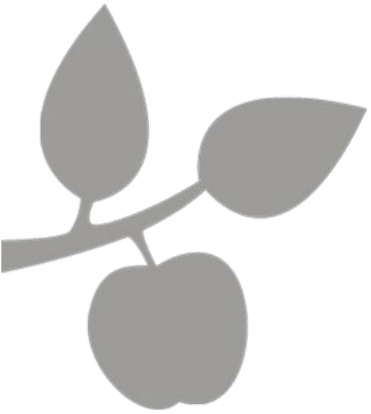
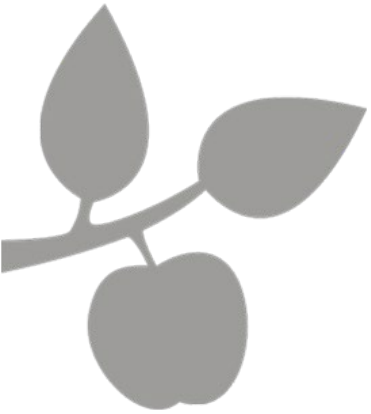


SDU Summer School

# Deep Learning

Summer 2022

## Welcome to the Summer School



# Recurrent Neural Networks

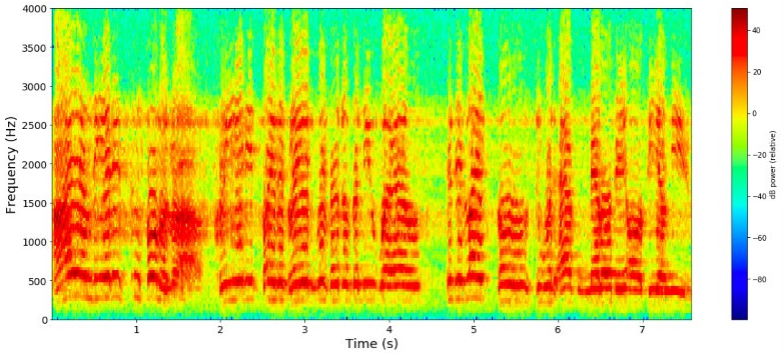
- **Introduction**
- **Unfolding a Graph**
- **Recurrent Neural Networks**
- **Long Term Memory**
  - Leaky Units
  - Long-Short Term Memory
- **Working with Texts in Keras**

# RNNs process sequential data

- Recurrent Neural Networks are a family of neural networks for processing sequential data
- Just as CNN is specialized for processing grid of values, e.g., image
  - RNN is specialized for processing a sequence of values $x^{(1)}, \ldots, x^{(\tau)}$
- Just as CNNs can readily scale images with large width/height and process variable size images
  - RNNs can scale to much longer sequences than would be practical for networks without sequence-based specialization
  - RNNs can also process variable-length sequences

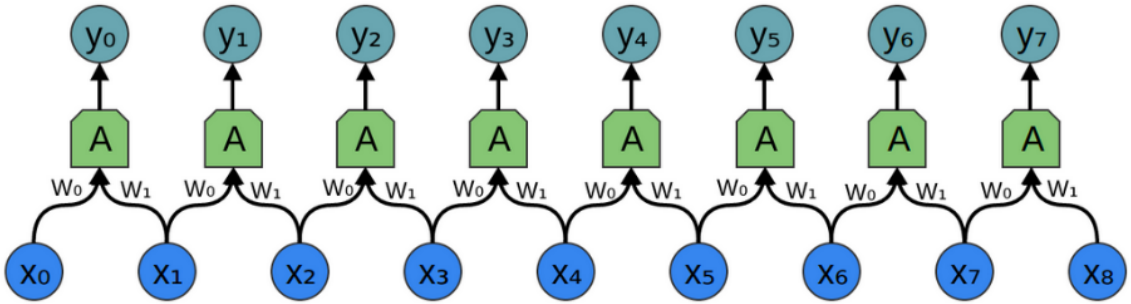
# Examples of Sequential Data and Tasks

- Sequence data: sentences, speech, stock market, signal data
- Sequence-to-sequence Tasks
  - Speech recognition
    - decompose sound waves into frequency and amplitude using Fourier transforms yielding a spectrogram




  - Named Entity Recognition
    - Input: Jim bought 300 shares of Acme Corp. in 2006
    - NER: $[\text{Jim}]_{\text{Person}}$ bought 300 shares of $[\text{Acme Corp.}]_{\text{Organization}}$ in $[\text{2006}]_{\text{Time}}$
- Sequence-to-symbol
  - Sentiment
  - Speaker recognition

# Recall: 1-D Convolution




Kernel $g(t)$:

$[\ldots 0, w_1, w_0, 0 \ldots]$

Equations for outputs of this network:

$$y_0 = \sigma(W_0 x_0 + W_1 x_1 - b)$$

$$y_1 = \sigma(W_0 x_1 + W_1 x_2 - b)$$

etc. upto $y_8$

Note that kernel gets flipped in convolution

We can also write the equations in terms of elements of a general $8 \times 8$ weight matrix $W$ as:

$$y_0 = \sigma(W_{0,0} x_0 + W_{0,1} x_1 + W_{0,2} x_2 \ldots)$$

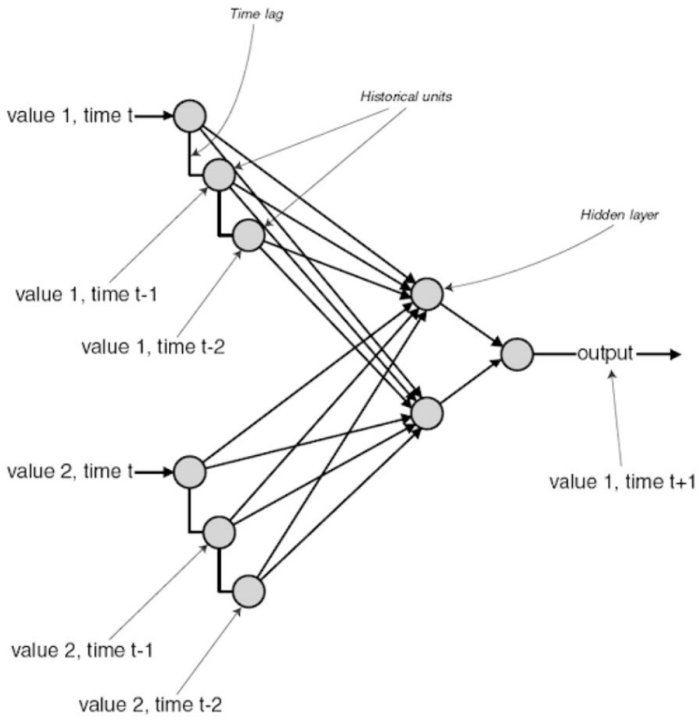
$$y_1 = \sigma(W_{1,0} x_0 + W_{1,1} x_1 + W_{1,2} x_2 \ldots)$$

where $W = \begin{bmatrix} w_0 & w_1 & 0 & 0 & \ldots \\ 0 & w_0 & w_1 & 0 & \ldots \\ 0 & 0 & w_0 & w_1 & \ldots \\ 0 & 0 & 0 & w_0 & \ldots \\ \ldots & \ldots & \ldots & \ldots & \ldots \end{bmatrix}$

- http://colah.github.io/posts/2014-07-Understanding-Convolutions/

# Time Delay Neural Networks

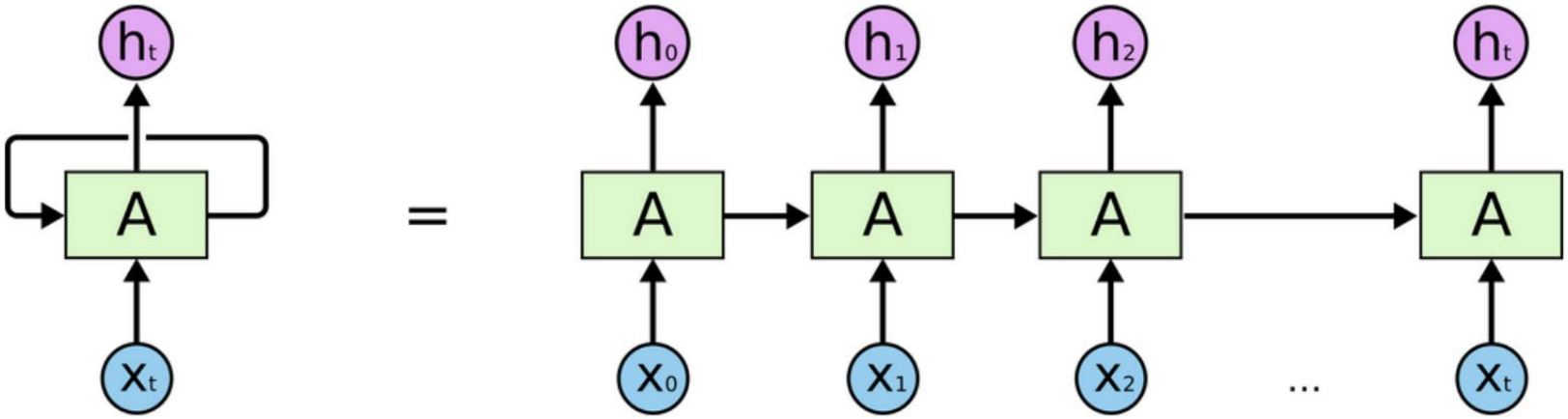
- Time-delay neural networks perform convolution across 1-D temporal sequence
  - Convolution operation allows a network to share parameters across time, but is shallow
    - Each member of output is dependent upon a small no. of neighboring members of the input
    - Parameter sharing manifests in the application of the same convolutional kernel at each time step




- A TDNN remembers the previous few training examples and uses them as input into the network.

# RNN vs. TDNN

- RNNs share parameters in a different way
  - Each member of output is a function of previous members of output
  - Each output produced using same update rule applied to previous outputs
  - This recurrent formulation results in sharing of parameters through a very deep computational graph
- An unrolled RNN



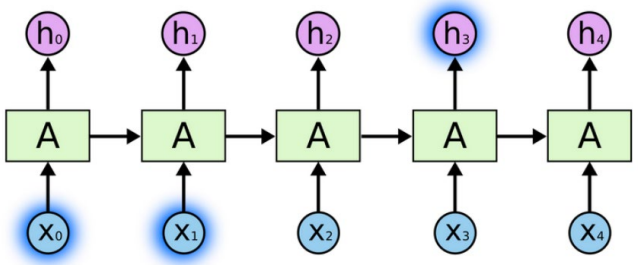
# RNNs share same weights across Time Step

- To go from multi-layer networks to RNNs:
  - Need to share parameters across different parts of a model
  - Separate parameters for each value of input cannot generalize to sequence lengths not seen during training
  - Share statistical strength across different sequence lengths and across different positions in time

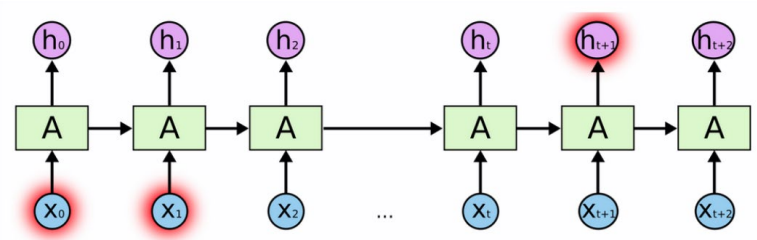
- Sharing important when information can occur at multiple positions in the sequence
  - Given “I went to Nepal in 1999 ” and “In 1999, I went to Nepal ”, an ML method to extract year, should extract 1999 whether in position 6 or 2
  - A feed-forward network that processes sentences of fixed length would have to learn all of the rules of language separately at each position
  - An RNN shares the same weights across several time steps

# Problem of Long-Term Dependencies

- Easy to predict last word in “the clouds are in the sky”
  - When gap between relevant information and place that it’s needed is small, RNNs can learn to use the past information




- “I grew up in France... I speak fluent French.”
  - Large gap between relevant information and point where it is needed

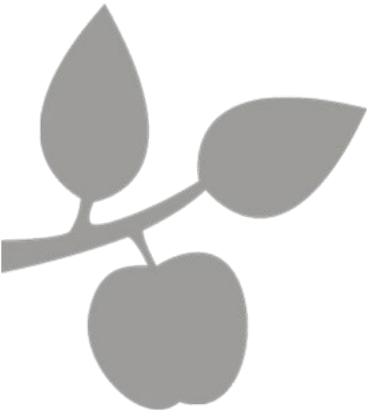



- In principle RNNs can handle it, but fail in practice
  - LSTMs offer a solution

# RNN operating on a sequence

- RNNs operate on a sequence that contain vector $x^{(t)}$ with time step index $t$, ranging from 1 to $\tau$
  - Sequence $x^{(1)}, \ldots, x^{(\tau)}$
  - RNNs operate on minibatches of sequences of length $\tau$

- Some remarks about sequences
  - The steps need not refer to passage of time in the real world
  - RNNs can be applied in two-dimensions across spatial data such as image
  - Even when applied to time sequences, network may have connections going backwards in time, provided entire sequence is observed before it is provided to network



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# Unfolding Computational Graphs

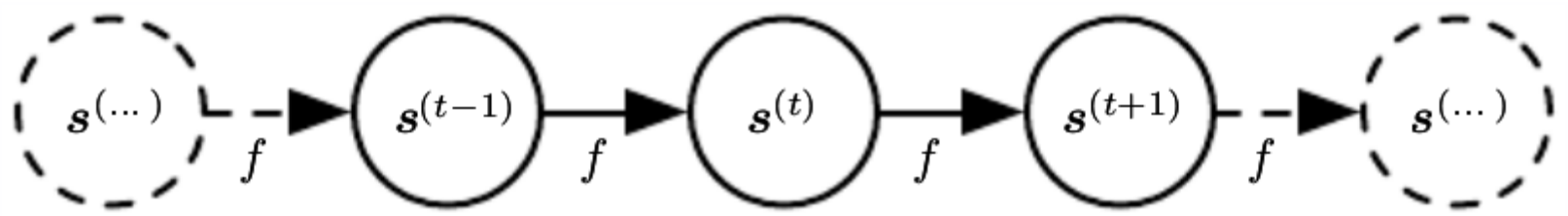
- Recall: A Computational Graph is a way to formalize the structure of a set of computations
  - Such as mapping inputs and parameters to outputs and loss
- We can unfold a recursive or recurrent computation into a computational graph that has a repetitive structure
  - Corresponding to a chain of events
- Unfolding this graph results in sharing of parameters across a deep network structure

# Unfolded dynamical system

- The classical dynamical system described by

$$\boldsymbol{s}^{(t)} = f\left(\boldsymbol{s}^{(t-1)}; \boldsymbol{\theta}\right)$$

is illustrated as an unfolded computational graph:




- Each node represents state at some time $t$
- Function $f$ maps state at time t to the state at $t + 1$
- The same parameters (the same value of $\theta$ used to parameterize $f$) are used for all time steps

# Dynamical system driven by external signal

- As another example, consider a dynamical system driven by external (input) signal $\boldsymbol{x}^{(t)}$

$$\boldsymbol{s}^{(t)} = f\left(\boldsymbol{s}^{(t-1)}, \boldsymbol{x}^{(t)}; \boldsymbol{\theta}\right)$$

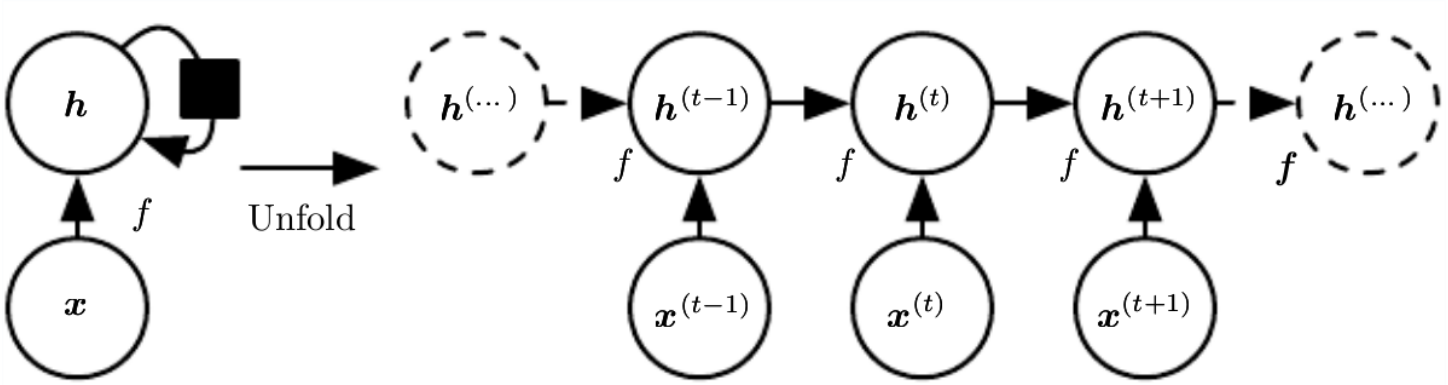
  - State now contains information about the whole past input sequence

- Recurrent neural networks can be built in many ways
  - Much as almost any function is a feedforward neural network, any function involving recurrence can be considered to be a recurrent neural network

# Defining values of hidden units in RNNs

- Many recurrent neural nets use same equation (as dynamical system with external input) to define values of hidden units
  - To indicate that the state is hidden rewrite using variable $\boldsymbol{h}$ for state

$$\boldsymbol{h}^{(t)} = f\left(\boldsymbol{h}^{(t-1)}, \boldsymbol{x}^{(t)}; \boldsymbol{\theta}\right)$$




- Typical RNNs have extra architectural features such as output layers that read information out of state $\boldsymbol{h}$ to make predictions

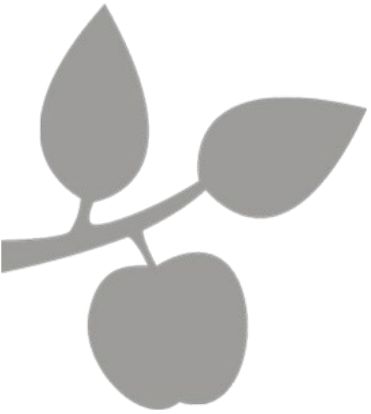
# Predicting the Future from the Past

- When RNN is required to perform a task of predicting the future from the past, network typically learns to use $\boldsymbol{h}^{(t)}$ as a lossy summary of the past sequence of inputs up to time point $t$
- The summary is in general lossy since it maps a sequence of arbitrary length $(\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(t)})$ to a fixed length vector $\boldsymbol{x}^{(1)}$
- Depending on criterion, summary keeps some aspects of past sequence more precisely than other aspects
  - RNN used in statistical language modeling, typically to predict next word from past words
  - it may not be necessary to store all information upto time $t$ but only enough information to predict rest of sentence

# Unfolding process allows learning a single model

- The unfolding process introduces two major advantages:
  1. Regardless of sequence length, learned model has same input size
     - because it is specified in terms of transition from one state to another state rather than specified in terms of a variable length history of states
  2. Possible to use same function $f$ with same parameters at every step

- These two factors make it possible to learn a single model $f$
  - that operates on all time steps and all sequence lengths
  - rather than needing separate model $g^{(t)}$ for all possible time steps
- Learning a single shared model allows:
  - Generalization to sequence lengths that did not appear in the training
  - Allows model to be estimated with far fewer training examples than would be required without parameter sharing



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# Three design patterns of RNNs

- Design 1: Output: each time step; Recurrence: hidden units
- Design 2: Output: each time step; Recurrence: output units
- Design 3: Output: one at the end; Recurrence: hidden units

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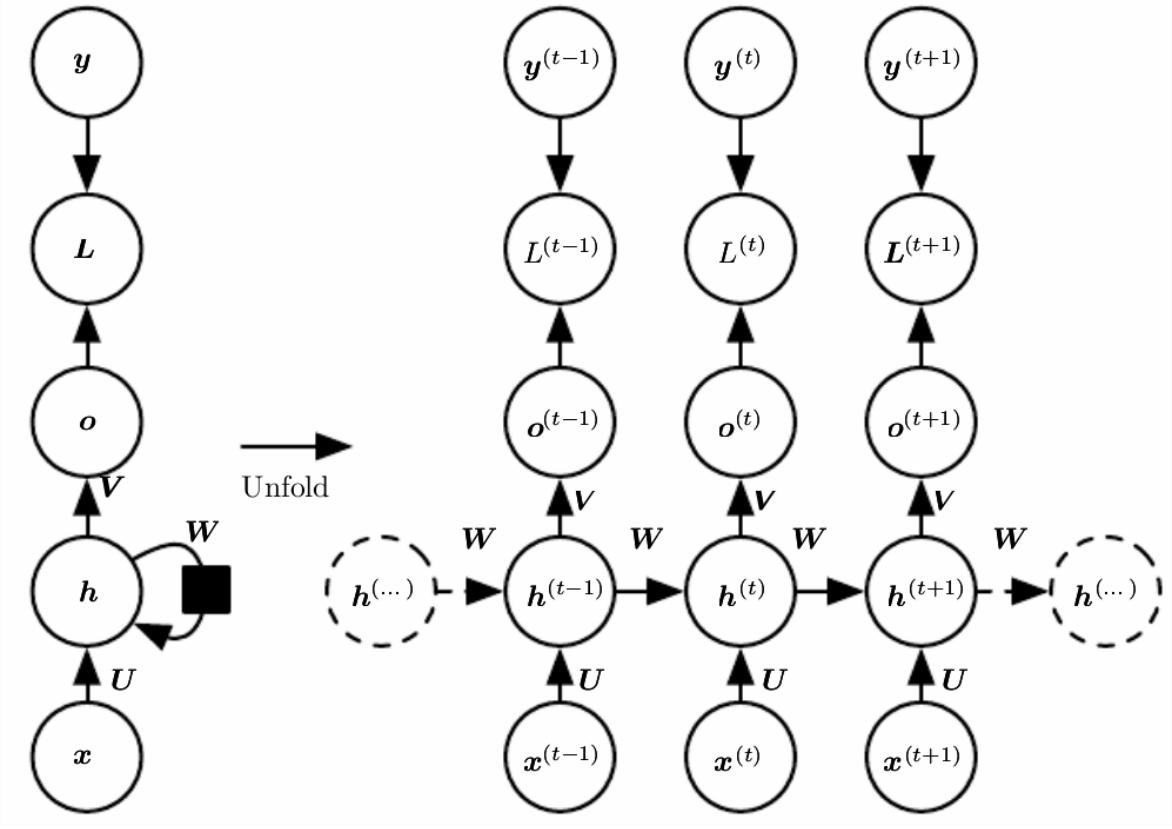

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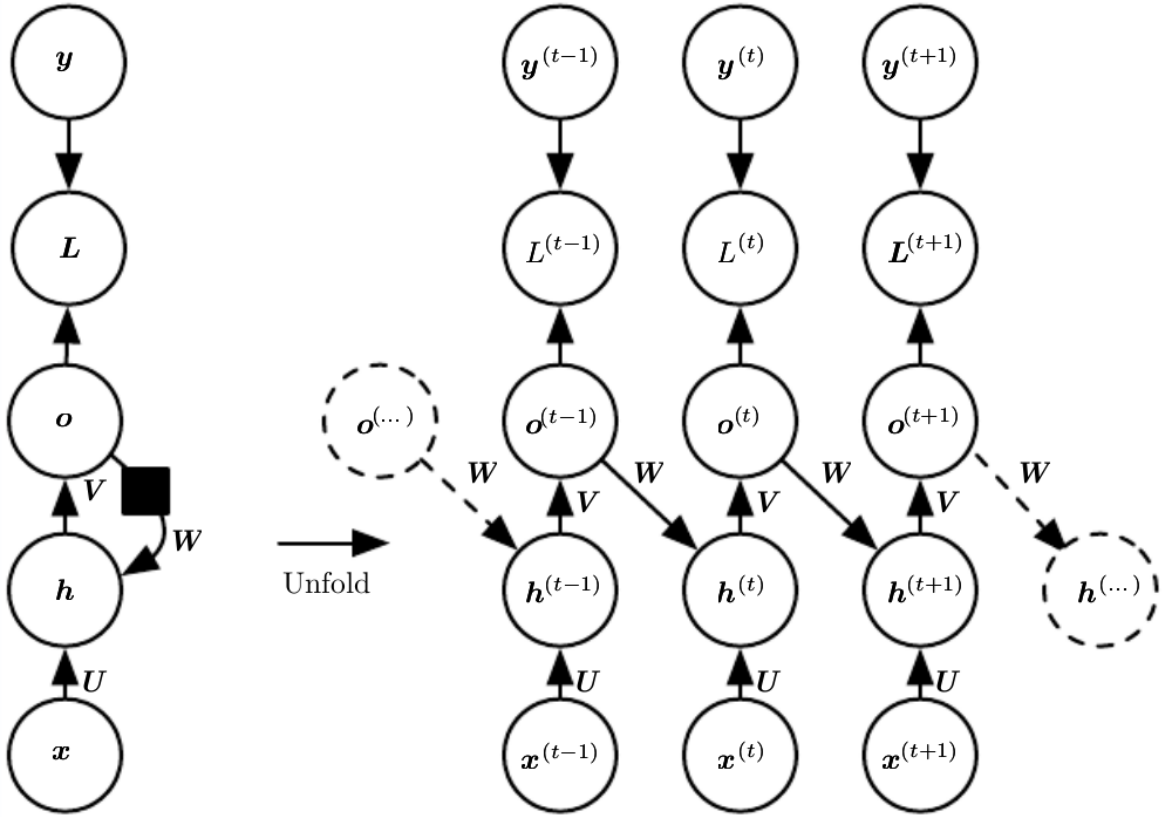

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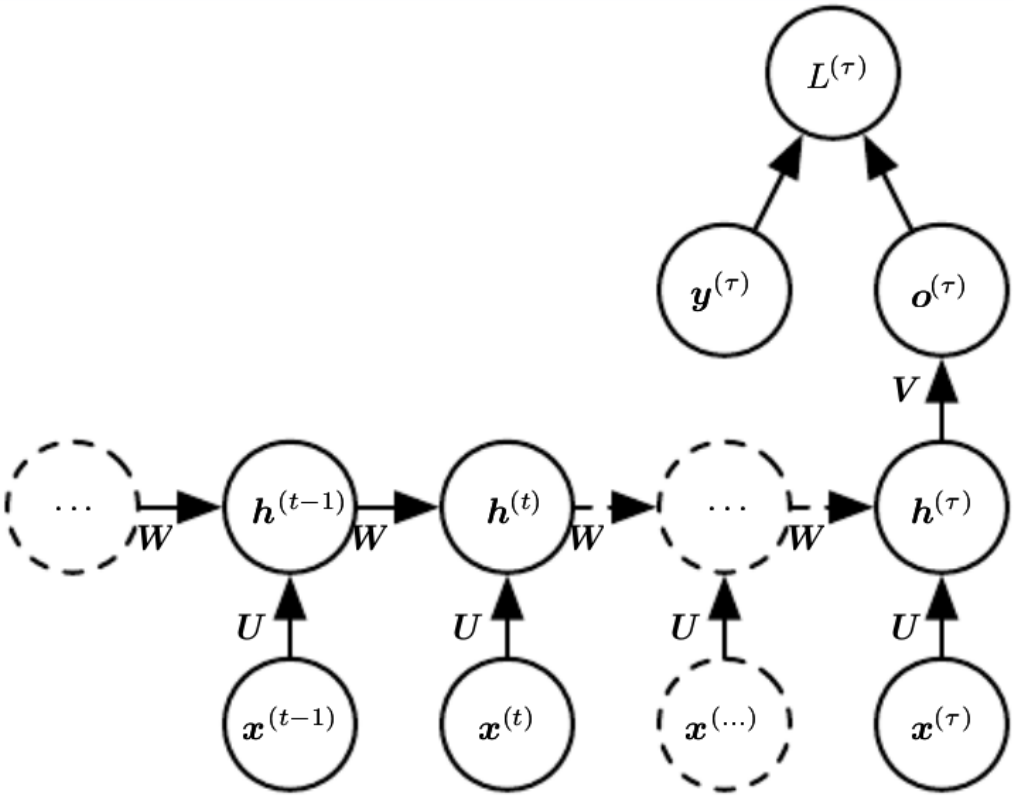
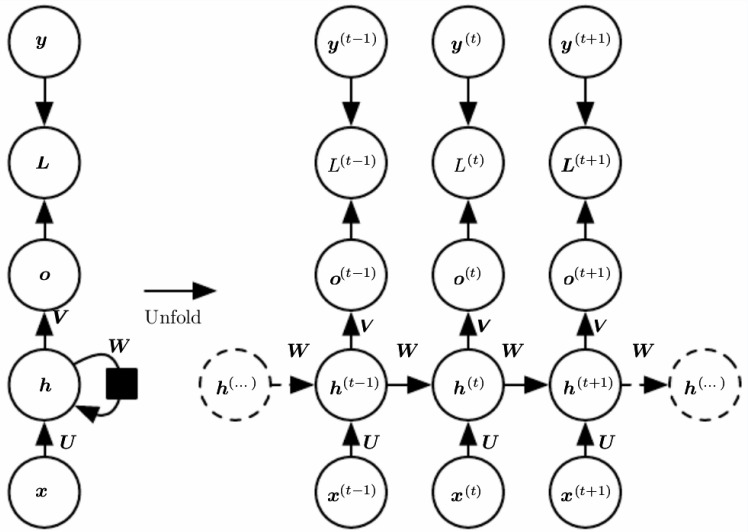


# Design 1: RNN with recurrence between hidden units

- Maps input sequence $\boldsymbol{x}$ to output $\boldsymbol{o}$ values
  - Loss $L$ measures how far each $\boldsymbol{o}$ is from the corresponding target $\boldsymbol{y}$
  - With softmax outputs we assume $\boldsymbol{o}$ is the unnormalized log probabilities
  - Loss $L$ internally computes $\boldsymbol{y} = \mathrm{softmax}(\boldsymbol{o})$ and compares to target y
  - Let's assume we have tanh activation function

- Any function computable by a Turing Machine is computable by such an RNN of finite size



# Design 1: Forward Calculation

- We need to specify initial state $\boldsymbol{h}^{(0)}$, then for each time point:

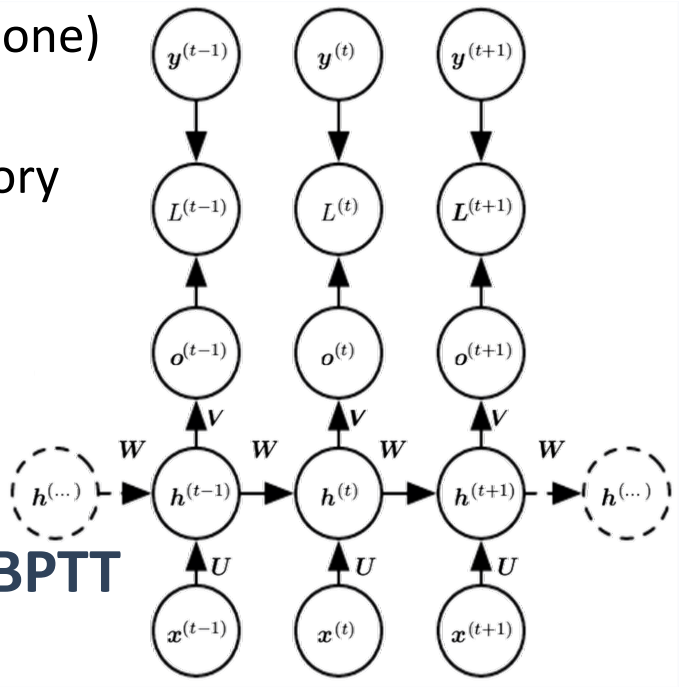
$$\boldsymbol{a}^{(t)} = \boldsymbol{b} + \boldsymbol{W}\boldsymbol{h}^{(t-1)} + \boldsymbol{U}\boldsymbol{x}^{(t)}$$
$$\boldsymbol{h}^{(t)} = \tanh\left(\boldsymbol{a}^{(t)}\right)$$
$$\boldsymbol{o}^{(t)} = \boldsymbol{c} + \boldsymbol{V}\boldsymbol{h}^{(t)}$$
$$\hat{\boldsymbol{y}}^{(t)} = \mathrm{softmax}\left(\boldsymbol{o}^{(t)}\right)$$

- The Loss function can simply defined as the sum of the loss at each timepoint:

$$L = \sum_t L^{(t)} = -\sum_t \log p_{model}\left(\boldsymbol{y}^{(t)} | \left\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(t)}\right\}\right)$$

# Design 1: Gradient Calculation

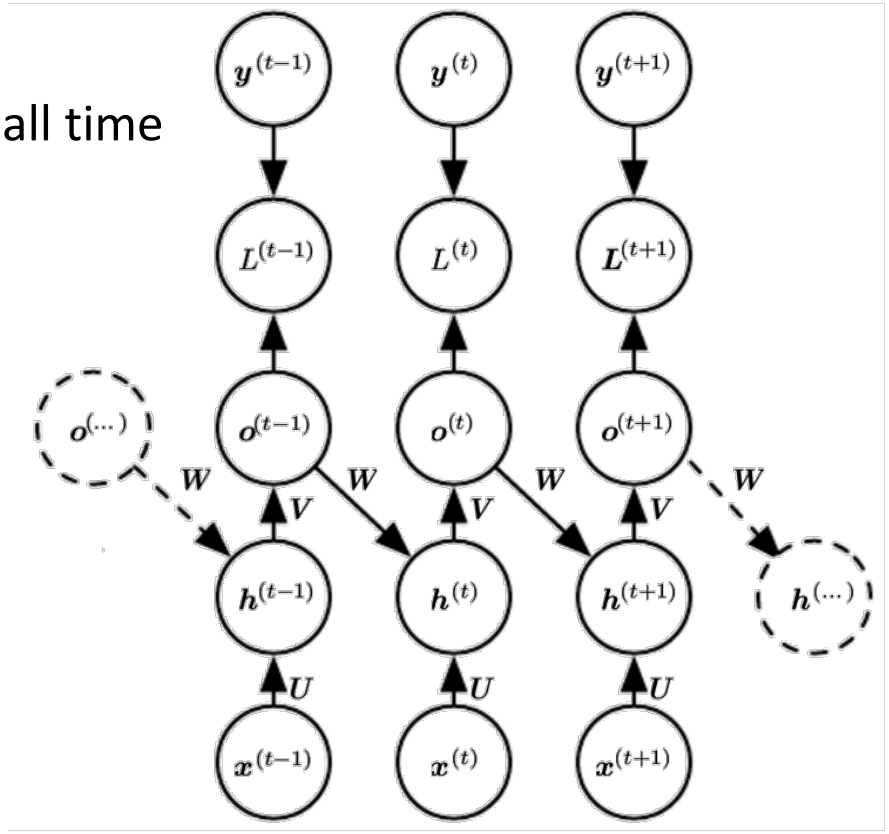
- Computing the gradient of this loss function with respect to the parameters is an expensive operation.
  - Requires forward propagation pass through the unrolled graph
  - followed by a backward pass
  - The runtime is $O(\tau)$ and cannot be reduced by parallelization (each time step may only be computed after the previous one)
  - The forward pass must be stored until they are reused during the backward pass, so the memory cost is also $O(\tau)$.




- The back-propagation algorithm applied to the unrolled graph with $O(\tau)$ cost is called **back-propagation through time** or **BPTT**

# Design 2: Recurrence from Output to Hidden

- Less powerful than Design 1
  - It cannot simulate a universal Turing Machine
  - It requires that the output capture all information of past to predict future
- Advantage
  - In comparing loss function to output all time steps are decoupled
    - Each step can be trained in isolation
  - Training can be parallelized
    - Gradient for each step can be computed in isolation
    - No need to compute output for the previous step first, because training set provides ideal value of output
- Trained with **Teacher Forcing**

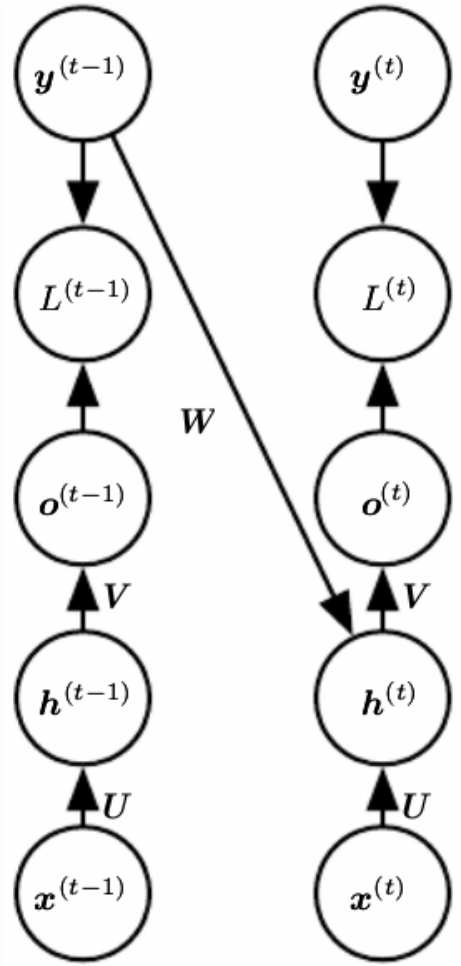


# Teacher Forcing

- Teacher forcing during training means
  - Instead of summing activations from incoming units (possibly erroneous)
  - Each unit sums correct teacher activations as input for the next iteration
- This means we assume that the previous step has produced the correct answer already.
- Since the correct values are already know, we can train each time-step in parallel and independently

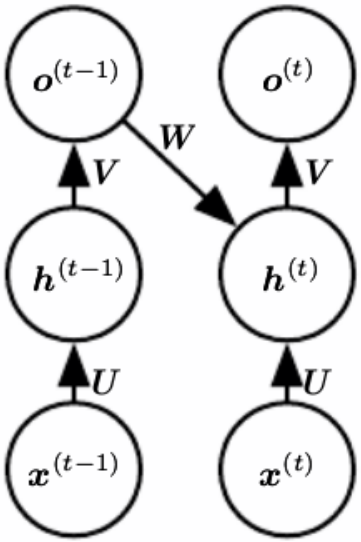
# Illustration of Teacher Forcing

**Train time**:
We feed the correct output $\boldsymbol{y}^{(t)}$ (from teacher) drawn from the training set as input to $\boldsymbol{h}^{(t+1)}$



Train time

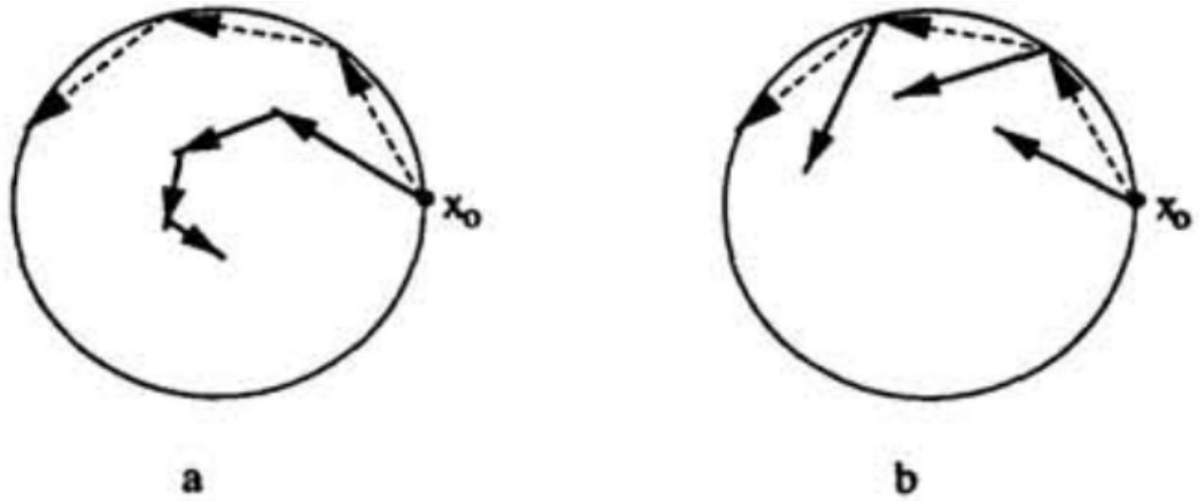
**Test time**:
True output is not known.
We approximate the correct output $\boldsymbol{y}^{(t)}$ with the model's output $\boldsymbol{o}^{(t)}$ and feed the output back to the model

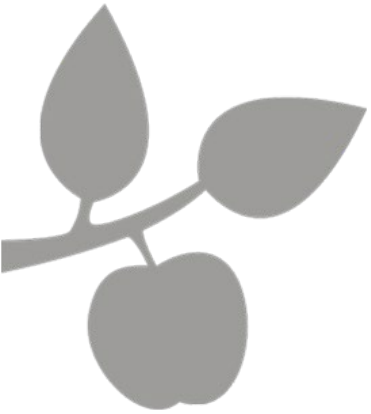


Test time

# Visualizing Teacher Forcing

- Imagine that the network is learning to follow a trajectory
- It goes astray (because the weights are wrong) but teacher forcing puts the net back on its trajectory





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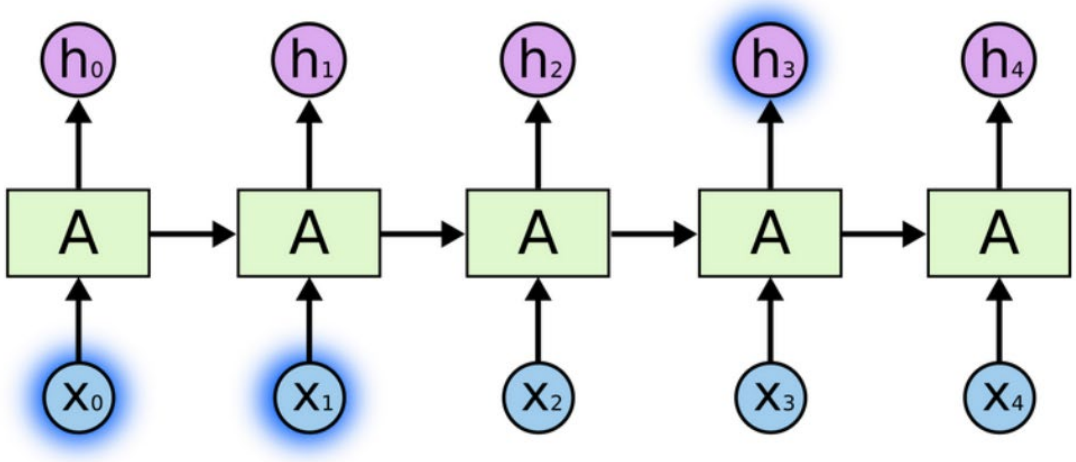
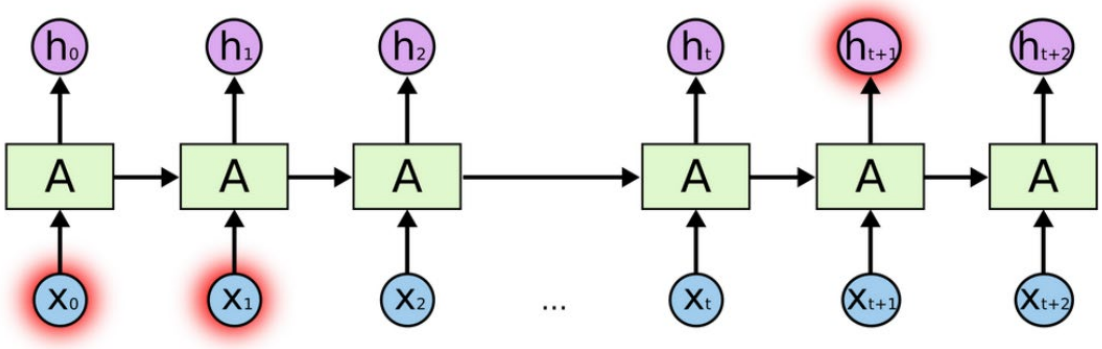
# Prediction with only recent previous information

- RNNs connect previous information to the present task
  - Previous video frames may help understand present frame
- Sometimes we need only look at recent previous information to predict
  - To predict the last word of “The clouds are in the sky” we don’t need any further context. It is obvious that the word is “sky”



# Long-term Connections not Possible

- here are cases where we need more context
- To predict the last word in the sentence “I grew up in France....I speak fluent French”
  - Using only recent information suggests that the last word is the name of a language. But more distant past indicates that it is French
  - It is possible that the gap between the relevant information and where it is needed is very large



# Challenge of Long-Term Dependencies

- Neural network optimization face a difficulty when computational graphs become deep, e.g.,
  - Feedforward networks with many layers
  - RNNs that repeatedly apply the same operation at each time step of a long temporal sequence

- Gradients propagated over many stages tend to either vanish (most of the time) or explode (damaging optimization)

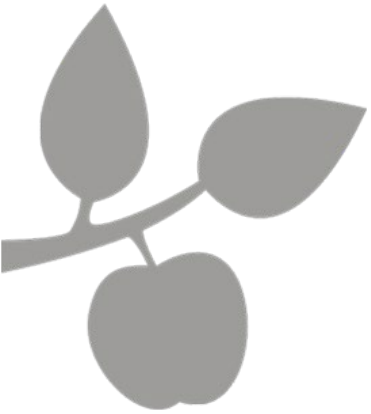
- The difficulty with long-term dependencies arise from exponentially smaller weights given to long-term interactions (involving multiplication of many Jacobians)

# Vanishing and Exploding Gradient Problem

- Suppose a computational graph consists of repeatedly multiplying by a matrix $\boldsymbol{W}$
- After $t$ steps this is equivalent to multiplying by $\boldsymbol{W}^t$
- Suppose W has an eigendecomposition $\boldsymbol{W} = \boldsymbol{V}\mathrm{diag}(\boldsymbol{\lambda})\boldsymbol{V}^{-1}$:

$$\boldsymbol{W}^t = (\boldsymbol{V}\mathrm{diag}(\lambda)\boldsymbol{V}^{-1})^t = \boldsymbol{V}\mathrm{diag}(\boldsymbol{\lambda})^t\boldsymbol{V}^{-1}$$

  - Any eigenvalues λ i that are not near an absolute value of 1 will either explode if they are greater than 1 in magnitude and vanish if they are less than 1 in magnitude
- Vanishing gradients make it difficult to know which direction the parameters should move to improve cost
- Exploding gradients make learning unstable



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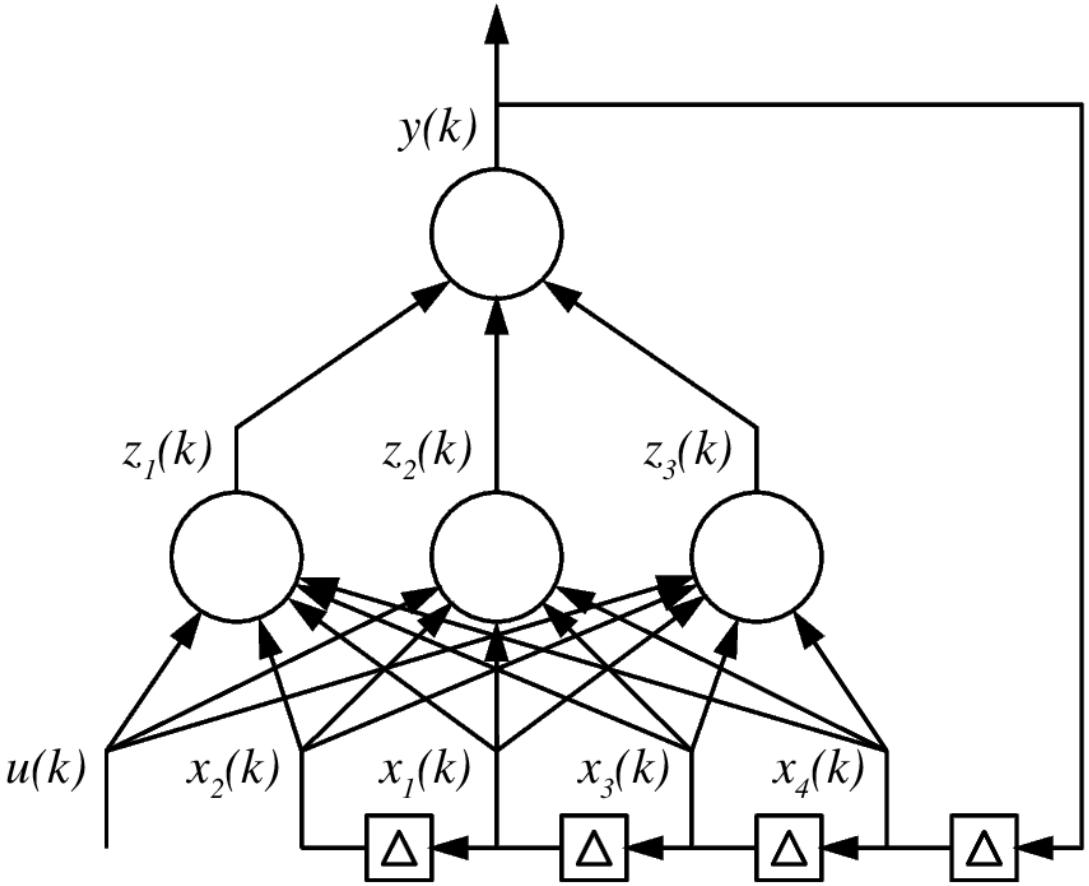
# Adding skip connections through time

- One way to obtain coarse time scales is to add direct connections from variables in the distant past to variables in the present

- In an ordinary RNN, recurrent connection goes from time $t$ to time $t + 1$.
  - Gradients can vanish/explode exponentially wrt no. of time steps

- Introduce time delay of $d$ to mitigate this problem
- Gradients diminish as a function of $\frac{\tau}{d}$ rather than $\tau$
- Allows learning algorithm to capture longer dependencies
  - Not all long-term dependencies can be captured this way

# Network with 4 output delays

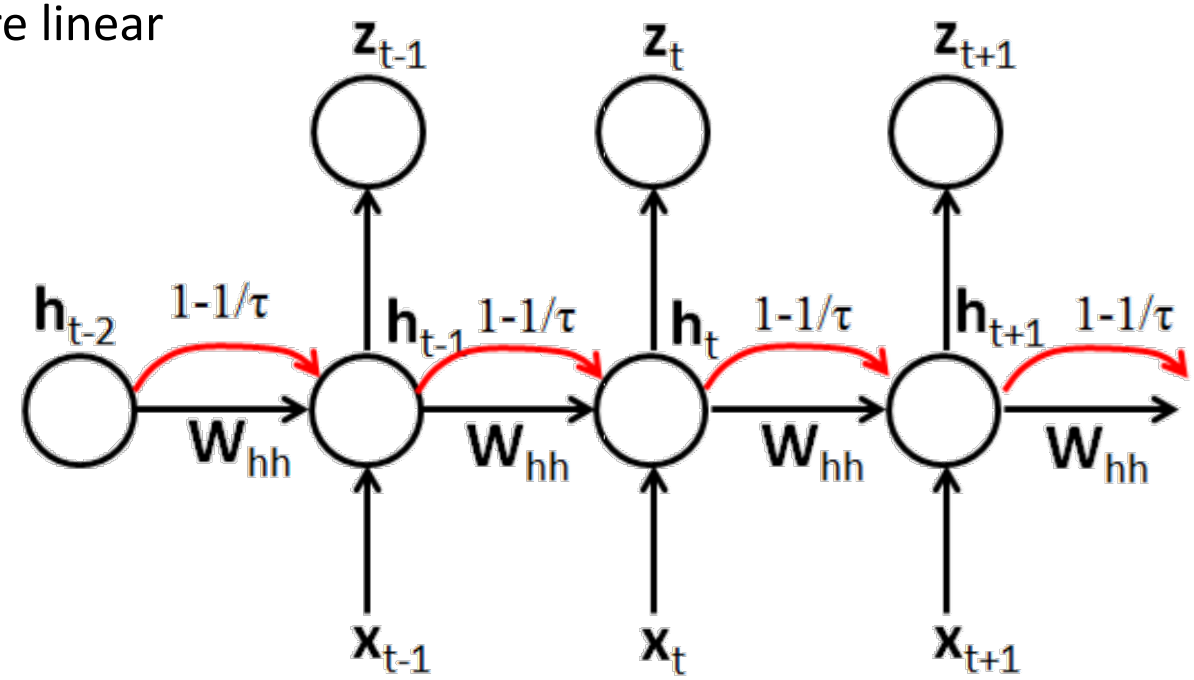



$$y(t) = \Psi\left(u(t), y(t-1), \ldots, y(t-D)\right)$$

# More General

$$h_{t+1} = \left(1 - \frac{1}{\tau}\right)\boldsymbol{h_t} + \frac{1}{\tau}\, g(\boldsymbol{W_{xh}x_t} + \boldsymbol{W_{hh}h_t} + \boldsymbol{b_h})$$

- The new value of the state $h_{t+1}$ is a combination of linear and non-linear parts of $h_t$
- The errors are easier to be back propagated through the paths of red lines, which are linear

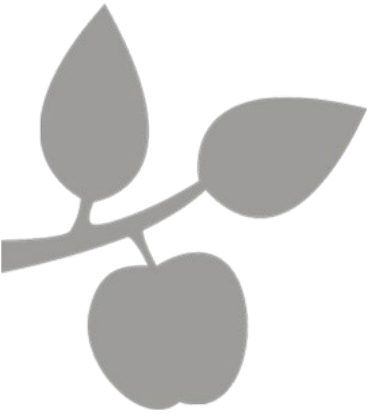


# Leaky units and a spectrum of time scales

- Rather than an integer skip of $d$ time steps, the effect can be obtained smoothly by adjusting a real-valued $\alpha$
- Example: Running Average
  - Running average $\mu^{(t)}$ of some value $v^{(t)}$ is

$$\mu^{(t)} = \alpha\mu^{(t-1)} + (1-\alpha)v^{(t)}$$

  - Called a linear self-correction
  - When $\alpha$ is close to $1$, running average remembers information from the past for a long time and when it is close to $0$, information is rapidly discarded.
- Hidden units with linear self connections behave similar to running average. They are called leaky units.
- Can obtain product of derivatives close to 1 by having linear self-connections and a weight near 1 on those connections

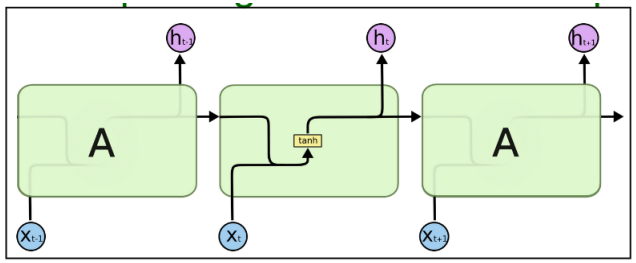


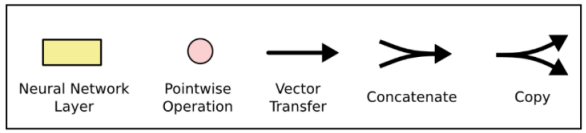
# Recurrent Neural Networks

- Introduction
- Unfolding a Graph
- Recurrent Neural Networks
- Long Term Memory
  - Leaky Units
  - Long-Short Term Memory

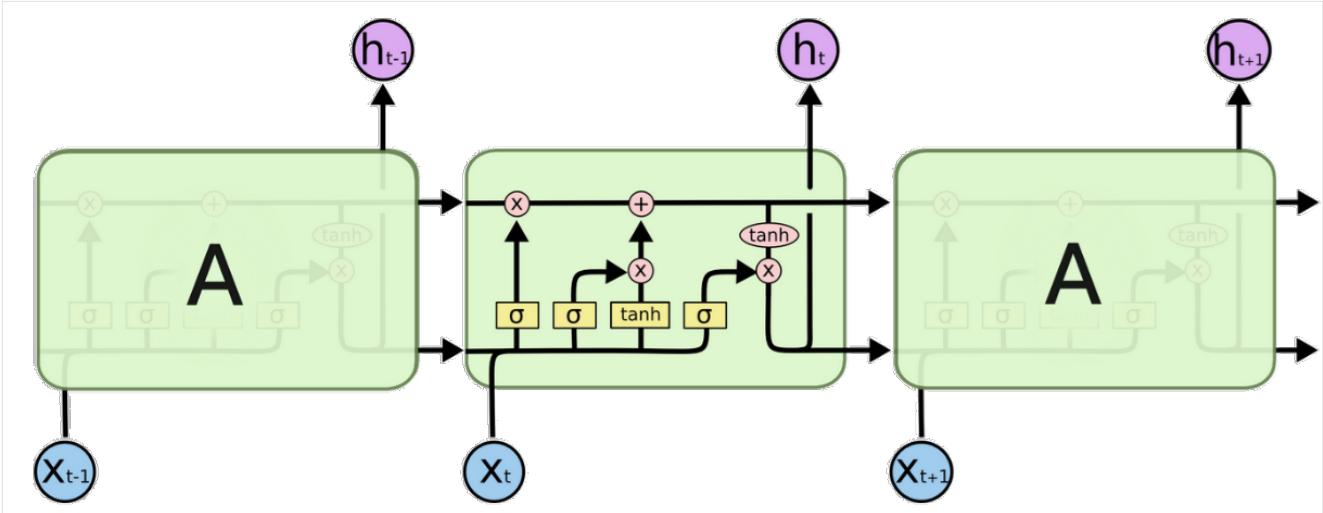
# Long Short Term Memory

- Explicitly designed to avoid the long-term dependency problem
- RNNs have the form of a repeating chain structure
  - The repeating module has a simple structure such as tanh

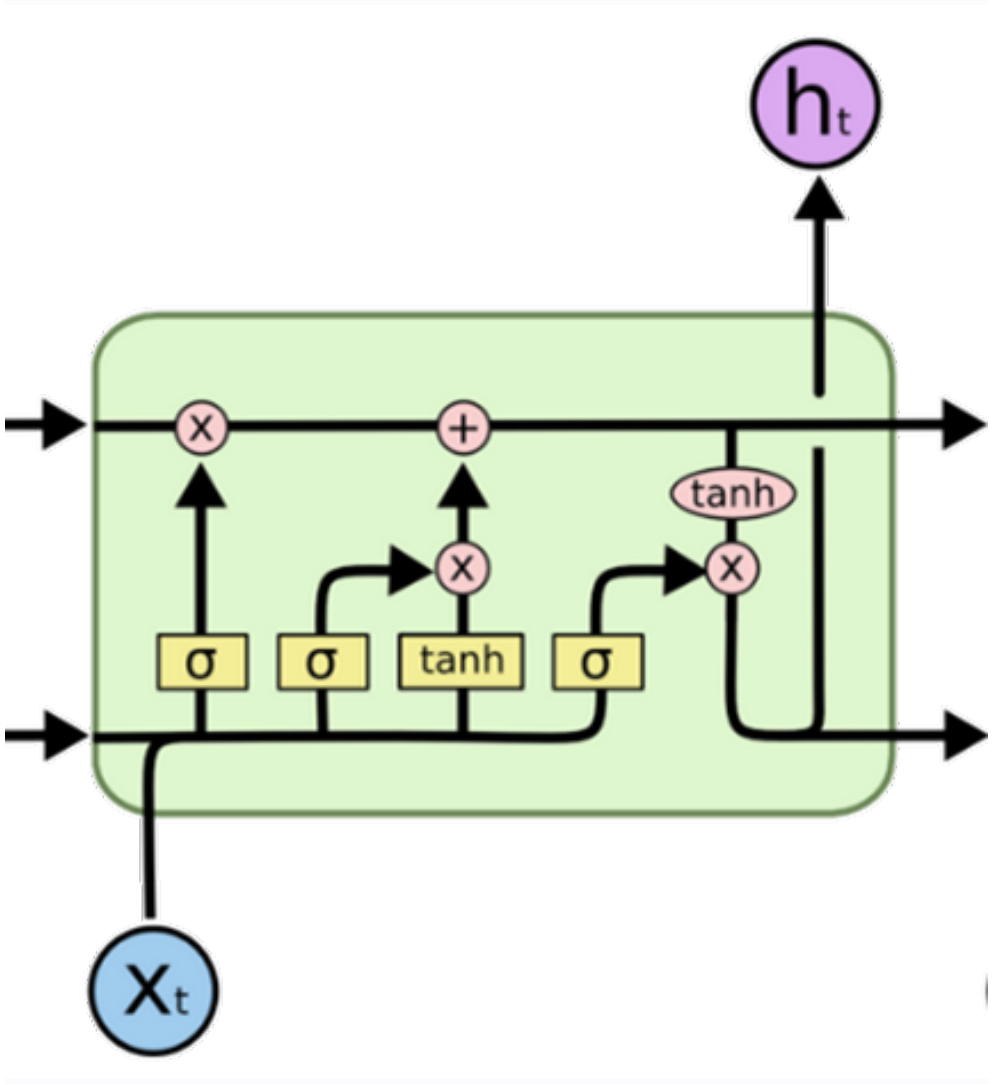



- LSTMs also have a chain structure

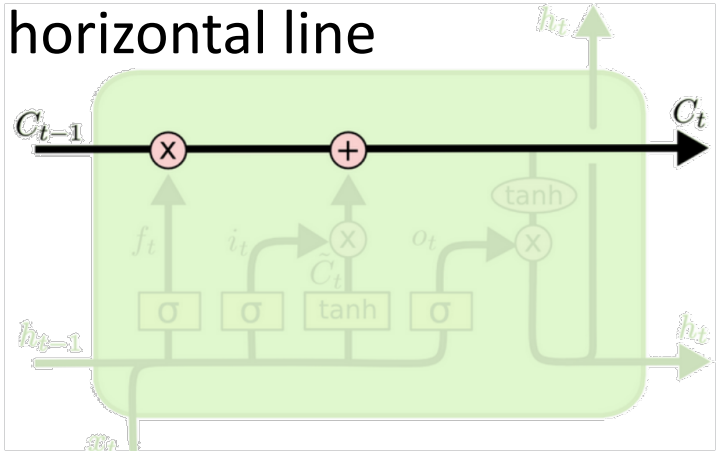


# LSTM Unit

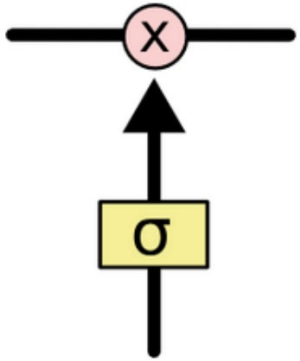


# Core idea behind LSTM

- The key to LSTM is the cell state, $C_t$, the horizontal line running through the top of the diagram
  - Like a conveyor belt
  - Runs through entire chain with minor interactions
  - LSTM does have the ability to remove/add information to cell state regulated by structures called gates



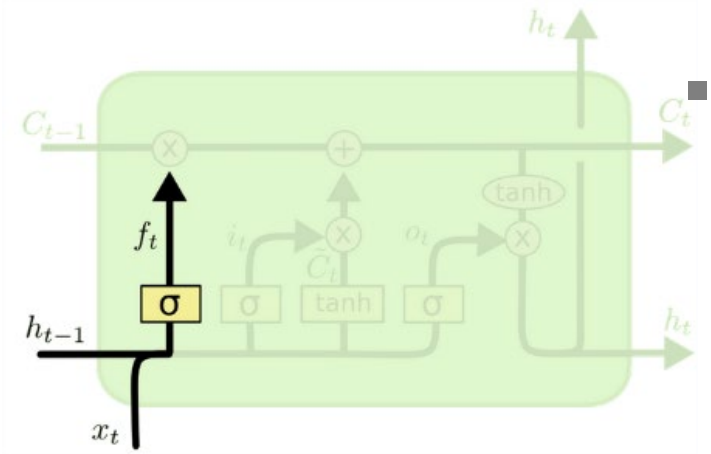

- Gates are an optional way to let information through
- Consist of a sigmoid and a multiplication operation
- Sigmoid outputs a value between 0 and 1
  - 0 means let nothing through
  - 1 means let everything through




- LSTM has three of these gates, to protect and control cell state

# Step-by-step LSTM walk through

- Example: predict next word based on previous ones
  - Cell state may include the gender of the present subject
- First step: information to throw away from cell state



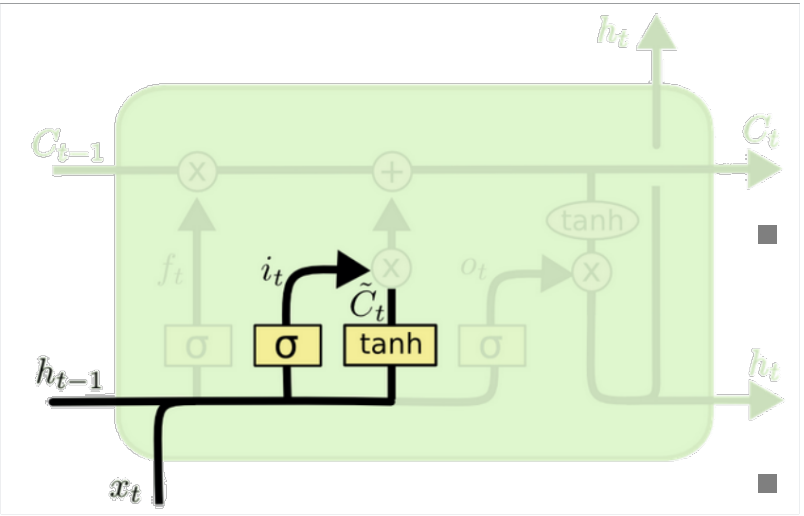

- Called forget gate layer
  - Uses $h^{(t-1)}$ and $x^{(t)}$ and outputs a number between 0 and 1 for each $C^{(t-1)}$

$$f^{(t)} = \sigma\left(\boldsymbol{W}_f \cdot \left[\boldsymbol{h}^{(t-1)}, \boldsymbol{x}^{(t)}\right] + b_f\right)$$

- In language model
  - Consider trying to predict the next word based on all previous ones.
  - The cell state may include the gender of the present subject so that the proper pronouns can be used
  - When we see a new subject we want to forget old subject

# LSTM walk through: Second step

- Next step is to decide as to what new information we're going to store in the cell state




- First a sigmoid layer called Input gate layer:
  - decides which values we will update
- Next a tanh layer creates a vector of new candidate values $\tilde{C}^{(t)}$ that could be added to the state.
- In the third step we will combine these two to create an update to the state

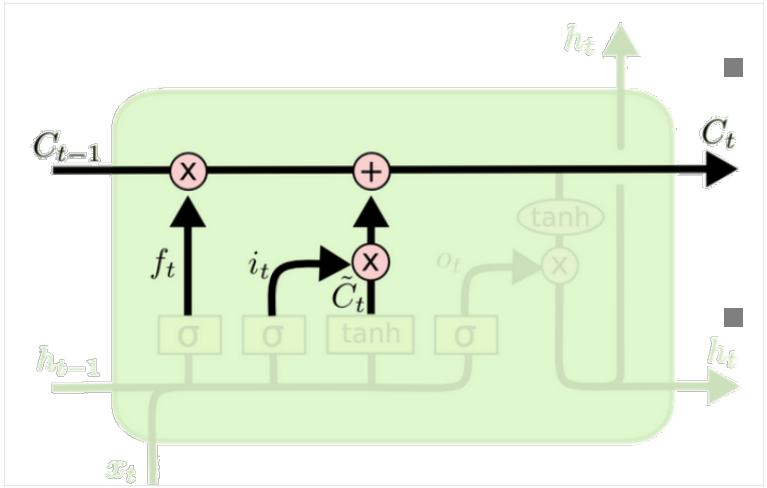
- In language model:

we'd want to add the gender of the new subject to the cell state, to replace the old One we are forgetting

$$i^{(t)} = \sigma\left(\boldsymbol{W}_i \cdot \left[\boldsymbol{h}^{(t-1)}, \boldsymbol{x}^{(t)}\right] + b_i\right)$$
$$\tilde{C}^{(t)} = \tanh\left(\boldsymbol{W}_C \cdot \left[\boldsymbol{h}^{(t-1)}, \boldsymbol{x}^{(t)}\right] + b_C\right)$$

# LSTM walk through: Third step

- It's now time to update old cell state C t-1 into new cell state C t
  - The previous step decided what we need to do
  - We just need to do it




- We multiply the old state by $f^{(t)}$, forgetting the things we decided to forget earlier.
- Then we add $i^{(t)} \cdot \tilde{C}^{(t)}$

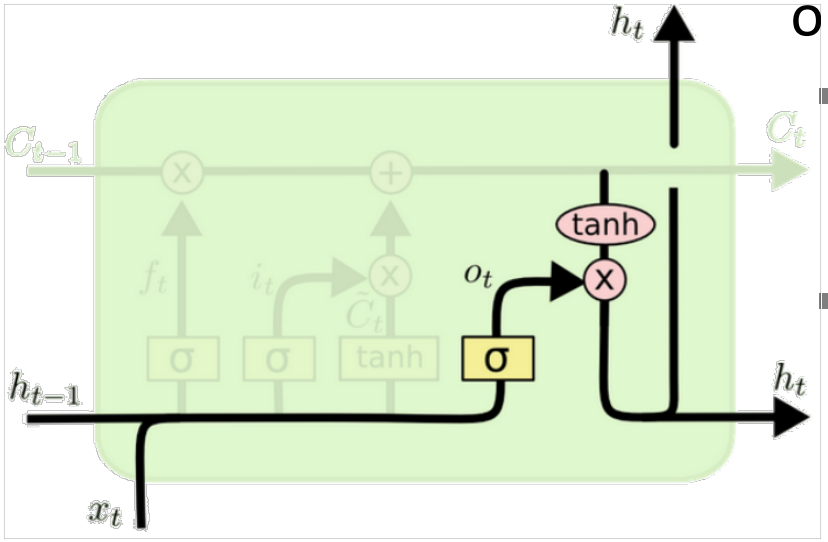
$$C^{(t)} = f^{(t)} \cdot C^{(t-1)} + i^{(t)} \cdot \tilde{C}^{(t)}$$

- In language model:

this is where we'd actually drop the information about the old subject's gender and add the new information, as we decided in previous steps

# LSTM walk through: Fourth step

- Finally we decide what we are going to output
  - This output will be a filtered version of our cell state
    - First we run a sigmoid layer which decides what parts of cell state we're going to output.
    - Then we put the cell state through tanh (to push values to be between -1 and 1)

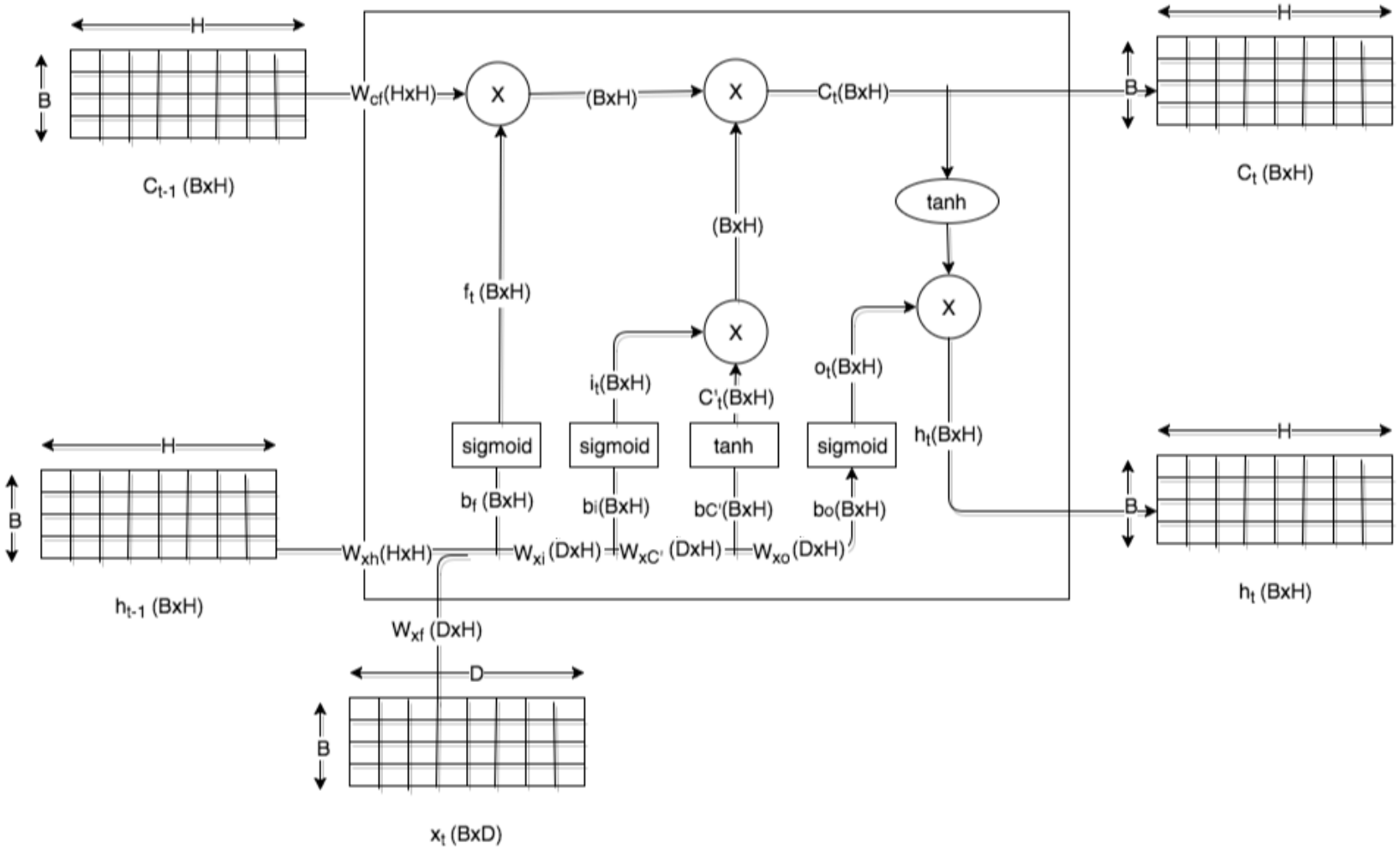



$$\boldsymbol{o}^{(t)} = \sigma\left(\boldsymbol{W}_o \cdot \left[\boldsymbol{h}^{(t-1)}, \boldsymbol{x}^{(t)}\right] + \boldsymbol{b}_o\right)$$
$$\boldsymbol{h}^{(t)} = \boldsymbol{o}_t \cdot \tanh\left(\boldsymbol{C}^{(t)}\right)$$

- In language model:

Since it just saw a subject it might want to output information relevant to a verb, in case that is what is coming next, e.g., it might output whether the subject is singular or plural so that we know what form a verb should be conjugated into if that's what follows next.

# Sizes of the LSTMs




- https://www.quora.com/In-LSTM-how-do-you-figure-out-what-size-the-weights-are-supposed-to-be

# Sizes of the LSTMs

- With B indicating the batch size, D the input data size and H the size of the hidden layer.

$$i_t \in \mathbb{R}^B \times \mathbb{R}^H$$

$$f_t \in \mathbb{R}^B \times \mathbb{R}^H$$

$$c_t \in \mathbb{R}^B \times \mathbb{R}^H$$

$$o_t \in \mathbb{R}^B \times \mathbb{R}^H$$

$$h_t \in \mathbb{R}^B \times \mathbb{R}^H$$

$$x_t \in \mathbb{R}^B \times \mathbb{R}^D$$

$$h_{t-1} \in \mathbb{R}^B \times \mathbb{R}^H$$

$$c_{t-1} \in \mathbb{R}^B \times \mathbb{R}^H$$

$$W_{xi} \in \mathbb{R}^D \times \mathbb{R}^H$$

$$W_{xf} \in \mathbb{R}^D \times \mathbb{R}^H$$

$$W_{xo} \in \mathbb{R}^D \times \mathbb{R}^H$$

$$W_{hi} \in \mathbb{R}^H \times \mathbb{R}^H$$

$$W_{hf} \in \mathbb{R}^H \times \mathbb{R}^H$$

$$W_{ho} \in \mathbb{R}^H \times \mathbb{R}^H$$

$$b_i \in \mathbb{R}^B \times \mathbb{R}^H$$

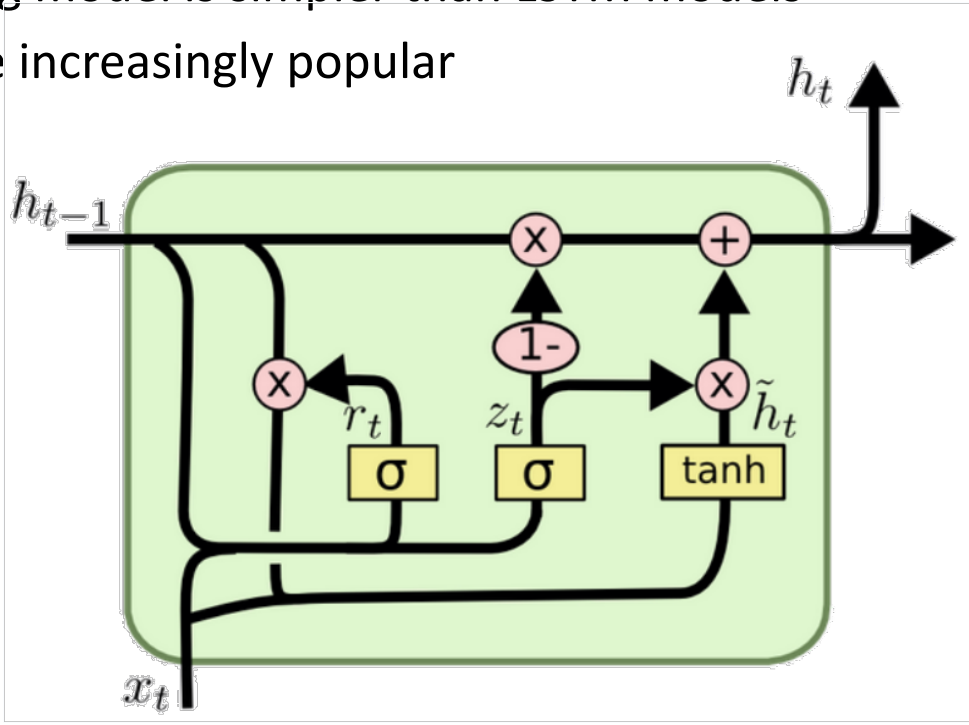
$$b_f \in \mathbb{R}^B \times \mathbb{R}^H$$

$$b_c \in \mathbb{R}^B \times \mathbb{R}^H$$

$$b_o \in \mathbb{R}^B \times \mathbb{R}^H$$

# Gated Recurrent Unit (GRU)

- A dramatic variant of LSTM
  - It combines the forget and input gates into a single update gate
  - It also merges the cell state and hidden state, and makes some other changes
  - The resulting model is simpler than LSTM models
  - Has become increasingly popular



# Accumulating Information over Longer Duration

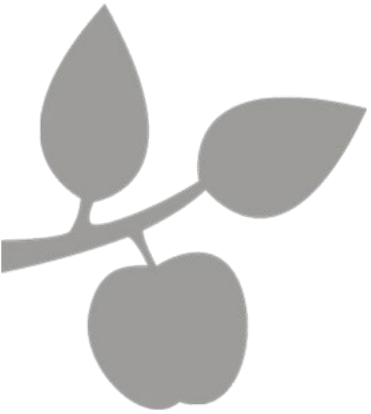
- Leaky Units Allow the network to accumulate information
  - Such as evidence for a particular feature or category
  - Over a long duration

- However, once the information has been used, it might be useful to forget the old state
  - E.g., if a sequence is made of sub-sequences and we want a leaky unit to accumulate evidence inside each sub-sequence, we need a mechanism to forget the old state by setting it to zero

- Gated/LSTM RNN:
  - Instead of manually deciding when to clear the state, we want the neural network to learn to decide when to do it

# LSTM

- Contribution of LSTMs:
  - clever idea of introducing self-loops to produce paths where the gradient can flow for long durations
- A crucial addition: make weight on this self-loop conditioned on the context, rather than fixed
  - By making weight of this self-loop gated (controlled by another hidden unit), time-scale can be changed dynamically
  - Even for an LSTM with fixed parameters, time scale of integration can change based on the input sequence
    - Because time constants are output by the model itself
- LSTM found extremely successful in:
  - Unconstrained handwriting recognition, Speech recognition
  - Handwriting generation, Machine Translation
  - Image Captioning, Parsing



# Recurrent Neural Networks

- **Introduction**
- **Unfolding a Graph**
- **Recurrent Neural Networks**
- **Long Term Memory**
  - Leaky Units
  - Long-Short Term Memory
- **Working with Texts in Keras**

# About Text

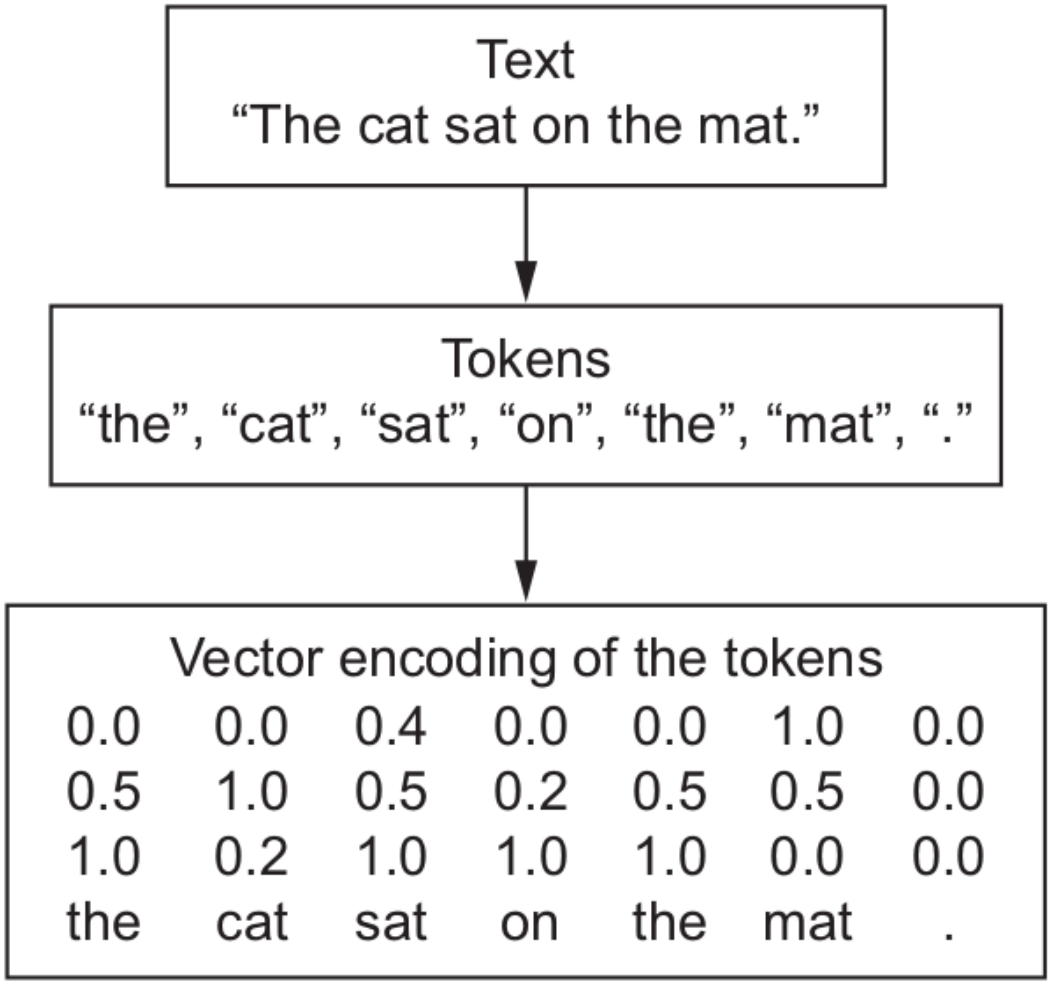
- Text is one of the most widespread forms of sequence data.
- Can be interpreted as sequence of characters or a sequence of words; interpretation as words more common.
- The deep-learning sequence-processing models can use text to produce a basic form of natural-language understanding
  - Document classification
  - Sentiment analysis
  - Author identification
  - question-answering ( QA ) (in a constrained context).

# Text as Input

- We cannot feed text directly into networks
- They only “eat” numerical tensors

- We need to **vectorize** text into numeric tensors
  - Segment text into words, and transform each word into a vector.
  - Segment text into characters, and transform each character into a vector.
  - Extract n-grams of words or characters, and transform each n-gram into a vector.
    - N-grams are overlapping groups of multiple consecutive words or characters.

# Example


Text
“The cat sat on the mat.”
Tokens
“the”, “cat”, “sat”, “on”, “the”, “mat”, “.”
Vector encoding of the tokens
0.0 0.0 0.4 0.0 0.0 1.0 0.0
0.5 1.0 0.5 0.2 0.5 0.5 0.0
1.0 0.2 1.0 1.0 1.0 0.0 0.0
the cat sat on the mat .

# What are N-grams

- Word n-grams are groups of N (or fewer) consecutive words that you can extract from a sentence.

- Example: “The cat sat on the mat.”

- Set of 2-grams:
  - {"The", "The cat", "cat", "cat sat", "sat", "sat on", "on", "on the", "the", "the mat", "mat"}

- Set of 3-grams:
  - {"The", "The cat", "cat", "cat sat", "The cat sat", "sat", "sat on", "on", "cat sat on", "on the", "the", "sat on the", "the mat", "mat", "on the mat"}

# One-hot Encoding of Words and Characters

- One-hot encoding is the most common, most basic way to turn a token into a vector.
  - Associate a unique integer index with every word (or token)
  - Turn the integer index i into a binary vector of size N (the size of the vocabulary); the vector is all zeros except for the $i$th entry, which is 1.
  - Like we have done for the encoding of categorical data

# Using Keras for One-Hot Encoding

```
from keras.preprocessing.text import Tokenizer

samples = ['The cat sat on the mat.', 'The dog ate my homework.’]

# Tokenizer, only consider the 1000 most common words
tokenizer = Tokenizer(num_words=1000)
tokenizer.fit_on_texts(samples)

# Turn strings into list of integers
sequences = tokenizer.texts_to_sequences(samples)

# Or directly get the one hot encoding
one_hot_results = tokenizer.texts_to_matrix(samples, mode='binary’)

# Retrive the word index
word_index = tokenizer.word_index
print('Found %s unique tokens.' % len(word_index))
```

# Vectorize a Sequence

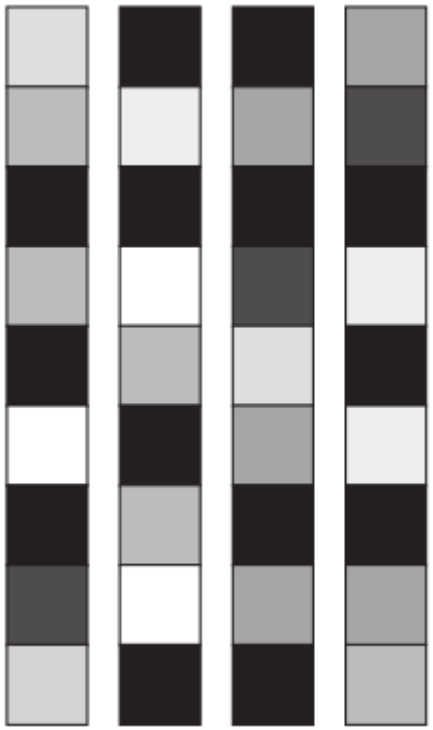
```
def vectorize_sequences(sequences, dimension=10000):
    results = np.zeros((len(sequences), dimension))
    for i, sequence in enumerate(sequences):
        results[i, sequence] = 1.
    return results
```

- You cannot feed a list of integer or one-hot encoded Matrix of different shapes into your model.
- Solution: One-hot encode your lists to turn them into vectors of 0s and 1s.
  - This would means, for instance, turning the sequence [3, 5] into a 10,000-dimensional vector that would be all 0s except for indices 3 and 5, which would be 1s.
  - Then you could use as the first layer in your network a Dense layer, capable of handling floating-point vector data.

# Word Embeddings

- Vectors obtained through one-hot encoding are binary, sparse (mostly made of zeros), and very high-dimensional (same dimensionality as the number of words in the vocabulary)

- Word embeddings are low-dimensional floating-point vectors (that is, dense vectors, as opposed to sparse vectors)



# Why Embeddings?

- Let's look at the sentences with almost the same meaning:
  - "Have a good day"
  - "Have a great day"
- Using our vocabulary V = {Have, a, good, great, day} and one-hot embedding, we end with, for instance:
  - Have = [1,0,0,0,0]; a=[0,1,0,0,0]; good=[0,0,1,0,0]; great=[0,0,0,1,0]; day=[0,0,0,0,1]
- Now, the distance between "good" and "great" is the same as between "day" and "great". That means learning that this is basically the same sentence, we need to make the connection between good and great
- It would be much better, if these two words would be represented almost identically in the space. => That's what embeddings do

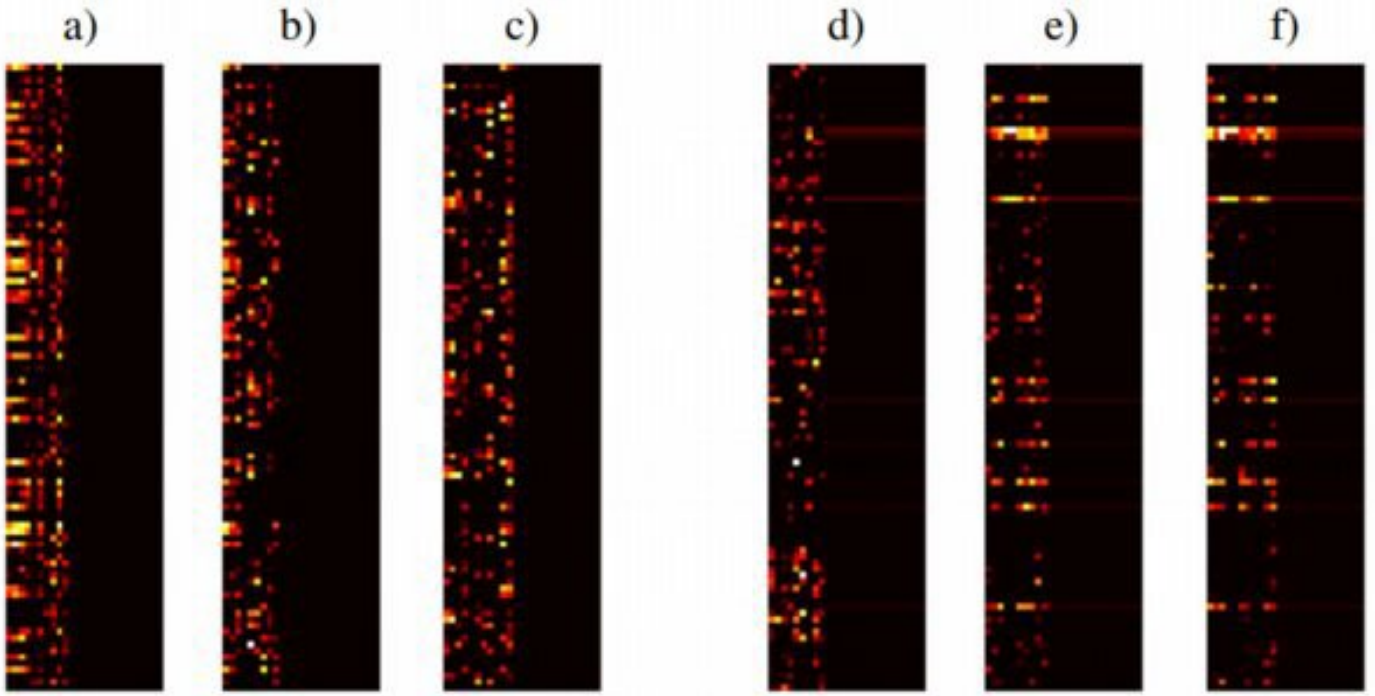
# How to obtain Embeddings?

- Learn word embeddings jointly with the main task you care about (such as document classification or sentiment prediction).
  - In this setup, you start with random word vectors and then learn word vectors in the same way you learn the weights of a neural network.

- Load into your model word embeddings that were precomputed using a different machine-learning task than the one you're trying to solve. These are called pretrained word embeddings.
  - word2vec
  - GloVe

# Difference between KERAS and word2vec

a) "Here are 21 healthy fall soups to stock your freezer"
b) "Himalaya might miss 50% of its ice in eighty years"
c) "Alps may lose 70% of snow by end of the century"




Convolution1D activations (100×25)
Embedding trained from scratch

Convolution1D activations (100×25)
Embedding transfered from *word2vec*

# Embeddings in Keras

```
from keras.layers import Embedding
embedding_layer = Embedding(1000, 64)
```

- The Embedding layer takes at least two arguments: the number of possible tokens (here, 1,000: 1 + maximum word index)
- The dimensionality of the embeddings (here, 64).

- The Embedding layer takes as input a 2D tensor of integers, of shape (samples, sequence_length)
  - Sequences that are shorter must be padded with zeros, sequences that are longer must be truncated.
- Returns a 3D floating-point tensor of shape (samples, sequence_length, embedding_dimensionality)

# RNNs in Keras

- The simple RNN takes inputs of the shape (batch_size, timesteps, input_features)

- Can be run in two different modes:
  - It can return either the full sequences of successive outputs for each timestep:
    (a 3D tensor of shape (batch_size, timesteps, output_features) )
  - Only the last output for each input sequence
    (a 2D tensor of shape (batch_size, output_features) ).

- These two modes are controlled by the return_sequences constructor argument.

- **Available RNNs: SimpleRNN, GRU, LSTM, …**

# RNNs in Keras

```
model.add(Embedding(10000, 32))
model.add(SimpleRNN(32))
model.summary()

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_22 (Embedding)     (None, None, 32)          320000
_________________________________________________________________
simplernn_10 (SimpleRNN)     (None, 32)                2080
=================================================================
Total params: 322,080
Trainable params: 322,080
Non-trainable params: 0
```

- Creates a simple RNN which only produces one output

# RNNs in Keras

```
model.add(Embedding(10000, 32))
model.add(SimpleRNN(32, return_sequences=True))
model.summary()

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_22 (Embedding)     (None, None, 32)          320000
_________________________________________________________________
simplernn_10 (SimpleRNN)     (None, None, 32)          2080
=================================================================
Total params: 322,080
Trainable params: 322,080
Non-trainable params: 0
```

- Creates a simple RNN which produces an output at every position

# Stack RNNs

```
model = Sequential()
model.add(Embedding(10000, 32))

# All RNNs need to return a value every timestep
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))

# The last layer of RNN can only return one value
model.add(SimpleRNN(32))
```