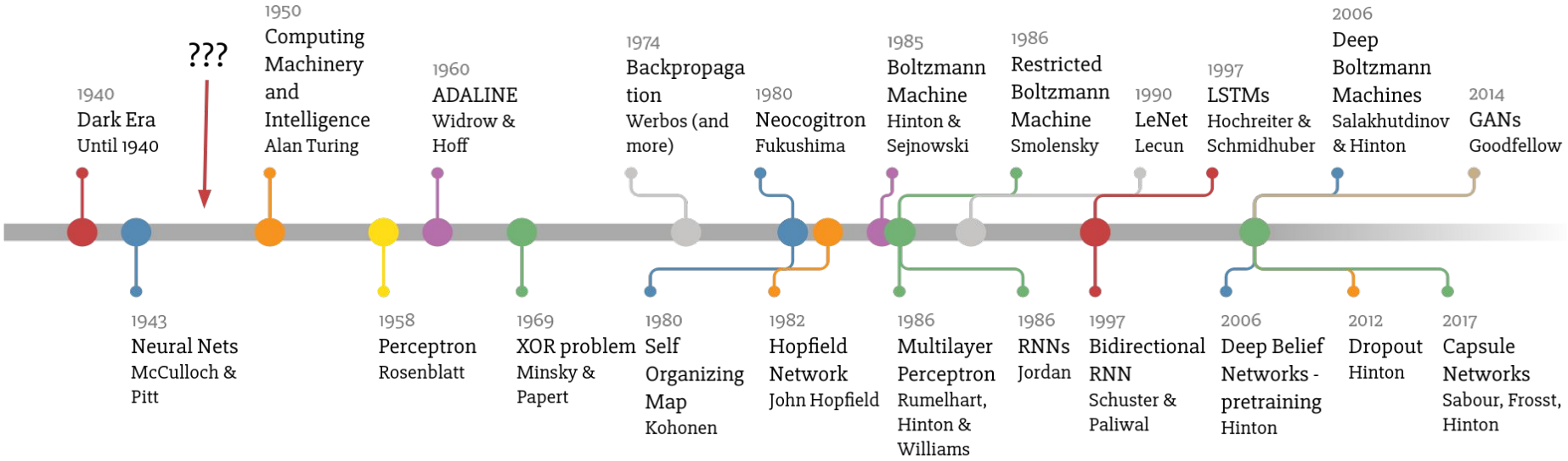
3. Neural networks is applied upon the vector sequences to learn semantic **composition** for final prediction;

➔ Human understand the word meaning firstly, then get the whole sentence meaning by composing these words' meaning together.



Intro to RNN

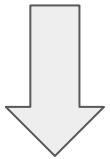
Deep Learning Timeline



Made by Favio Vázquez

Examples

- Tagging Task: Assuming we have a predefined set of tags, we assign a tag to each word in input sentences.
- Given an input sentence: I would like to arrive at Singapore on Mar. 29.

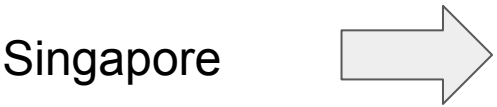


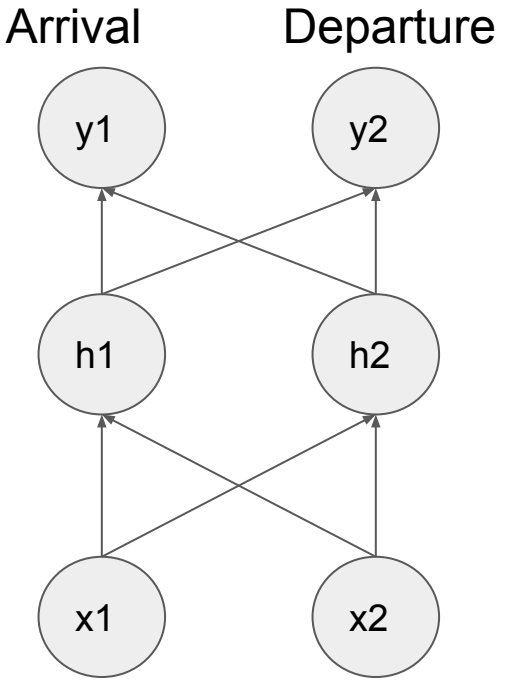
Singapore -> Dest. Place
Mar. 29 -> Time of Arrival

Feed-forward Network

- Input: Each word (word vector)
- Output: Prob. Scores that the input word belong to the tag

Singapore





Confusing Case

- Input Sentence 1:

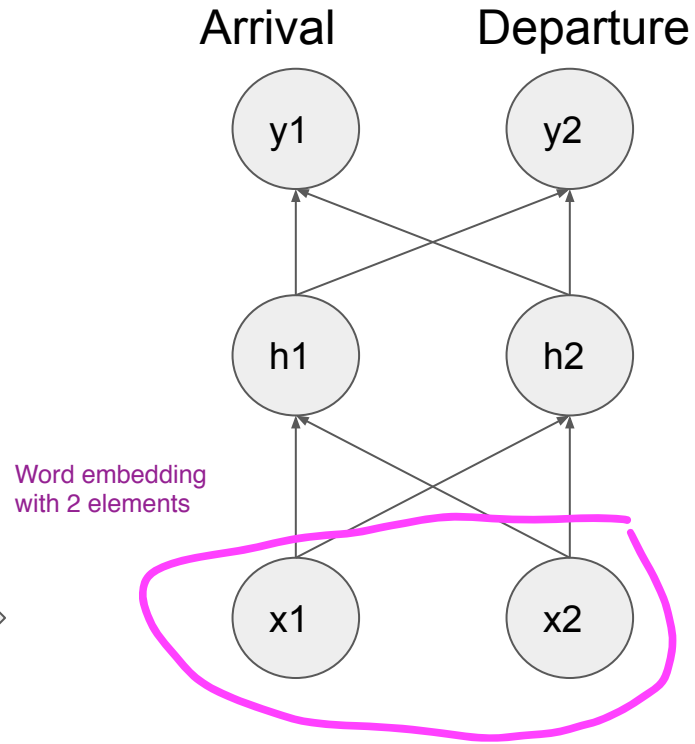
  I would like to arrive at Singapore on Mar. 29.

- Input Sentence 2:

  I would like to leave Singapore on Mar. 29.

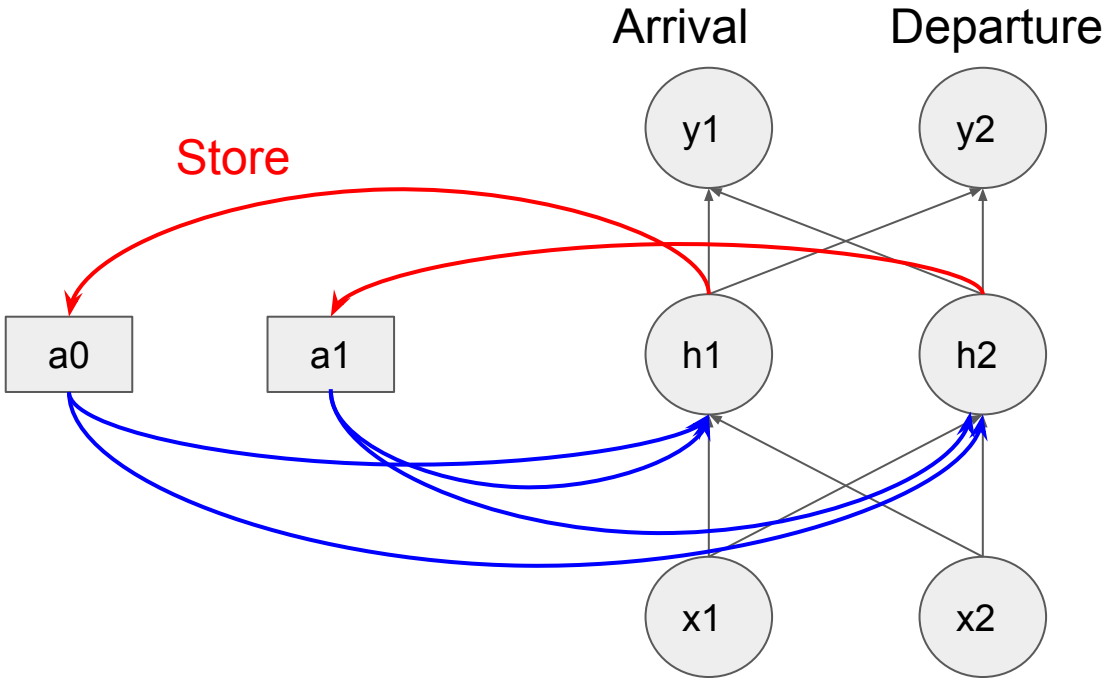
Neural Network needs Memory

Singapore



Neural Network with Memory

The outputs of hidden layer are stored in the memory.



Memory can be considered as another input

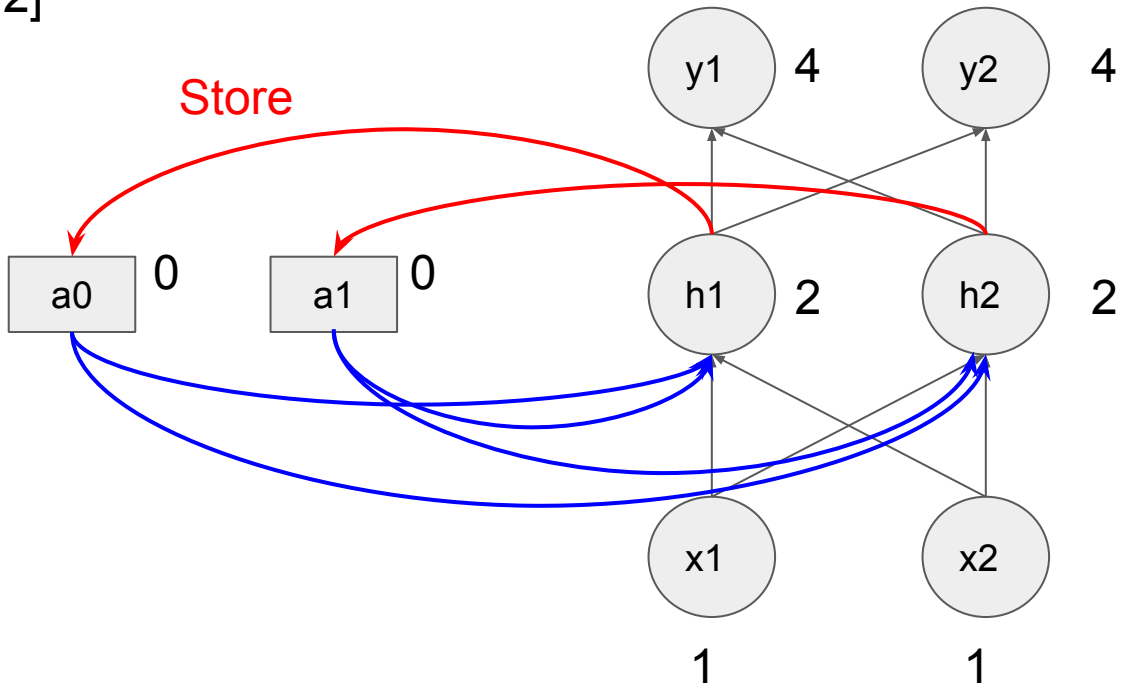
Neural Network with Memory

timestamp 1

Input Seq : [1, 1] [1, 1] [2, 2]
Output Seq: [4, 4]

Given initial values

All weights are 1, no bias,
linear activation

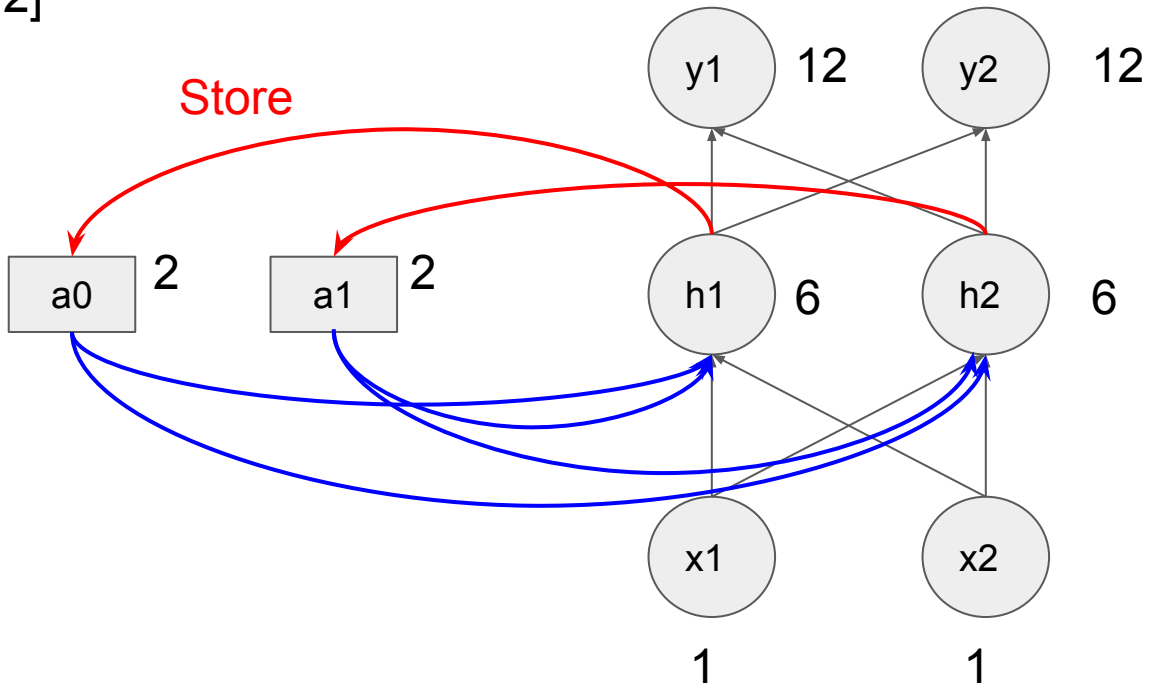


Neural Network with Memory

timestamp 2

Input Seq : [1, 1] [1, 1] [2, 2]
Output Seq: [4, 4] [12, 12]

Using previous hidden output

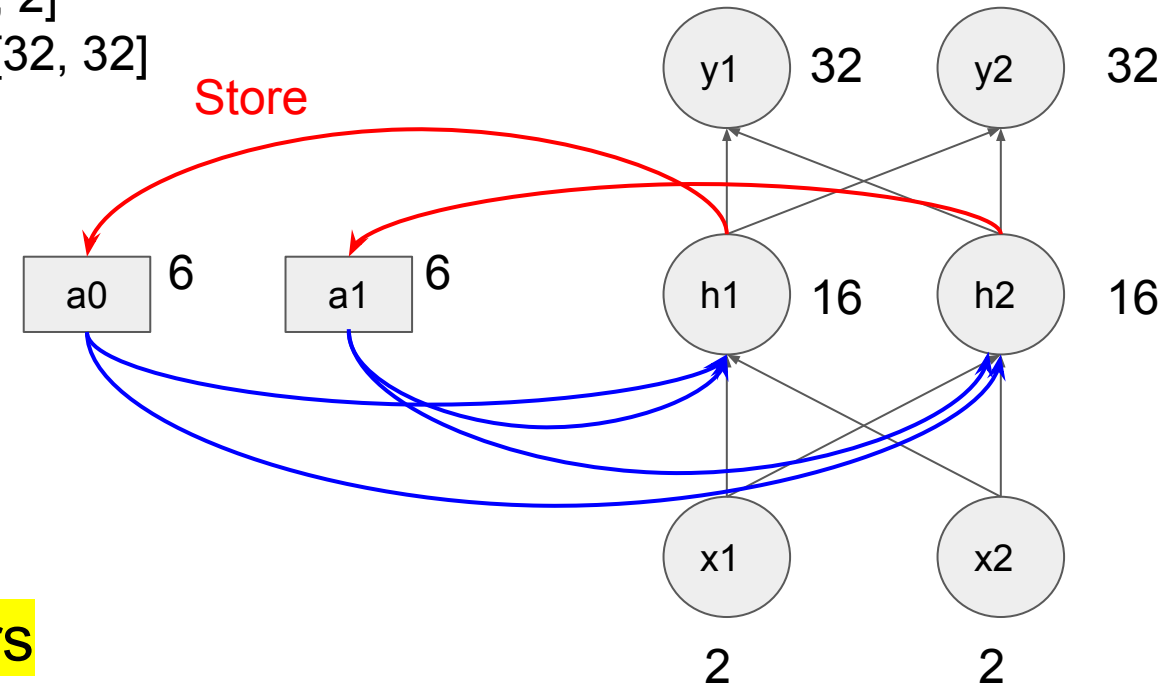


All weights are 1, no bias, linear activation

Neural Network with Memory

timestamp 3

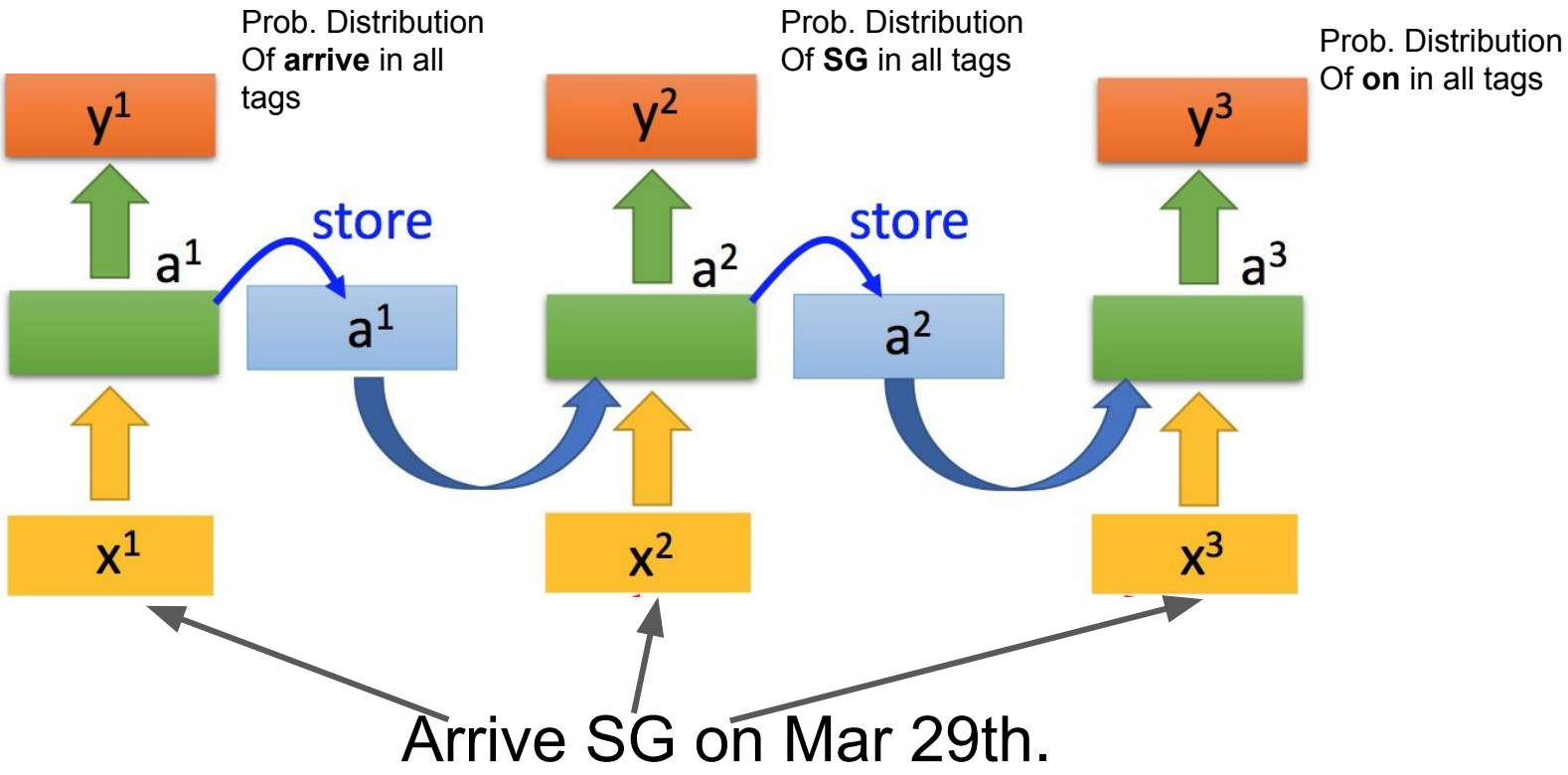
Input Seq : [1, 1] [1, 1] [2, 2]
Output Seq: [4, 4] [12, 12] [32, 32]



Try [1, 1] [2, 2], [1,1]

Sequence Order Matters

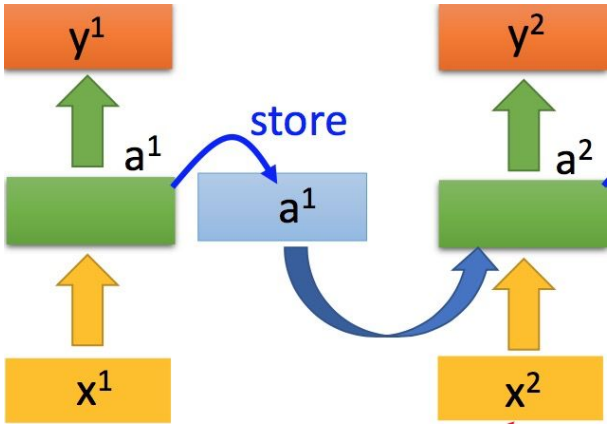
Back to Our Case



Back to Our Case

Prob. Distribution Of **arrive** in all tags

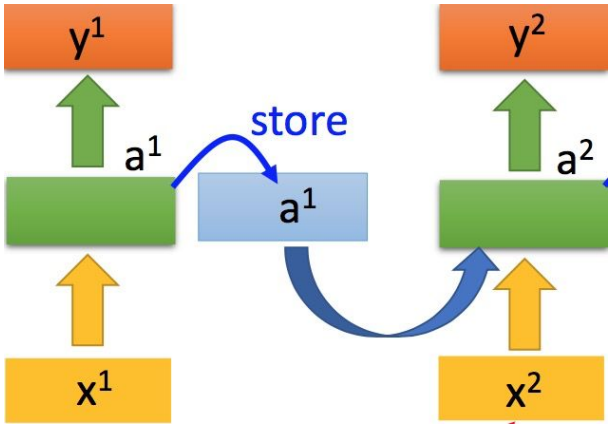
Prob. Distribution Of **SG** in all tags



Arrive SG

Prob. Distribution Of **leave** in all tags

Prob. Distribution Of **SG** in all tags



Leave SG

Are these two probs. distribution of SG same ? And Why?

Recurrent Neural Network (Elman 1990)

- Recurrent neural network is proposed to utilize information from **previous** time steps and **current** information to make reasoning at the current step

- A is the neural network that take x_t in and generate h_t

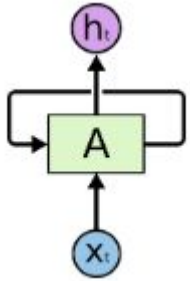


Image credits to Colah.

- **A loop** allows information to be passed from one step of the network to the next.

- Allows information to persist

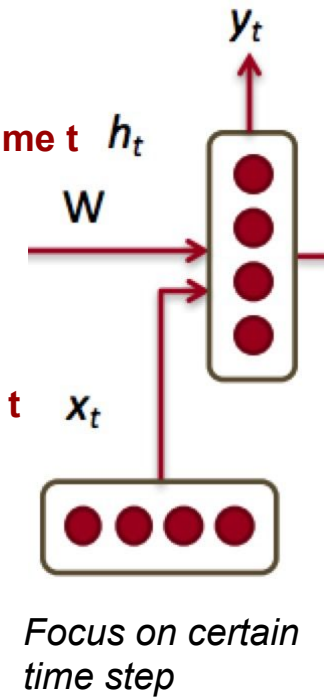
Neuron computation of RNN

- Model parameters are tied across all time steps (run the **same** RNN cell)

$$h_t = \sigma\left(W^{(hh)}h_{t-1} + W^{(hx)}x_{[t]}\right)$$

$$\hat{y}_t = \text{softmax}\left(W^{(S)}h_t\right)$$

When t=0, u can just set h_{t-1} to be a vector of zeros



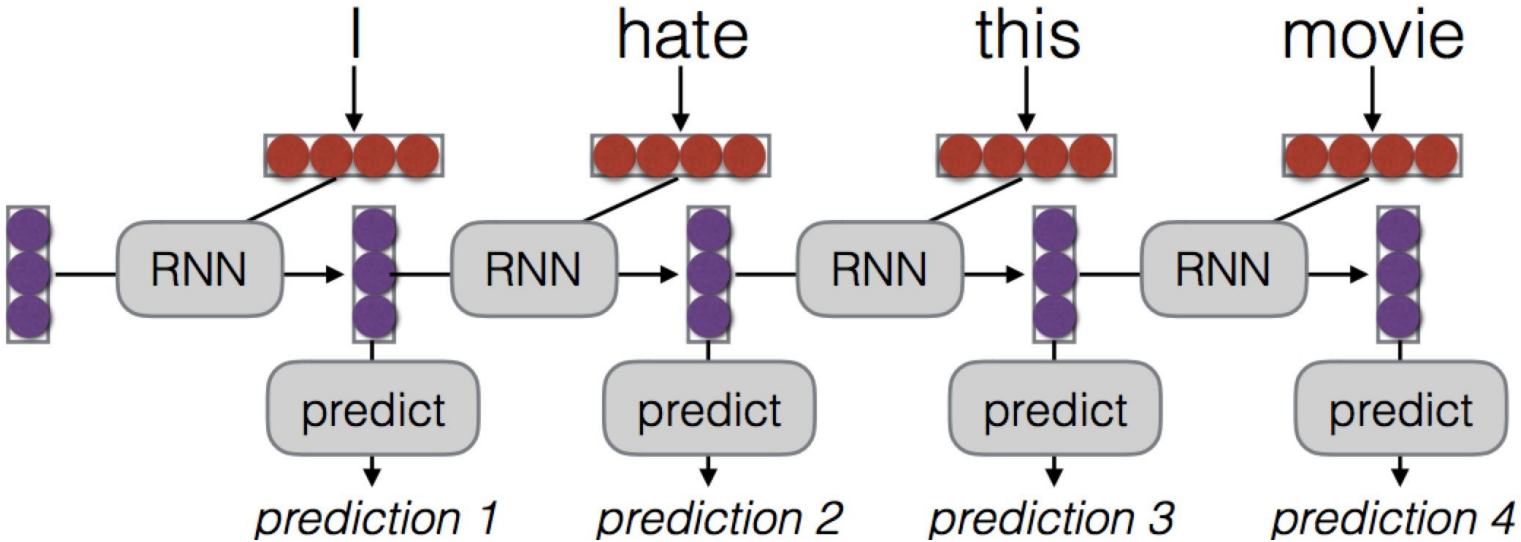
Focus on certain time step

- We need $h_0 \in \mathbb{R}^{D_h}$ as the initialization vector for the hidden layer at time step **0**.

- Inputs enter and move forward at each time step

Unrolling in Time

- Process the NLP sequence data



RNN’s Bottleneck

- RNN is not suitable for parallel computation.

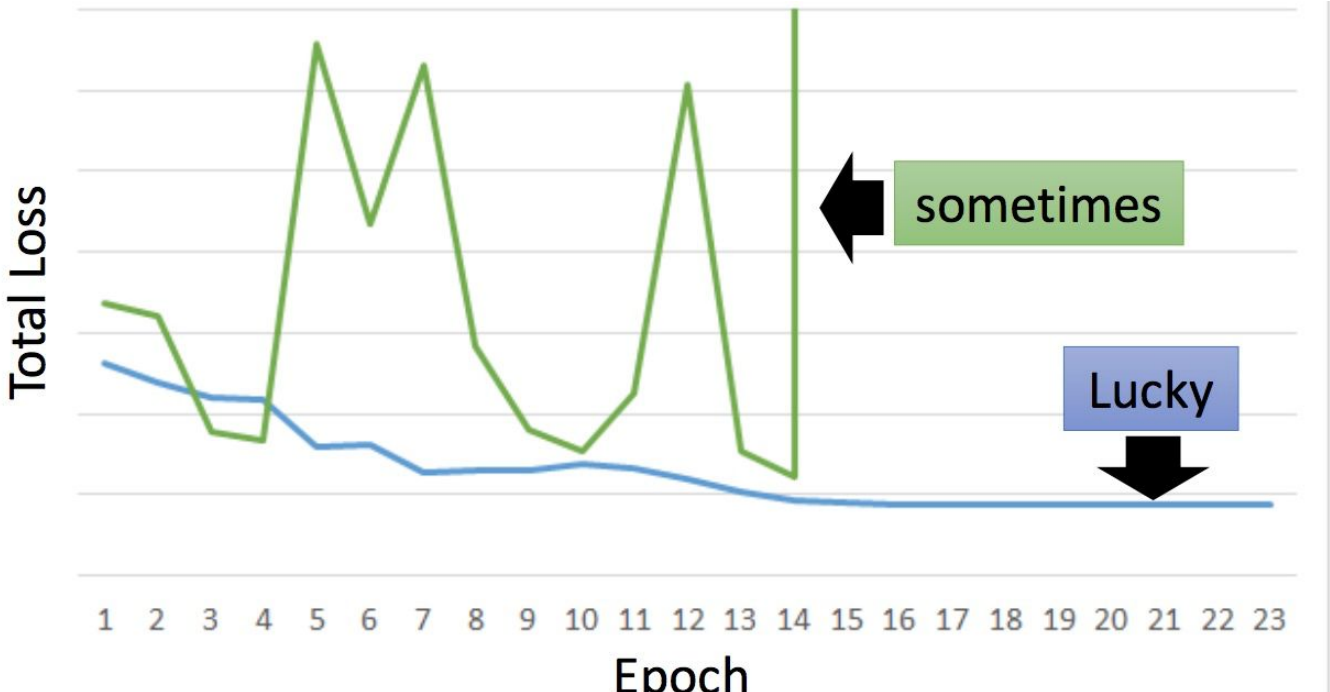
- RNN’s training is not easy
  - Gradient Vanishing
  - Gradient Exploding
  - Reminder on gradient descent algorithms:

$$W = W - \alpha \frac{dL}{dW}$$

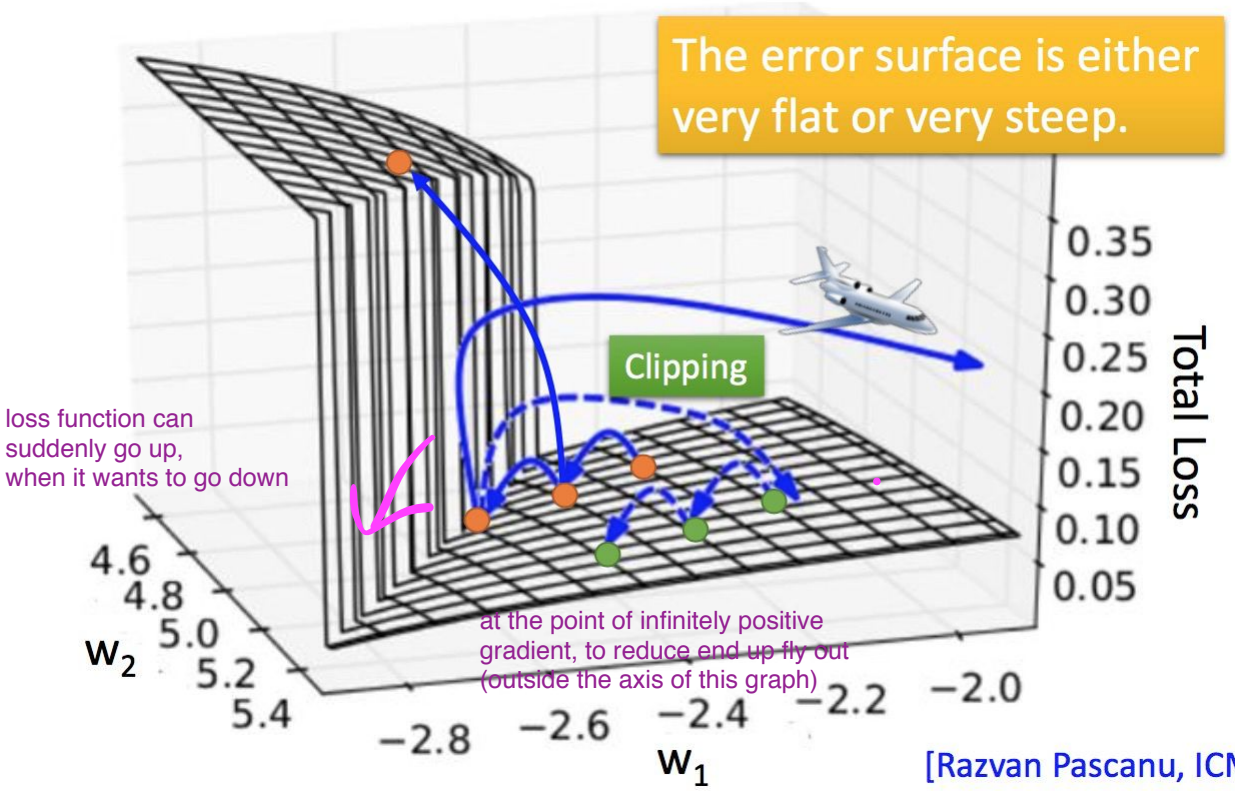
W is the layer weights;
L is the loss function;
Alpha is the learning rate, which represents how aggressive that our model parameters are updated.

RNN Training is Hard

- Real experiments on Language Models



Rough Error Surface of RNN



Exploding/Vanishing Gradient

[Razvan Pascanu, ICML'13]

Toy Example

In some case when w>1,
gradient can be very large
and when w<1,
gradient can be close to zero

w^10000

w = 1 ⇨ y_{1000} = 1

w = 1.01 ⇨ y_{1000} = 20000

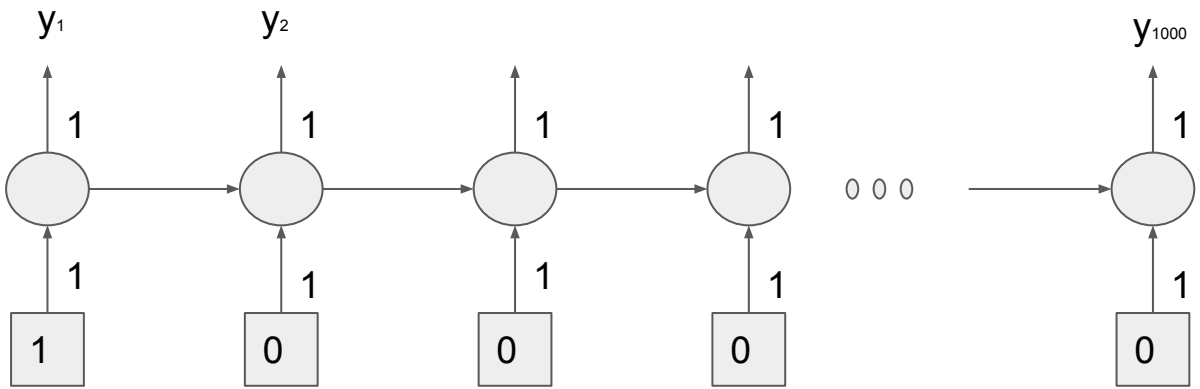
⇨ Large Gradient: dL/dw ⇘

w = 0.99 ⇨ y_{1000} ~= 0

w = 0.01 ⇨ y_{1000} ~= 0

⇨ Small Gradient: dL/dw ⇘

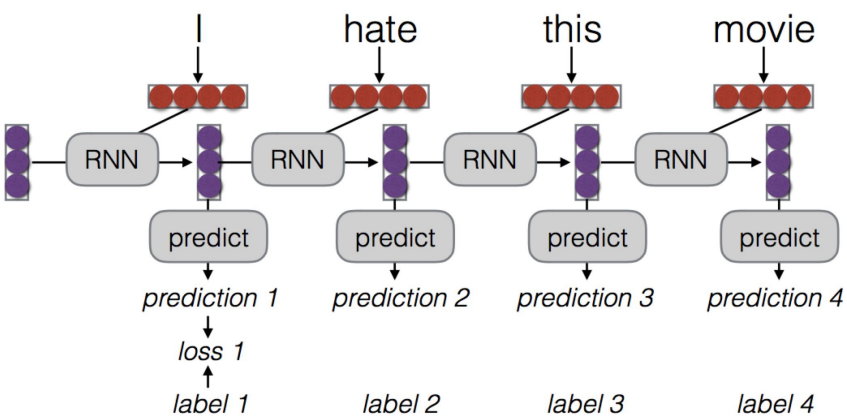
Irregular Error Surface

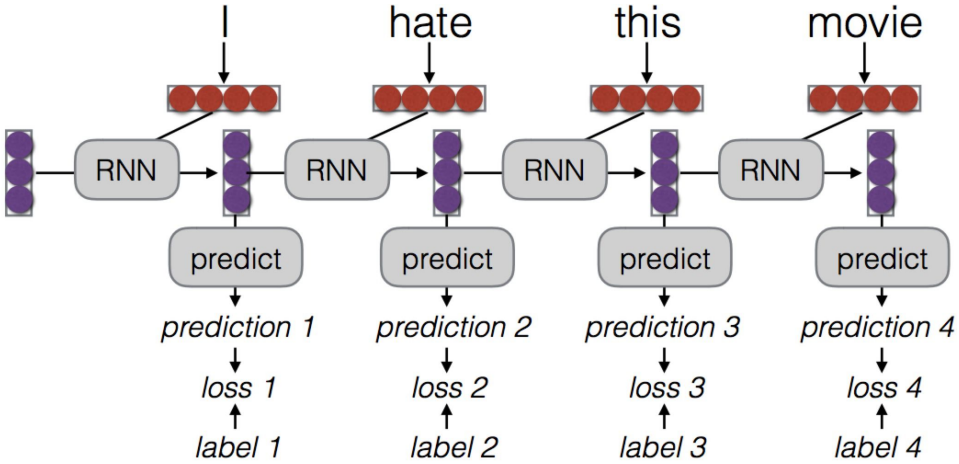


All weights are 1,
no bias,
linear activation

Loss Computation

- Total Loss
  - Total loss is the sum of loss computed on each time step.

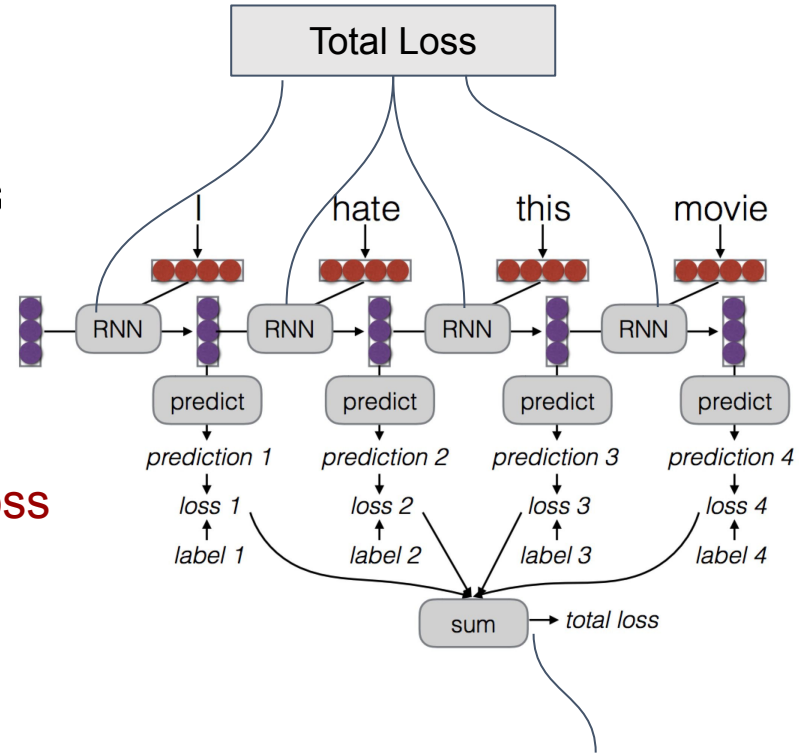




BPTT

- For RNN gradient computation, Backpropagation Through Time
- Weight is the same for all the time steps
- Inputs from many time step ago can modify output

1. Shared Model Parameters across time steps
2. Accumulated Derviatives



BPTT Equation

- RNN formulation

$$
\begin{aligned}
h_t &= \sigma\left(W^{(hh)} h_{t-1} + W^{(hx)} x_{[t]}\right) \\
\hat{y}_t &= \operatorname{softmax}\left(W^{(S)} h_t\right)
\end{aligned}
$$

- **Total error** is the sum of each error at time steps **t**

$$
\frac{\partial E}{\partial W} = \sum_{t=1}^{T} \frac{\partial E_t}{\partial W}
$$

- Apply **chain rule** for error at certain time step **t**

$$
\frac{\partial E_t}{\partial W} = \sum_{k=1}^{t} \frac{\partial E_t}{\partial y_t} \frac{\partial y_t}{\partial h_t} \frac{\partial h_t}{\partial h_k} \frac{\partial h_k}{\partial W}
$$

Exploding Gradient Solutions

- Truncated BPTT e.g. just 10 steps ago, don't go all the way back
- Clip gradients at threshold if too large, just replace by the threshold
- RMSprop to adjust learning rate

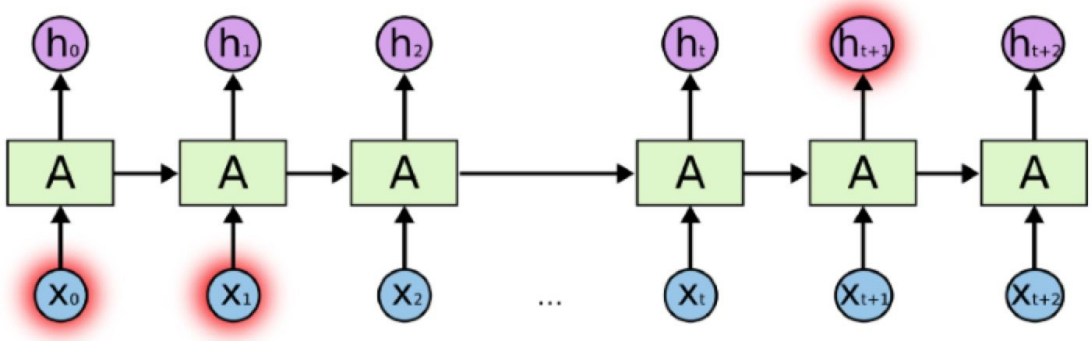
Vanishing Gradient Problem

Very serious problem

- The error at a time step **ideally** can tell a previous time step from many steps away to change during backprop
- **Can not capture long-term dependency**

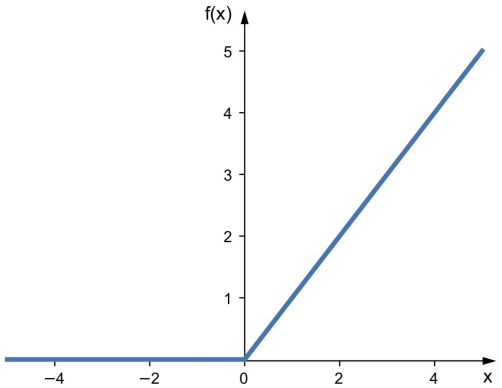
- The representation from time steps 0 and t can not travel to influence the time step t+1

- **Harder to detect**



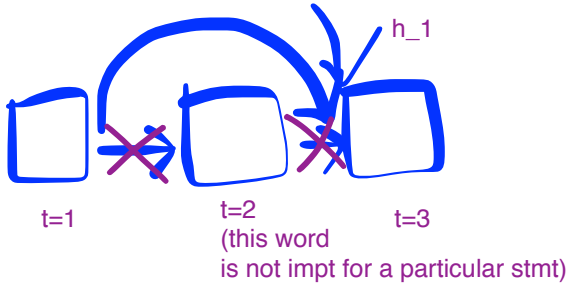
Vanishing Gradient Solutions

- RMSprop
- LSTM, GRUs (gated RNN)
- ReLu activation functions

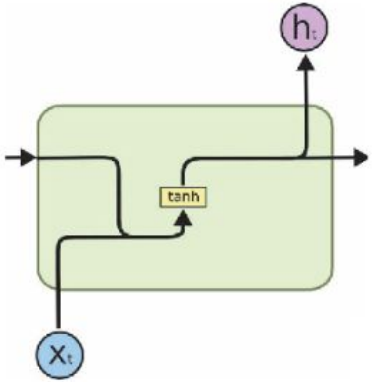


can make the gradient positive

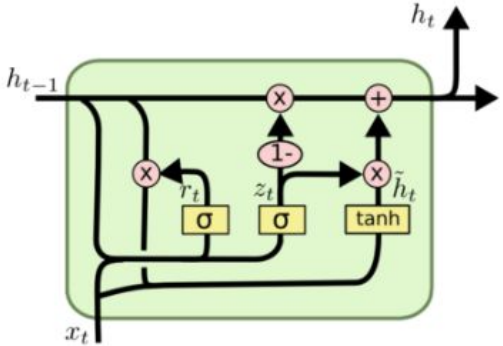
LSTM/GRU



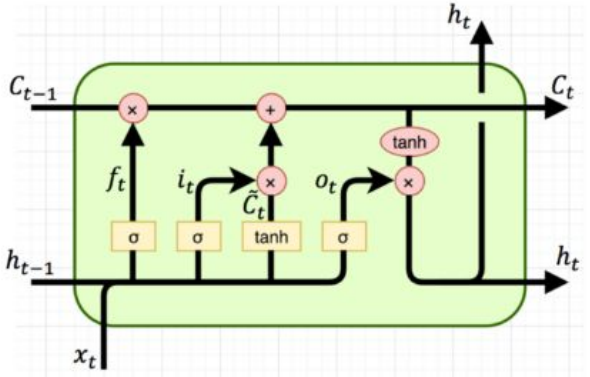
- LSTM/GRU are using gates in cell computation to control information flow



RNN



GRU



LSTM

RNN for Language Model

Recurrent Neural Network

- Recurrent neural network works in a chain way
- The method is in naturally suitable for processing sequences data
- A broad applications:
    - Speech Recognition
    - Time series Prediction
    - Language Modeling
    - Machine Translation

Language Models

- A language model computes **a probability for a sequence of words**:
  - P(w1,..., wT)
- Useful for machine translation/Question Answering
  - Word Ordering
    - p(the cat is small) > p(small is the cat)
  - Word Choice
    - p(walking home after school) > p(walking house after school)

Traditional Methods

- Probability is usually conditioned on **window of *n*** previous words
- An incorrect but practical **Markov** Assumption
- To estimate probabilities, compute for unigram and bigrams

$$p(w_2|w_1) = \frac{\text{count}(w_1, w_2)}{\text{count}(w_1)}$$

n=1

$$p(w_3|w_1, w_2) = \frac{\text{count}(w_1, w_2, w_3)}{\text{count}(w_1, w_2)}$$

n=2

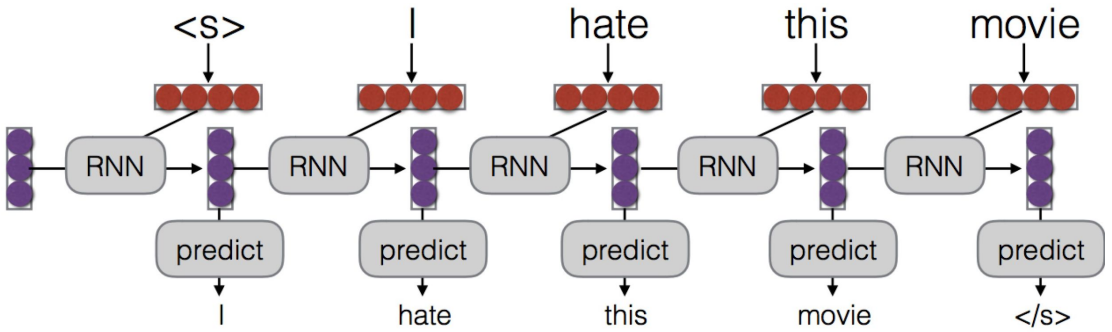
For traditional method, u need to maintain a large vocab list. RNN only needs to store the model parameters, i.e. weights

Traditional Methods

- A lot of n-grams and extremely large combinations
    - Requires large RAM requirements
- Use one machine with 140GB RAM for 2.8days to built a model on 126 billion tokens.

RNN-based Language Model

- Language Modelling here is one of **tagging** task
- Each label/tag is the next word!



At a single time step:

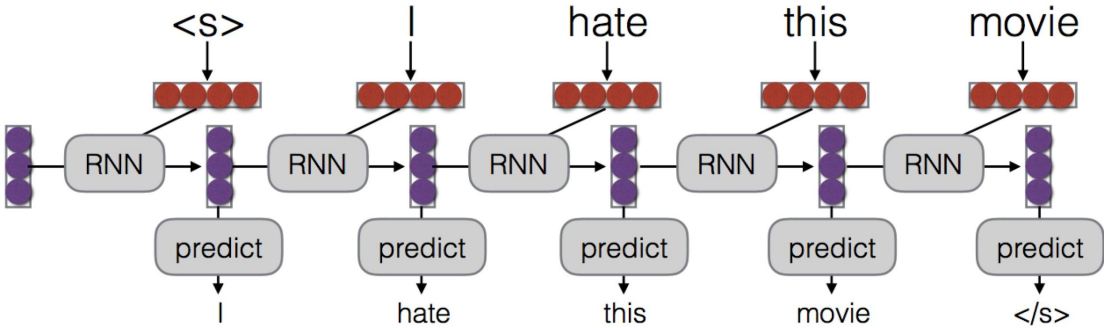
$$h_t = \sigma\left(W^{(hh)}h_{t-1} + W^{(hx)}x_{[t]}\right)$$

$$\hat{y}_t = \text{softmax}\left(W^{(S)}h_t\right)$$

$$\hat{P}(x_{t+1} = v_j \mid x_t, \ldots, x_1) = \hat{y}_{t,j}$$

RNN-based Language Model

- This task is for sequential labelling, i.e., each time step has its own target value
- At each time step, the learned hidden representation are fed into two layers:
  - Predict the target value (softmax or linear regression)
  - Compute the hidden features at the next time step



Intro to CNN

Convolutional Neural Network

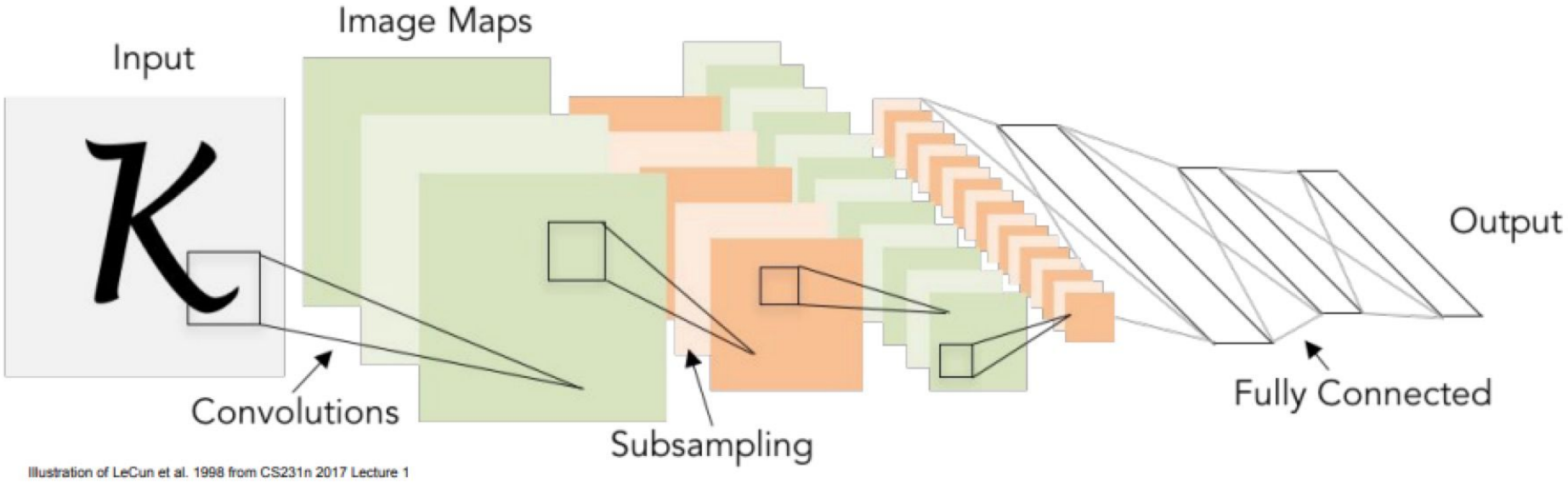
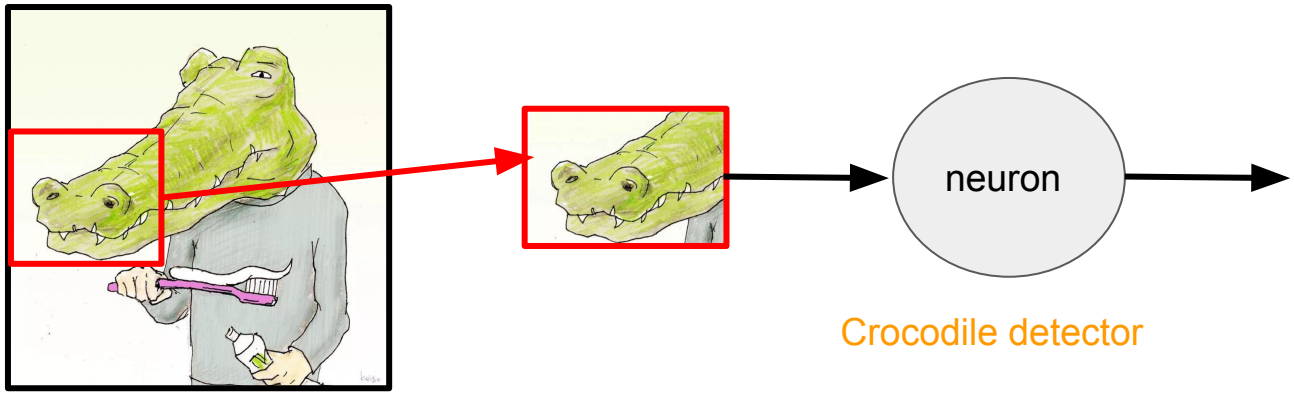


Illustration of LeCun et al. 1998 from CS231n 2017 Lecture 1

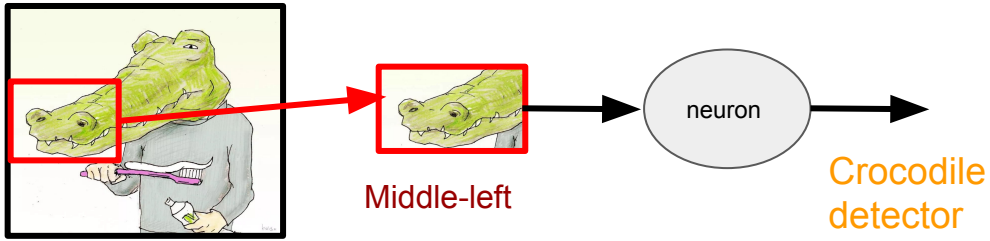
Local Features Matter

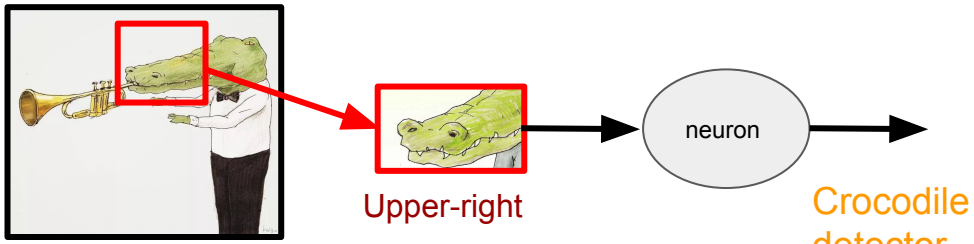
- Discriminative patterns are much smaller than the whole image
- A neuron does not have to see the whole image
- Less parameters required



Location Insensitive

- The same patterns appear in different regions
- A neuron should be location insensitive.





Subsampling Works

- Subsampling the pixels will not change the object
- We can subsample the pixels to make images smaller -> less parameters required

Crocodile

subsampling

Crocodile

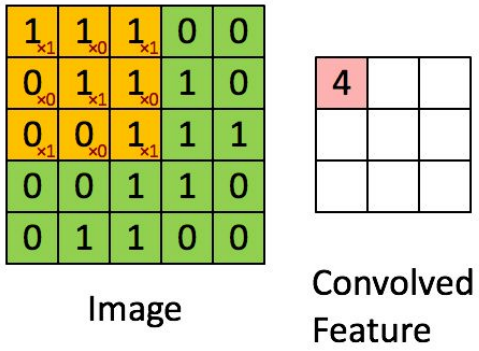
CNN for Images

CNN:

1. **Convolutional Layer:** from local regions in images to feature map

2. **Pooling Layer:** reduce the dimensionality of feature maps

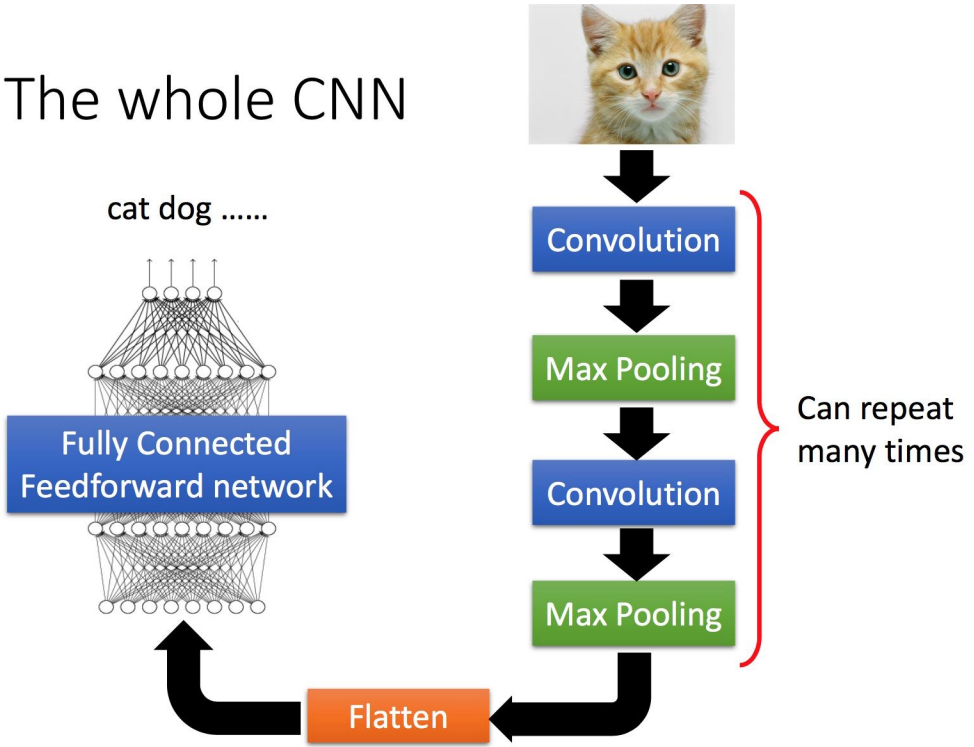
3. 2d example ->
   Yellow shows filter weights
   Green shows input



Stanford UFLDL

CNN for Images

- Convolution Layer:
  - Local features matters
  - Location Insensitive
- Max Pooling Layer:
  - Subsampling works



CNN for Text

CNN works for Text

Images

- Local Features Matter
- Locations Insensitive
- Subsampling Works

Texts

- Key n-grams define semantics

  *Pulp fiction's director is Quentin. I **am obsessed of** it.*

- Locations of key n-grams Insensitive?

  *I **am obsessed of** Pulp fiction, whose director is Quentin.*

  *Pulp fiction's director is Quentin. I **am obsessed of** it.*

  I owe you ten dollars
  You owe me ten dollars.

- Doc. Summarization

Combinations

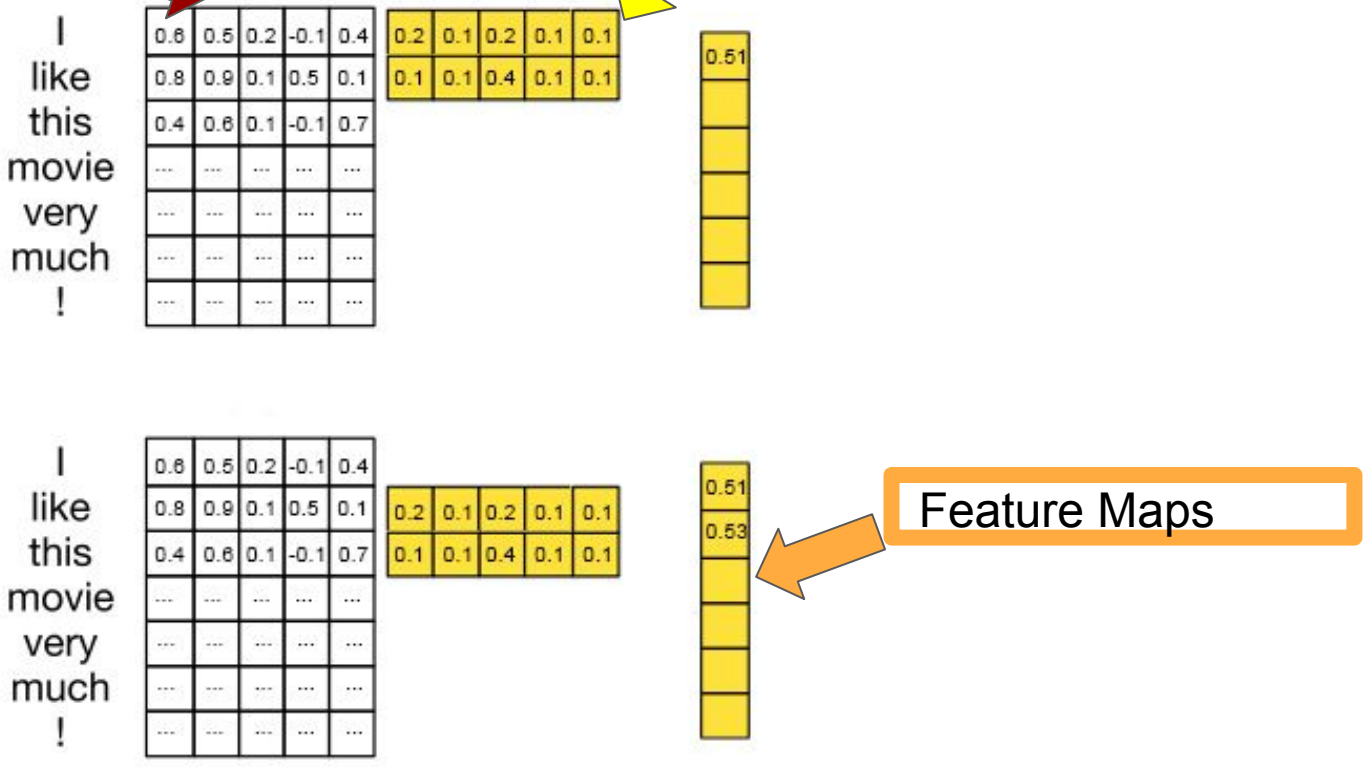
E.g., *I hate this movie*

- Compute vectors for every possible phrase
    - *I hate this movie* ----> I hate; hate this; this movie
- Compute these vectors for these phrases

Convolution Operation

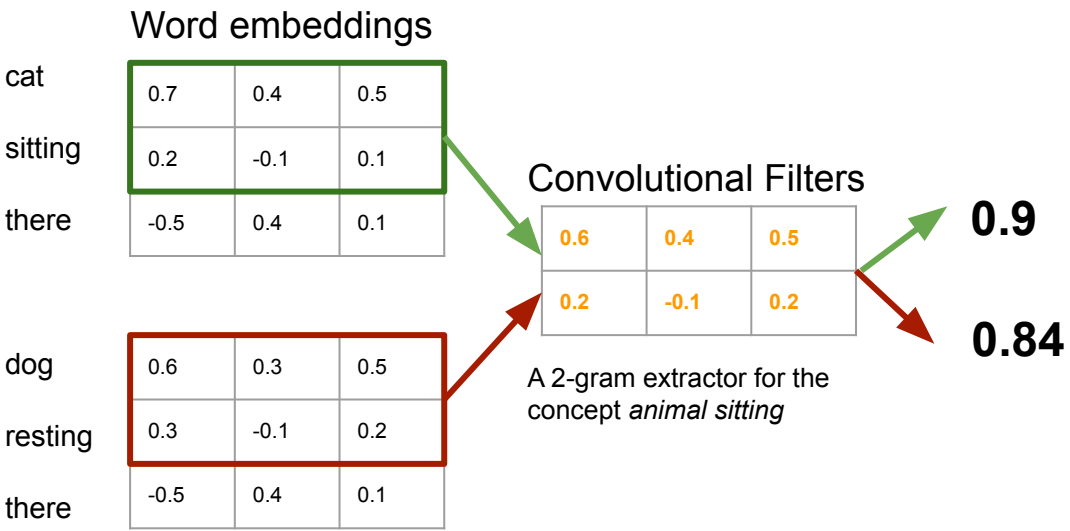
Word Vectors

Filters updated during training



Feature Maps

Toy Example



- This convolution provides high activations for 2-grams with certain meaning
- Can be extended to 3-grams, 4-grams, etc.
- Can have various filters, need to track many n-grams.
- They are called 1D since we only slice the windows only in one direction

Why is it better than BoW?

Convolution Operation

$$p = \tanh\left(W \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + b\right)$$

Word Vector: $c \in R^k$

d features maps, n-grames

[ ]: concatenation operation

W: linear matrix $W \in R^{d \times nk}$

b: bias vector $b \in R^d$

W and b are the network parameters to be learned.

Convolution Layer Weights

W: linear matrix $W \in R^{d \times nk}$

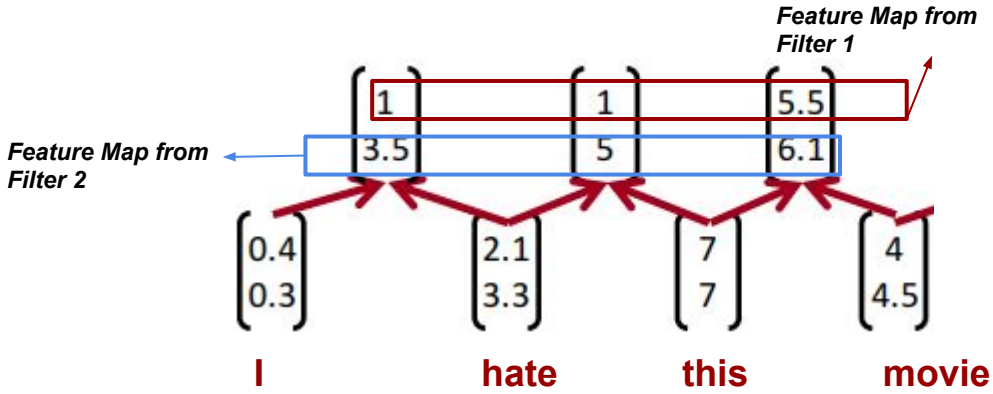
- Each **row vector** in linear matrix can be regarded as one **n-gram extractor**, i.e., filter.
- Number of row d can be regarded as number of extractors.
- The output is the feature value for the input n-words.
- They are called 1D because we slide the window only in one direction.

0.4 0.3 2.1 3.3 (2-gram, window of 2)
dot pdt with
0.1 0.2 0.3 0.4 (filter 1)

0.4 0.3 2.1 3.3 (2-gram, window of 2)
dot pdt with
0.3 0.4 0.5 0.6 (filter 2)

then 2.1 3.3 7 7(2-gram, window of 2)
dot pdt with
0.1 0.2 0.3 0.4 (feature map 1)

then 2.1 3.3 7 7(2-gram, window of 2)
dot pdt with
0.3 0.4 0.5 0.6 (filter 2)

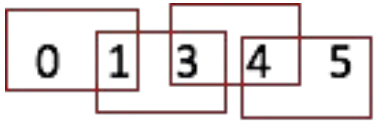


Padding

Padding: After convolution, the lengths of feature maps depends on padding

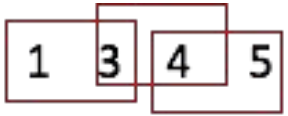
Toy Sequence: 1, 3, 4, 5

a. To be the same as the input length **(*same*)**



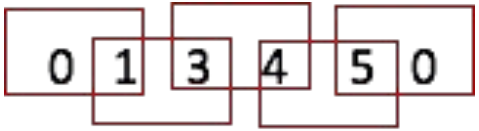
1st word is impt, consider it separately

b. Input length - window size + 1 **(*valid or narrow*)**



Variable Feature Dimension after Convolution

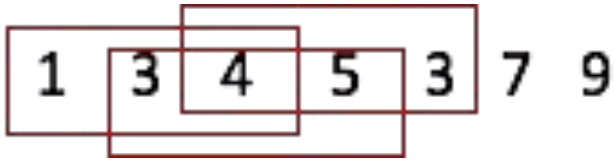
c. Input length + window size - 1 **(*wide*)**



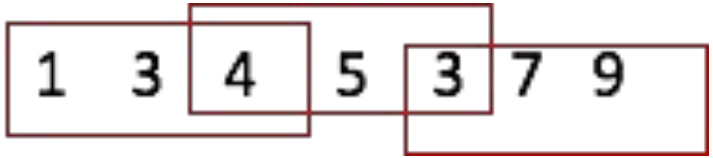
1st and last words are both impt, take them into consideration separately

Stride

- Control how the filters move along the input sequence
- **N-stride** means that the filter convolve around the input sequence by **shifting n units every time**.



Stride = 1



Stride = 2

Pooling Operation

1. Calculates some reduction function feature-wise
2. Pooling is conducted over the sequence direction
   a. **K-range Max pooling:** *Did u see this feature anywhere in the k window*

$$[5.5\ ;\ 6.1]^T$$

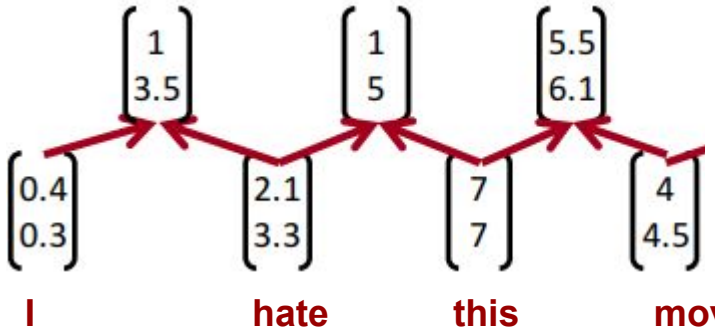
just care if the sentence contains the key n-gram

   b. **Average pooling:** *How prevalent is this feature over the entire range?*

$$[2.9\ ;\ 4.5]^T$$

Lose the order information.

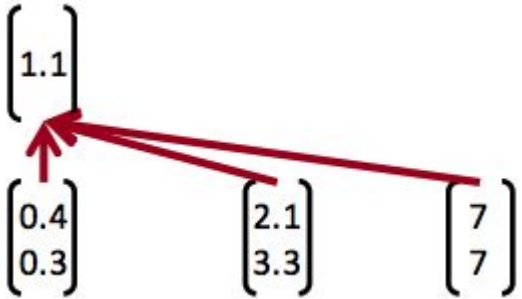
We do not care the position of the key n-grams in the sentence. Whether the key n-grams is in the sentence or not is important.



Convolution Operation Hyper-parameters

Windows size n: how many words are considered together?

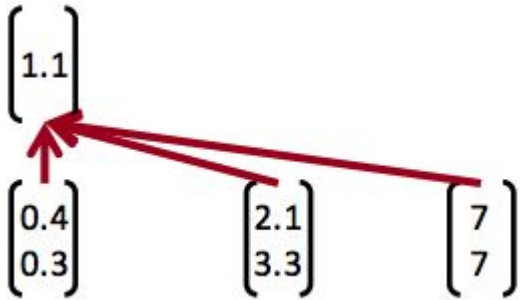
Output dimension d: how many filters are used for word windows?



Windows Size

Windows size n: capture the n-gram features in convolutional layer

- CNN **automatically** learns the values of its filters
- Compared to n-grams model, CNN is **efficient** and **compact** in representation without representing all vocabulary

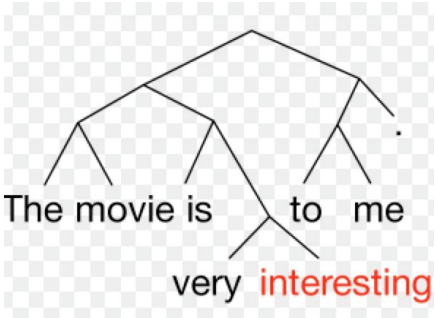


Stride Size

Stride size: how much you want to shift your filter at each step

- It is usually set to be one
- If large stride size, build a model that behaves somewhat similarly to a tree

stride size=2



Multiple Filters

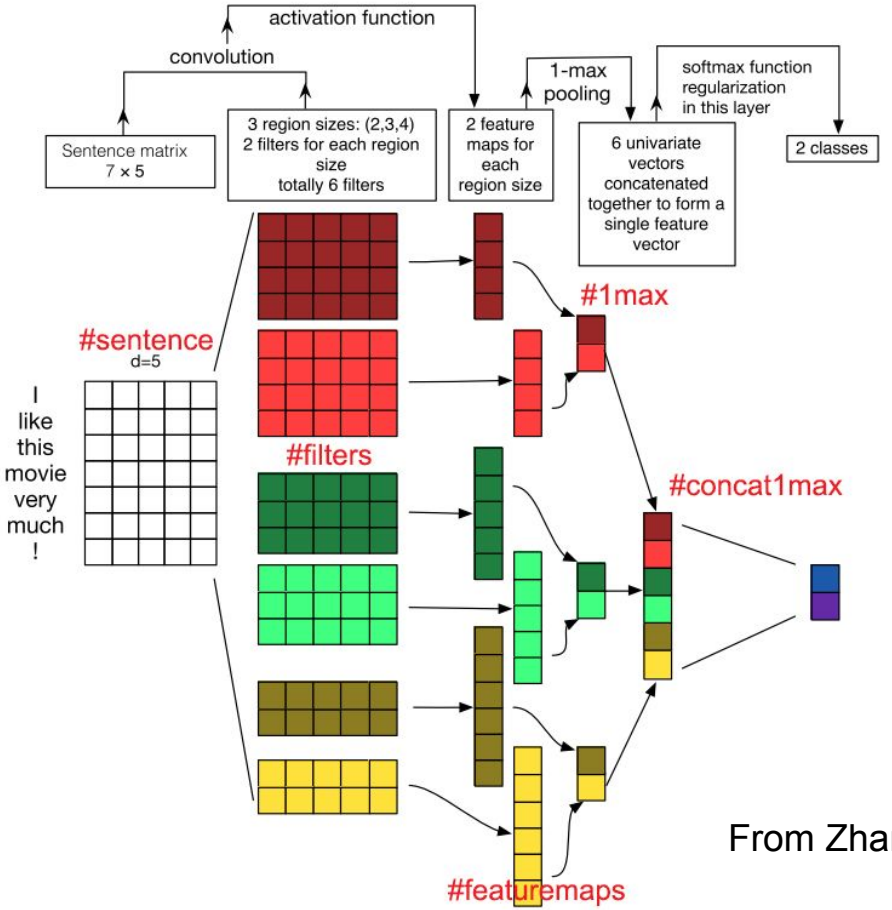
- Use multiple filter weights w (initialize randomly)
- Use different window sizes n
- Then, we can have features for bigrams, tri-grams, 4-grams

Classification after one CNN layer

1. First one convolution, followed by one max-pooling
2. Obtain final features vectors: z = [c_1,....,c_m] where m is the number of filters
3. Apply softmax layers on final vector

$$y = softmax\left(W^{(S)}z + b\right)$$

CNN Framework



From Zhang 2015

Multiple Channels

- Like image, CNN is applied on R-G-B channels
- For NLP, different word embeddings can be regarded as different channels

CNN for NLP

1. n-grams features are important (window size)
2. Location of key n-grams are trivial (pooling)
3. Stack of Convolutional layer or large window size can also capture long-range information