

# Deep Learning

## 11. Recurrent neural networks

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# Introduction

Previously: Fully connected networks, convolutional networks: are used to process data of fixed shape

Recurrent networks: can process data of varying length

Most of the data around is sequential: text, sound, video

# Basic RNN

We can process a sequence of vectors  $\mathbf{x}$  by applying a **recurrence formula** at every time step:

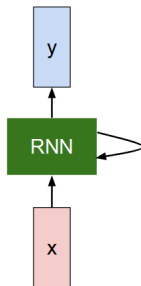
$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state

some function with parameters  $W$

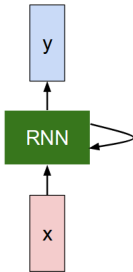
old state

input vector at some time step



# Basic RNN

The state consists of a single “hidden” vector  $\mathbf{h}$ :



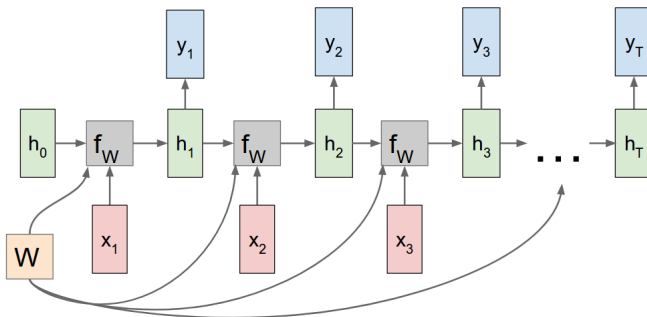
$$h_t = f_W(h_{t-1}, x_t)$$



$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

$$y_t = W_{hy}h_t$$

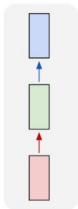
# Computational graph



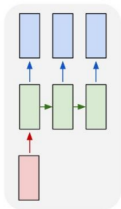
# RNN types

## Recurrent Neural Networks: Process Sequences

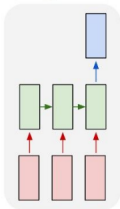
one to one



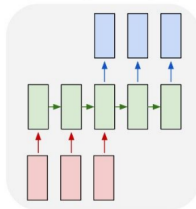
one to many



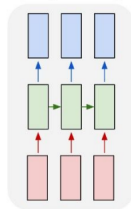
many to one



many to many



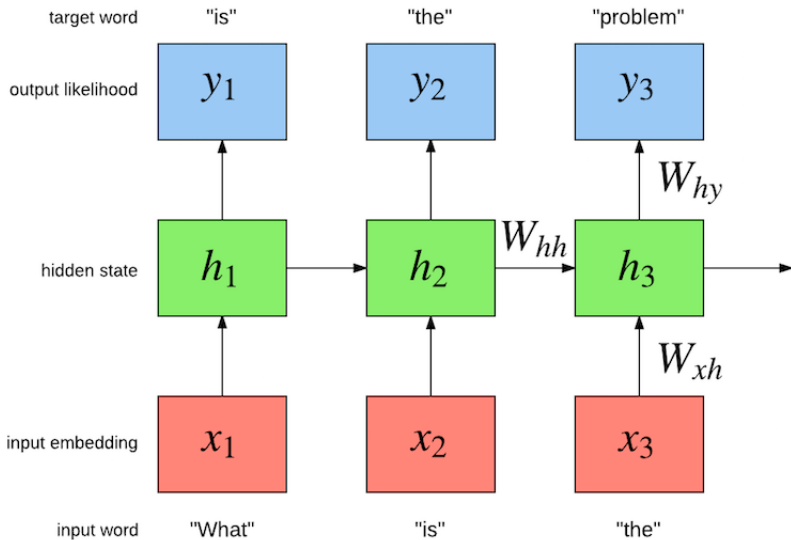
many to many



# RNN usage examples

- One to many: image captioning
- Many to one: sentiment classification
- Many to many: machine translation, video frames classification, speech recognition

# Language modeling





# Language model generation

Model trained on Wikipedia texts (generates symbol by symbol):

Naturalism and decision for the majority of Arab countries' capitalide was grounded by the Irish language by [[John Clair]], [[An Imperial Japanese Revolt]], associated with Guangzham's sovereignty. His generals were the powerful ruler of the Portugal in the [[Protestant Immineners]], which could be said to be directly in Cantonese Communication, which followed a ceremony and set inspired prison, training. The emperor travelled back to [[Antioch, Perth, October 25|21]] to note, the Kingdom of Costa Rica, unsuccessful fashioned the [[Thrales]], [[Cynth's Dajoard]], known in western [[Scotland]], near Italy to the conquest of India with the conflict. Copyright was the succession of independence in the slop of Syrian influence that was a famous German movement based on a more popular servicious, non-doctrinal and sexual power post. Many governments recognize the military housing of the [[Civil Liberalization and Infantry Resolution 265 National Party in Hungary]], that is sympathetic to be to the [[Punjab Resolution]] (PJS)[<http://www.humah.yahoo.com/guardian.cfm/7754800786d17551963s89.htm> Official economics Adjoint for the Nazism, Montgomery was swear to advance to the resources for those Socialism's rule, was starting to signing a major tripad of aid exile.]]

# Language model generation

## Trained on math articles written in Latex (symbol by symbol)

For  $\bigoplus_{n=1,\dots,m}$  where  $\mathcal{L}_{m,*} = 0$ , hence we can find a closed subset  $\mathcal{H}$  in  $\mathcal{H}$  and any sets  $\mathcal{F}$  on  $X$ ,  $U$  is a closed immersion of  $S$ , then  $U \rightarrow T$  is a separated algebraic space.

*Proof.* Proof of (1). It also start we get

$$S = \mathrm{Spec}(R) = U \times_X U \times_X U$$

and the comparico in the fibre product covering we have to prove the lemma generated by  $\coprod Z \times_U U \rightarrow V$ . Consider the maps  $M$  along the set of points  $\mathrm{Sch}_{\mathrm{fppf}}$  and  $U \rightarrow U$  is the fibre category of  $S$  in  $U$  in Section, ?? and the fact that any  $U$  affine, see Morphisms, Lemma ?? . Hence we obtain a scheme  $S$  and any open subset  $W \subset U$  in  $\mathrm{Sh}(G)$  such that  $\mathrm{Spec}(R') \rightarrow S$  is smooth or an

$$U = \bigcup U_i \times_S U_i$$

which has a nonzero morphism we may assume that  $f_i$  is of finite presentation over  $S$ . We claim that  $\mathcal{O}_{X,x}$  is a scheme where  $x, x', s' \in S'$  such that  $\mathcal{O}_{X,x'} \rightarrow \mathcal{O}_{X',x'}$  is separated. By Algebra, Lemma ?? we can define a map of complexes  $\mathrm{GL}_S(\mathcal{X}/S^{\mathrm{op}})$  and we win.  $\square$

To prove study we see that  $\mathcal{F}|_U$  is a covering of  $\mathcal{X}'$ , and  $T_i$  is an object of  $\mathcal{F}_{X/S}$  for  $i > 0$  and  $\mathcal{F}_i$  exists and let  $\mathcal{F}_i$  be a presheaf of  $\mathcal{O}_X$ -modules on  $\mathcal{C}$  as a  $\mathcal{F}$ -module. In particular  $\mathcal{F} = U/\mathcal{F}$  we have to show that

$$\tilde{M}^* = \mathcal{I}^* \otimes_{\mathrm{Spec}(k)} \mathcal{O}_{S,s} - i_X^{-1} \mathcal{F}$$

is a unique morphism of algebraic stacks. Note that

$$\mathrm{Arrows} = (\mathrm{Sch}/S)_{\mathrm{fppf}}^{\mathrm{op}}, (\mathrm{Sch}/S)_{\mathrm{fppf}}$$

and

$$V = \Gamma(S, \mathcal{O}) \longrightarrow (U, \mathrm{Spec}(A))$$

is an open subset of  $X$ . Thus  $U$  is affine. This is a continuous map of  $X$  is the inverse, the groupoid scheme  $S$ .

*Proof.* See discussion of sheaves of sets.  $\square$

The result to prove any open covering follows from the less of Example ?? . It may replace  $S$  by  $X_{\mathrm{spaces}, \mathrm{etale}}$  which gives an open subspace of  $X$  and  $T$  equal to  $S_{Zar}$ , see Descent, Lemma ?? . Namely, by Lemma ?? we see that  $R$  is geometrically regular over  $S$ .

**Lemma 0.1.** Assume (3) and (3) by the construction in the description.

Suppose  $X = \lim |X|$  (by the formal open covering  $X$  and a single map  $\mathrm{Proj}_X(\mathcal{A}) = \mathrm{Spec}(B)$  over  $U$  compatible with the complex

$$\mathrm{Set}(\mathcal{A}) = \Gamma(X, \mathcal{O}_{X, \mathcal{O}_X}).$$

When in this case of to show that  $\mathcal{Q} \rightarrow \mathcal{C}_{Z/X}$  is stable under the following result in the second conditions of (1), and (3). This finishes the proof. By Definition ?? (without element is when the closed subschemes are catenary. If  $T$  is surjective we may assume that  $T$  is connected with residue fields of  $S$ . Moreover there exists a closed subspace  $Z \subset X$  of  $X$  where  $U$  in  $X'$  is proper (some defining as a closed subset of the uniqueness it suffices to check the fact that the following theorem

(1)  $f$  is locally of finite type. Since  $S = \mathrm{Spec}(R)$  and  $Y = \mathrm{Spec}(R)$ .

*Proof.* This is form all sheaves of sheaves on  $X$ . But given a scheme  $U$  and a surjective étale morphism  $U \rightarrow X$ . Let  $U \cap U = \prod_{i=1,\dots,n} U_i$  be the scheme  $X$  over  $S$  at the schemes  $X_i \rightarrow X$  and  $U = \lim_i X_i$ .  $\square$

The following lemma surjective restrocomposes of this implies that  $\mathcal{F}_{x_0} = \mathcal{F}_{x_0} = \mathcal{F}_{X,\dots,0}$ .

**Lemma 0.2.** Let  $X$  be a locally Noetherian scheme over  $S$ ,  $E = \mathcal{F}_{X/S}$ . Set  $\mathcal{I} = \mathcal{I}_1 \subset \mathcal{I}_n$ . Since  $\mathcal{I}^n \subset \mathcal{I}^n$  are nonzero over  $i_0 \leq \mathfrak{p}$  is a subset of  $\mathcal{I}_{n,0} \circ \tilde{A}_2$  works.

**Lemma 0.3.** In Situation ?? . Hence we may assume  $\mathfrak{q}' = 0$ .

*Proof.* We will use the property we see that  $\mathfrak{p}$  is the next functor (??). On the other hand, by Lemma ?? we see that

$$D(\mathcal{O}_{X'}) = \mathcal{O}_X(D)$$

where  $K$  is an  $F$ -algebra where  $\delta_{n+1}$  is a scheme over  $S$ .  $\square$

# Basic RNN problems

- Vanishing - exploding gradient problems
- Hard to train
- It does not capture long-range dependencies

# Gated recurrent unit (GRU)

Enforce long-range dependencies:

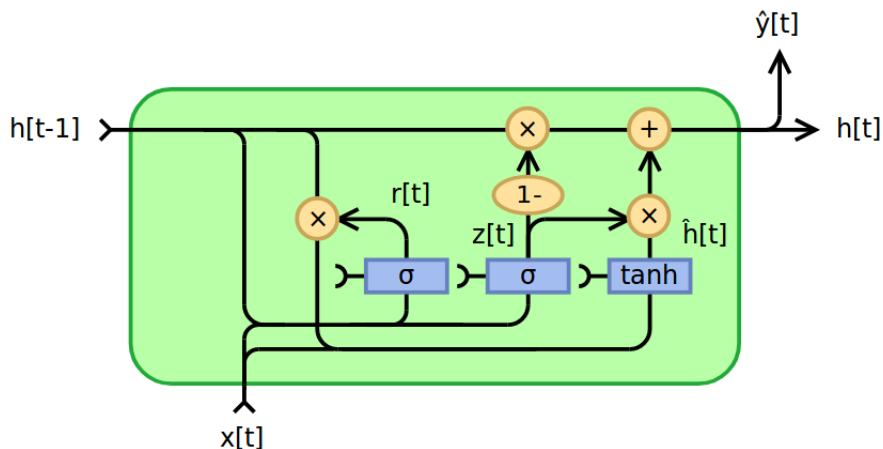
- $x_t$ : input vector
- $h_t$ : output vector
- $z_t$ : update gate vector
- $r_t$ : reset gate vector
- $W, U$  and  $b$ : parameter matrices and vector

$$z_t = \sigma_g(W_z x_t + U_z h_{t-1} + b_z)$$

$$r_t = \sigma_g(W_r x_t + U_r h_{t-1} + b_r)$$

$$h_t = (1 - z_t) \circ h_{t-1} + z_t \circ \sigma_h(W_h x_t + U_h (r_t \circ h_{t-1}) + b_h)$$

## GRU picture



# LSTM

LSTM: long-short term memory

$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f)$$

$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i)$$

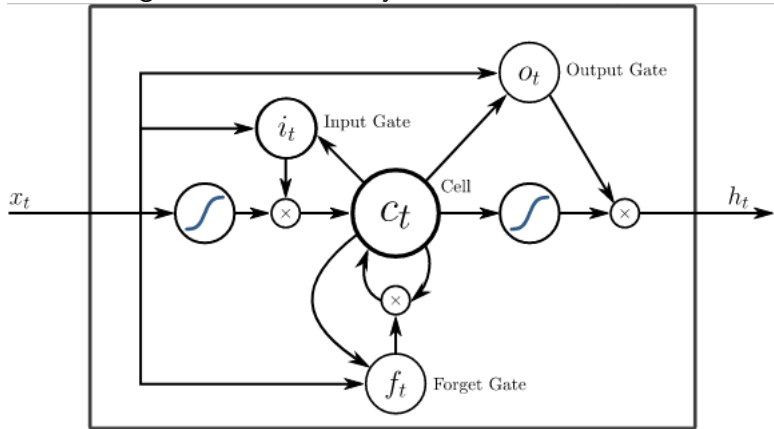
$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o)$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \sigma_c(W_c x_t + U_c h_{t-1} + b_c)$$

$$h_t = o_t \circ \sigma_h(c_t)$$

# LSTM picture

LSTM: long-short term memory



# Future dependency

Problems with feed-forward RNN-s: output could depend on future items in the sequence.

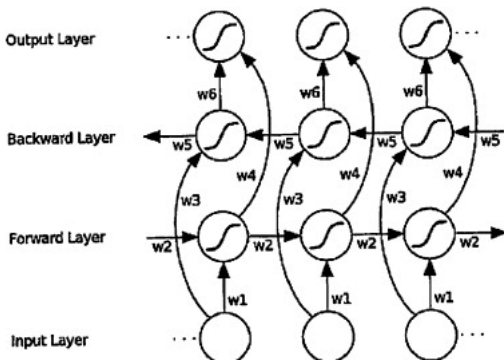
Example: names detection:

He said, "Teddy bears are on sale!"

He said, "Teddy Roosevelt was a great President!"

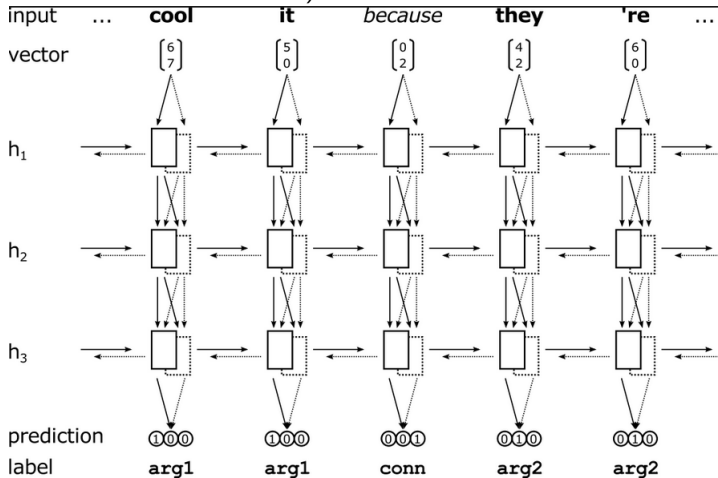


# Bidirectional net




# Deep RNN

Combine many levels of hidden states on top of each other (could use GRU or LSTM units):



# Word representation

Man	Woman	King	Queen	Apple	Orange
(5391)	(9853)	(4914)	(7157)	(456)	(6257)
$\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix}$



Problems: long if dictionary is big; we want representing vectors to be close if objects are similar.

# Word to vec

Use context window and randomly select pairs of words from it.  
Find embeddings based on logistic regression model for predicting target word in the context window of context word:

$$p(t|c) = \text{softmax}(\theta_t^T e_c)$$

$\theta$ : weights of logistic regression model

$e$ : embeddings

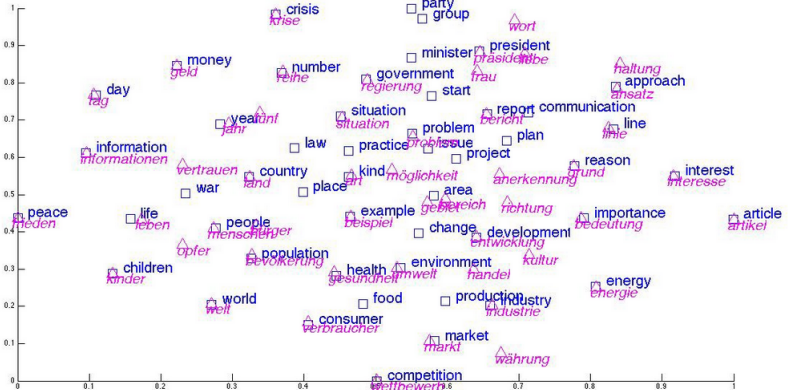
Optimize jointly for  $\theta$  and  $e$ .

# Embeddings arithmetic

Table 8: *Examples of the word pair relationships, using the best word vectors from Table 4 (Skip-gram model trained on 783M words with 300 dimensionality).*

Relationship	Example 1	Example 2	Example 3
France - Paris	Italy: Rome	Japan: Tokyo	Florida: Tallahassee
big - bigger	small: larger	cold: colder	quick: quicker
Miami - Florida	Baltimore: Maryland	Dallas: Texas	Kona: Hawaii
Einstein - scientist	Messi: midfielder	Mozart: violinist	Picasso: painter
Sarkozy - France	Berlusconi: Italy	Merkel: Germany	Koizumi: Japan
copper - Cu	zinc: Zn	gold: Au	uranium: plutonium
Berlusconi - Silvio	Sarkozy: Nicolas	Putin: Medvedev	Obama: Barack
Microsoft - Windows	Google: Android	IBM: Linux	Apple: iPhone
Microsoft - Ballmer	Google: Yahoo	IBM: McNealy	Apple: Jobs
Japan - sushi	Germany: bratwurst	France: tapas	USA: pizza

## t-SNE



# GloVe

$X_{i,j}$ : frequency matrix of context words

$$\sum_i \sum_j f(X_{i,j})(\theta_i e_j + b_i + b'_j - \ln(X_{i,j}))^2 \rightarrow \min$$

## Example: Sentiment classification

The dessert is excellent.



Service was quite slow.



Good for a quick meal, but nothing special.



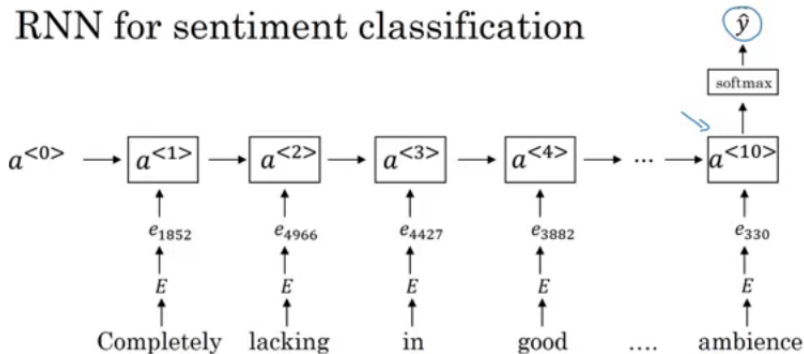
Completely lacking in good taste,  
good service, and good ambience.



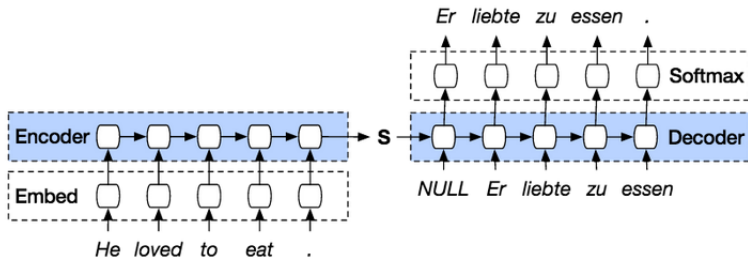


# Sentiment classification

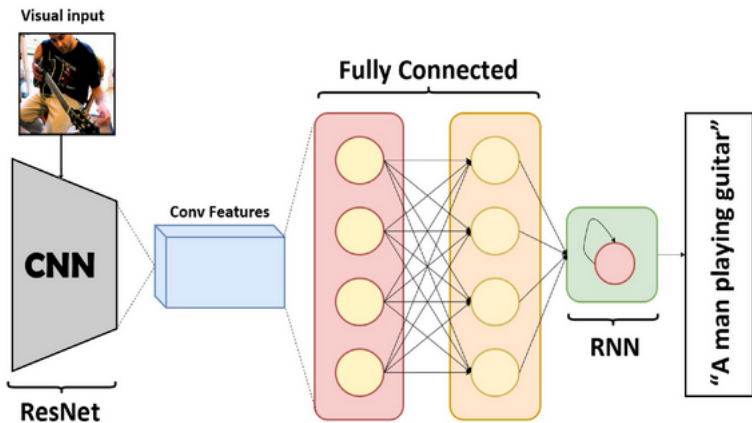
## RNN for sentiment classification



## Example: Automatic translation



# Image captioning



# Image caption examples

A young boy is playing basketball.



Two dogs play in the grass.



A dog swims in the water.



A group of people walking down a street.



A group of women dressed in formal attire.



Two children play in the water.



A skier is skiing down a snowy hill.



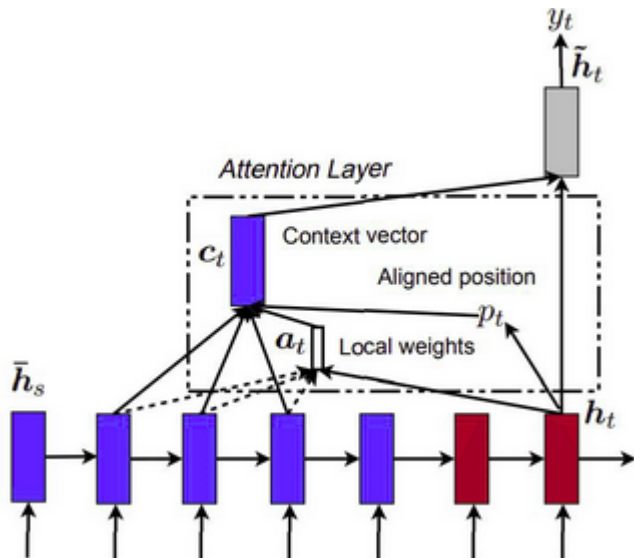
A little girl in a pink shirt is swinging.



A dog jumps over a hurdle.



# Attention model



# Trigger word detection

What is trigger word detection?



Amazon Echo  
(Alexa)



Baidu DuerOS  
(xiaodunihao)



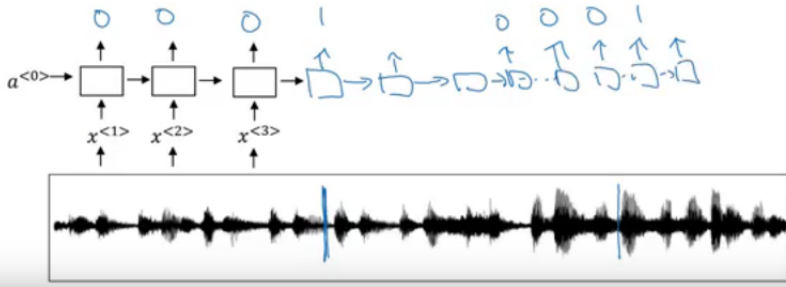
Apple Siri  
(Hey Siri)



Google Home  
(Okay Google)

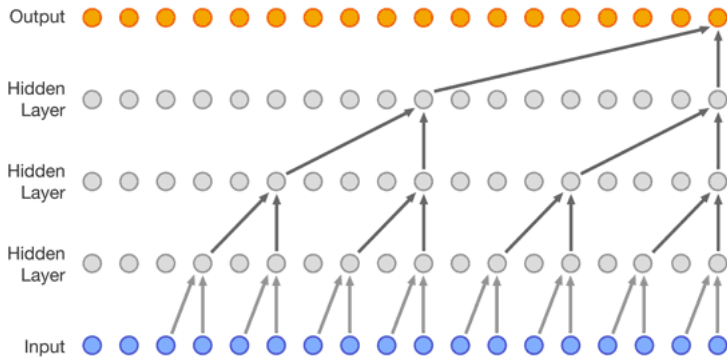
# Trigger word detection

## Trigger word detection algorithm



# WaveNet

Generating sound:





## Read more

Lecture about RNNs:

<https://www.youtube.com/watch?v=6niqTuYFZLQ>

RNNs course from Andrew Ng (simple explanations):

<https://www.youtube.com/playlist?list=PLBAGcD3siRDittPwQDGIIAWkjjz-RucAc7>

WaveNet (generating sound): <https://deepmind.com/blog/wavenet-generative-model-raw-audio/>

t-SNE: <https://lvdmaaten.github.io/tsne/>