

A g e n d a

a n u n c i o s v a r i o s

T a r e a 3 e n t r e g a l u n e s 5 d e J u n i o

m o d e l o s d e a n a l i t i c a (m a c h i n e l e a r n i n g - M L) S u p e r

R e d e s N e u r o n a l e s

R e s u m e n C o n v o l u t i o n a l N e u r a l N e t

L S T M

S e r i e s d e t i e m p o

S e c u e n c i a s

S e r i e s d e T i e m p o

L a p r e d i c c i ó n a c t u a l d e p e n d e d e l o s d a t o s h i s t ó r i c o s :

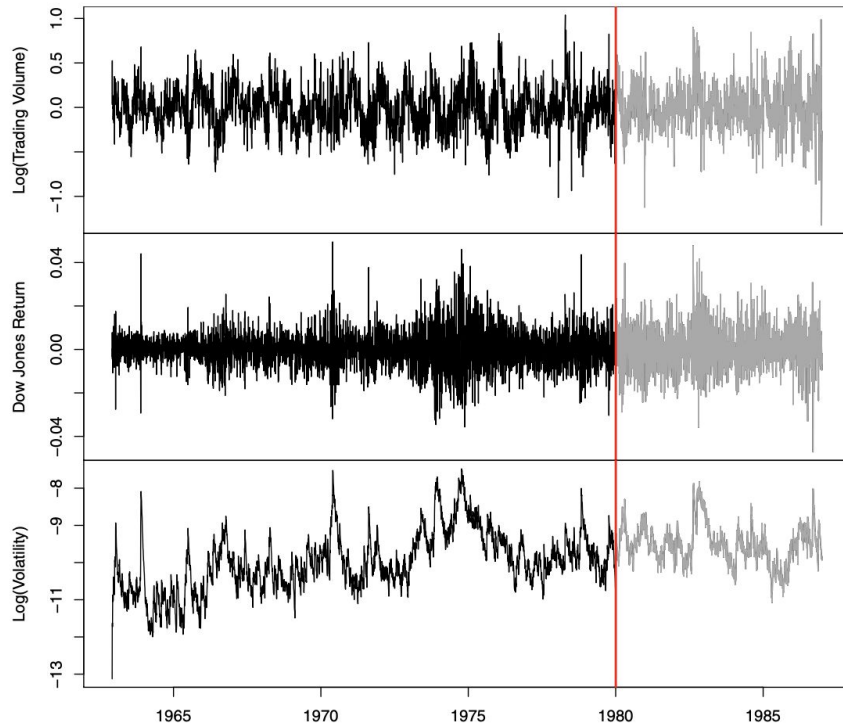


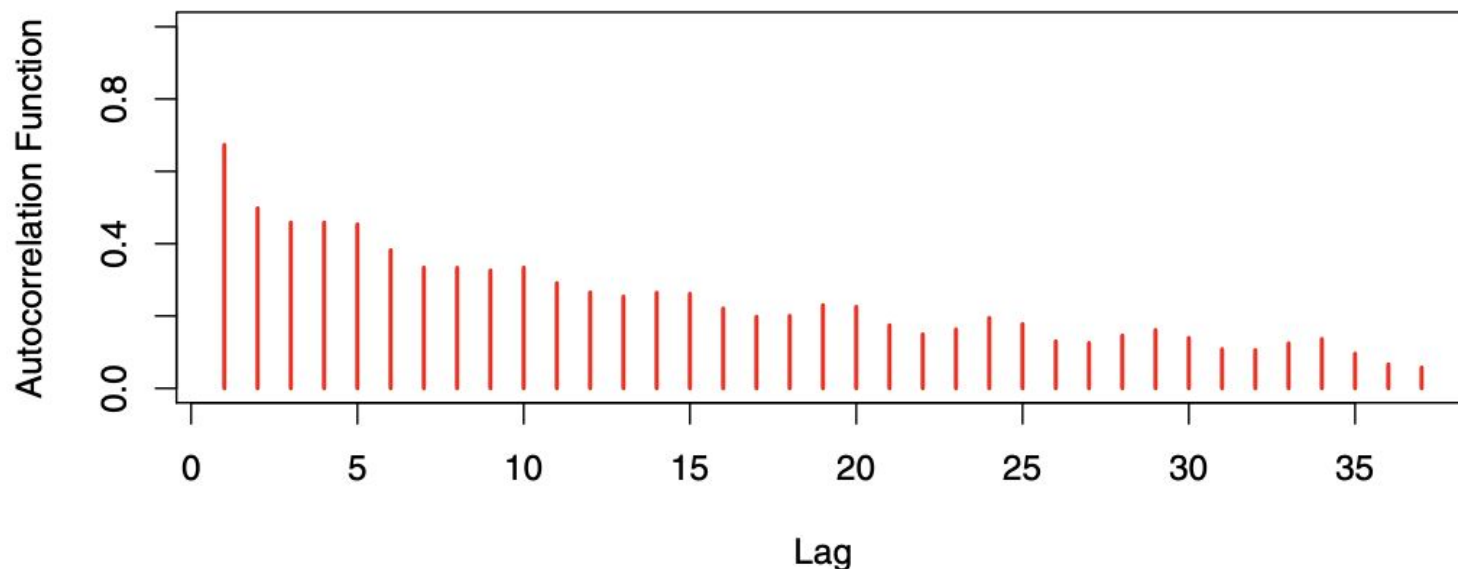
FIGURE 10.14. *Historical trading statistics from the New York Stock Exchange. Daily values of the normalized log trading volume, DJIA return, and log volatility are shown for a 24-year period from 1962–1986. We wish to predict trading volume on any day, given the history on all earlier days. To the left of the red bar (January 2, 1980) is training data, and to the right test data.*

$$X_1 = \begin{pmatrix} v_{t-L} \\ r_{t-L} \\ z_{t-L} \end{pmatrix}, \quad X_2 = \begin{pmatrix} v_{t-L+1} \\ r_{t-L+1} \\ z_{t-L+1} \end{pmatrix}, \dots$$

$$, X_L = \begin{pmatrix} v_{t-1} \\ r_{t-1} \\ z_{t-1} \end{pmatrix}, \quad \text{and } Y = v_t.$$

Series de Tiempo

Redes que permiten aprender las relaciones en las secue



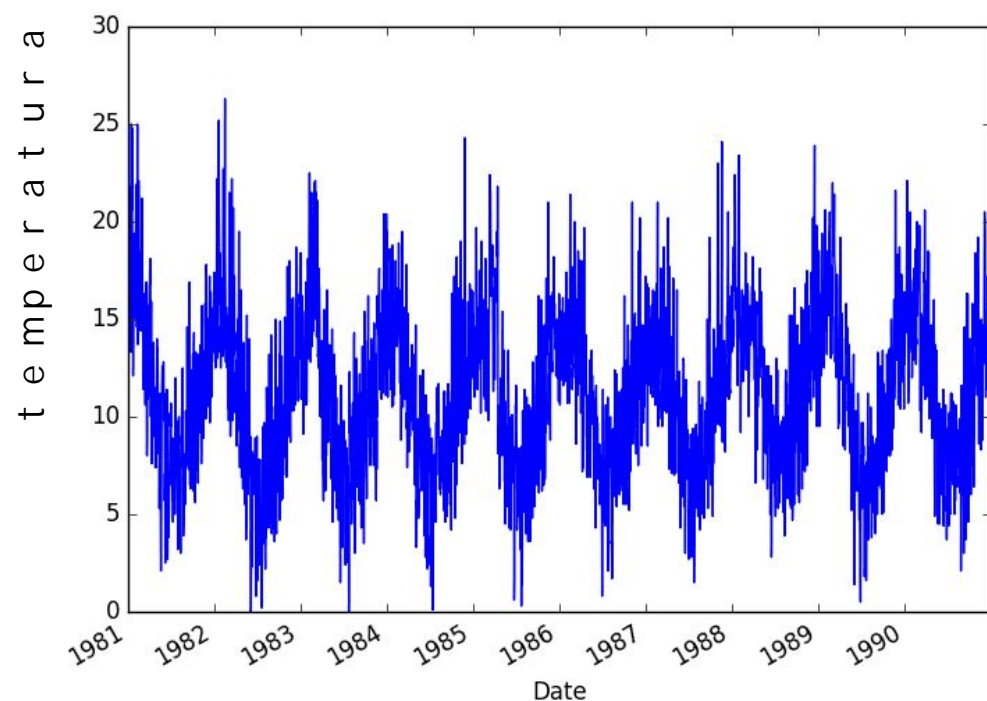
Es necesario defin

Window: numero de
Lag: Numero de obs
anteriores

FIGURE 10.15. *The autocorrelation function for `log-volume`. We see that nearby values are fairly strongly correlated, with correlations above 0.2 as far as 20 days apart.*

S e r i e s d e T i e m p o

S e a s o n a l i t y s o n l o s p e r i o d o s d e t i e m p o q u e t i e n e n u n p a

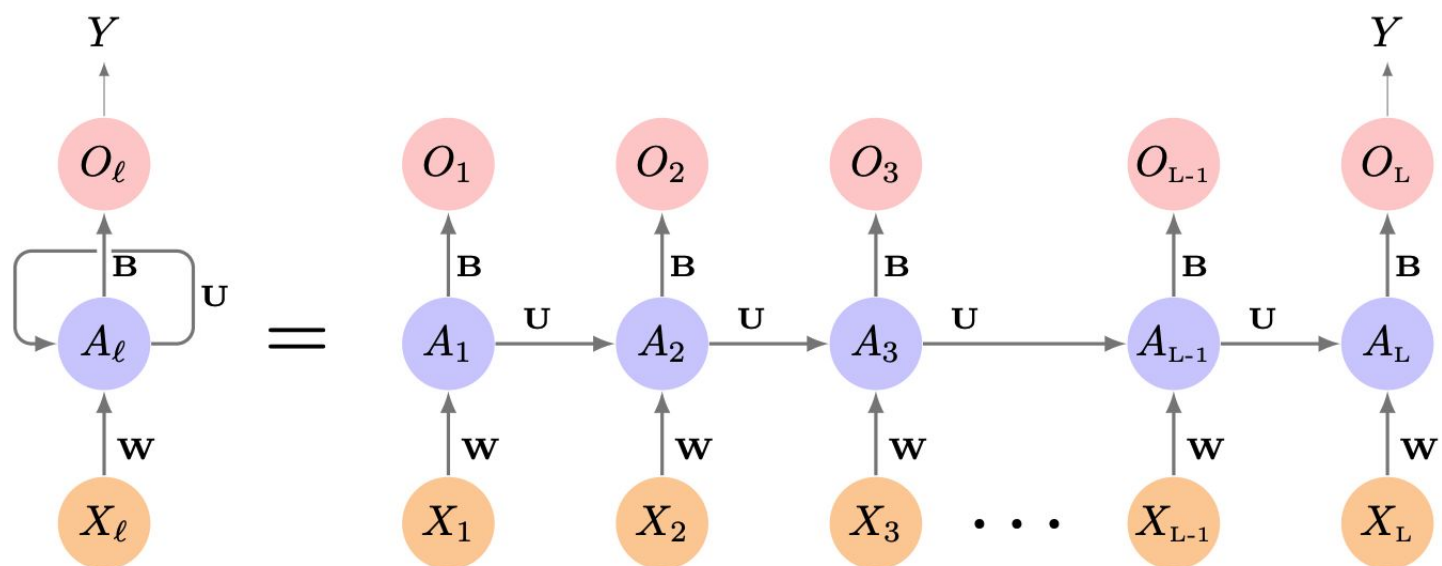


P e r i o d o s :

- d i a r i a
- s e m a n a l
- m e n s u a l
- t r i m e s t r a l
- s e m e s t r a l
- a n u a l

Recurrent neural nets

Redes que permiten aprender las relaciones en las secue



ERROR

$$(Y - O_L)^2,$$

$$A_{\ell k} = g\left(w_{k0} + \sum_{j=1}^p w_{kj} X_{\ell j} + \sum_{s=1}^K u_{ks} A_{\ell-1,s}\right), \quad O_{\ell} = \beta_0 + \sum_{k=1}^K \beta_k A_{\ell k}$$

A g e n d a

a n u n c i o s v a r i o s

T a r e a 3 e n t r e g a l u n e s 5 d e J u n i o

m o d e l o s d e a n a l i t i c a (m a c h i n e l e a r n i n g - M L) S u p e r

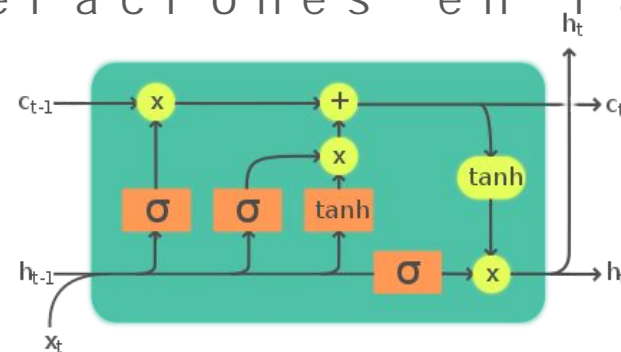
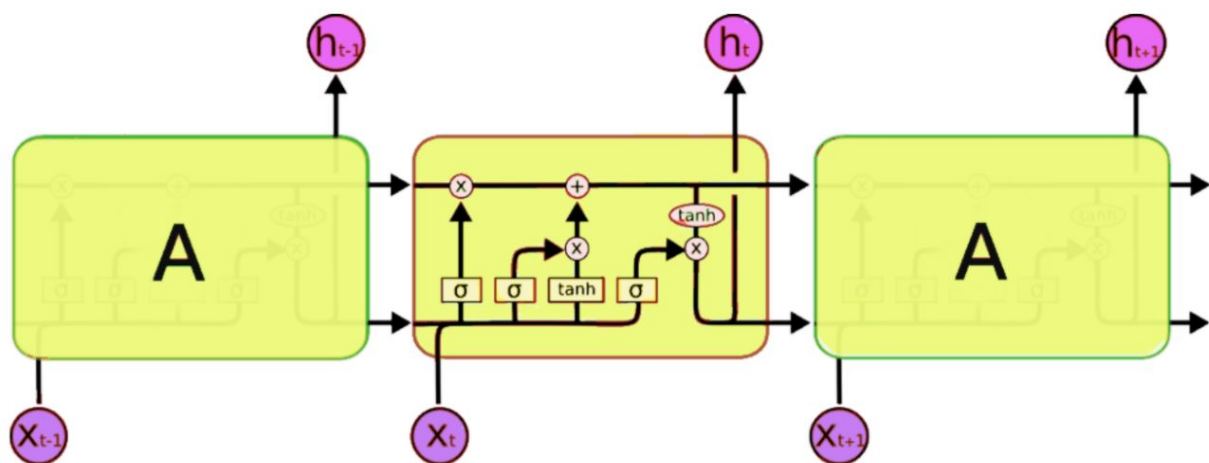
R e d e s N e u r o n a l e s

L S T M




S e c u e n c i a s

Recurrent neural nets, LSTM

Redes que permiten aprender las relaciones en las secue



Legend:

Layer	ComponentwiseCopy	Concatenate
		 

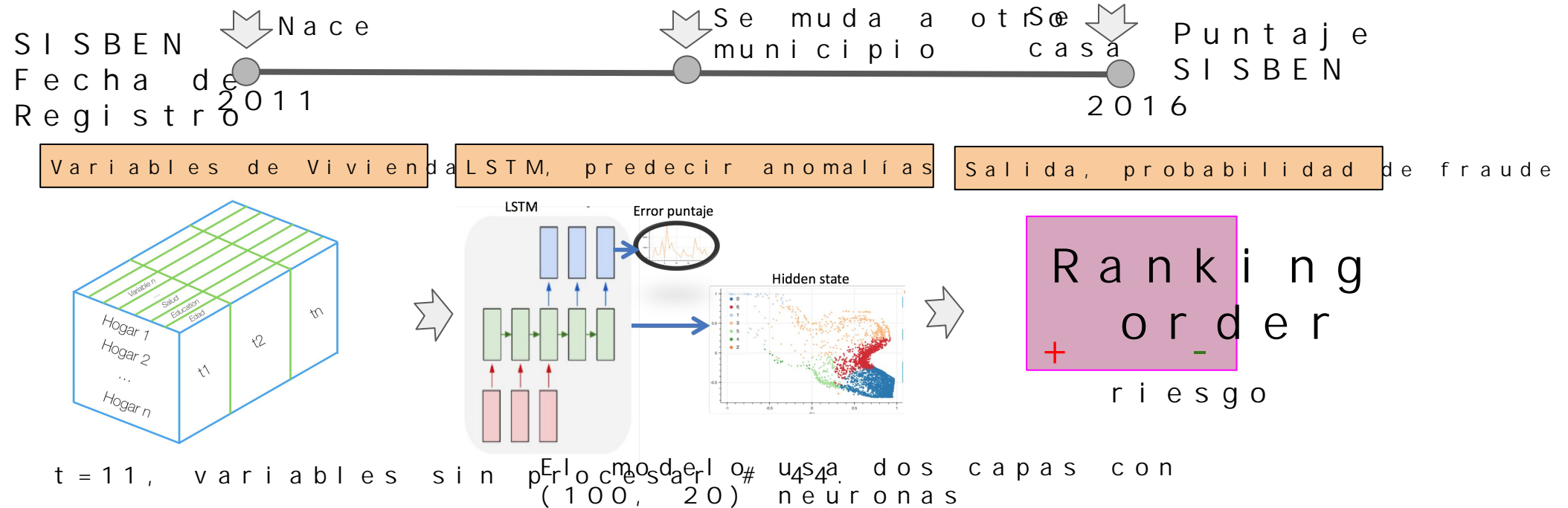
$$\begin{aligned}
 f_t &= \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \\
 i_t &= \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \\
 o_t &= \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \\
 \tilde{c}_t &= \sigma_c(W_c x_t + U_c h_{t-1} + b_c) \\
 c_t &= f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \\
 h_t &= o_t \odot \sigma_h(c_t)
 \end{aligned}$$

http://vision.stanford.edu/cs598_spring07/papers/Lecun98.pdf

Krizhevsky (2009) "Learning multiple layers of features from tiny images", avail

Recurrent neural nets, ejemplo

La secuencia de eventos es una variable



http://vision.stanford.edu/cs598_spring07/papers/Lecun98.pdf
Krizhevsky (2009) "Learning multiple layers of features from tiny images", available

Recurrent neural nets, ejemplo

Ajuster en las series de tiempo

Preparar datos

Stemming: Reducir a la raíz las palabras para que sean
o conjugación

Estud~~e~~s ant

Ju~~ga~~m~~os~~

Lemmatization: Utilizar el origen de las palabras
was = be
were = be
are = be

http://vision.stanford.edu/cs598_spring07/papers/Lecun98.pdf

Krizhevsky (2009) "Learning multiple layers of features from tiny images", available

* Gareth James, An Introduction to Statistical Learning

Recurrent neural nets, LSTM para

Redes que permiten aprender las relaciones en las secue
one_hot: es un vector donde cada palabra es

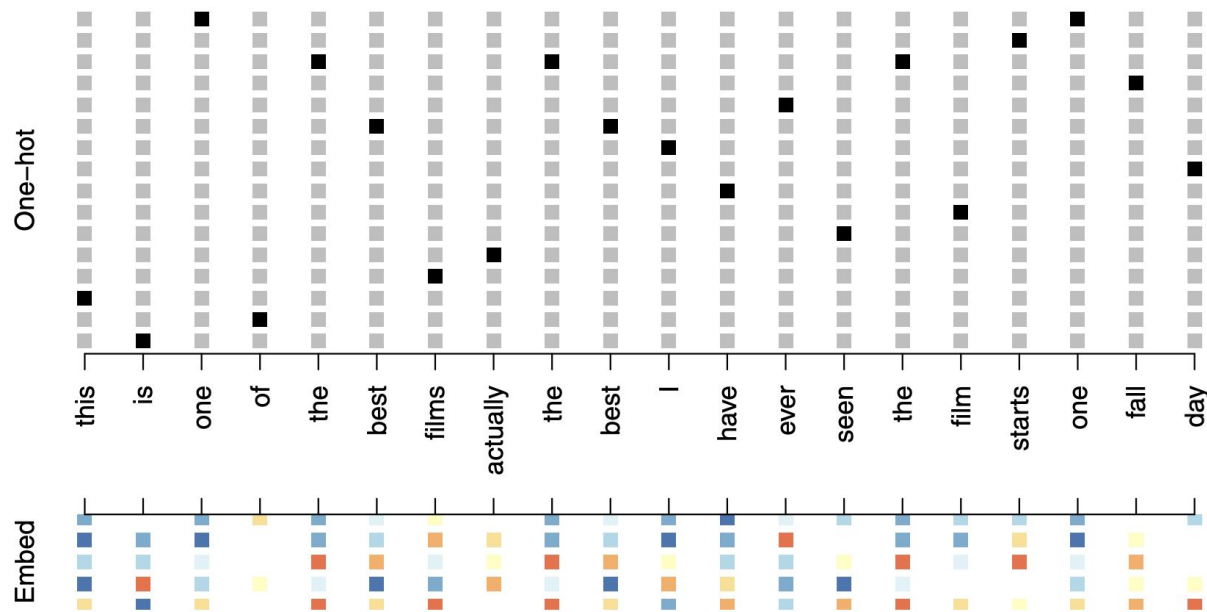


FIGURE 10.13. *Depiction of a sequence of 20 words representing a single document: one-hot encoded using a dictionary of 16 words (top panel) and embedded in an m -dimensional space with $m = 5$ (bottom panel).*

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Recurrent neural nets, LSTM para

Ajuster en las series de tiempo

Utilizar word2vec: Embedding para representar las supervisado.

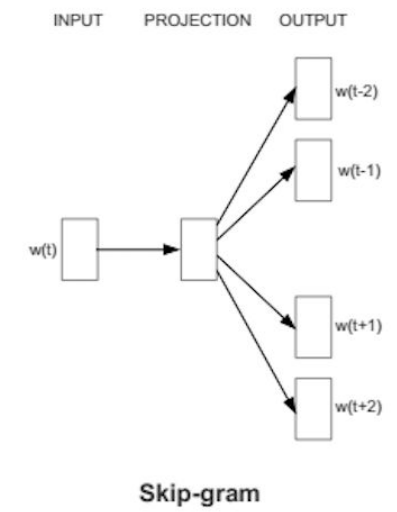
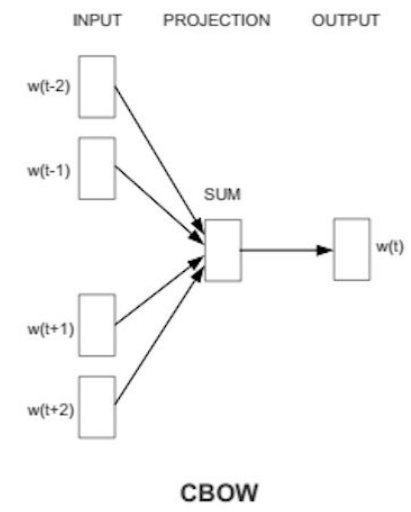
Instead of only looking two words before the target word, we can also look at two words after it.

Jay was hit by a _____ bus in...

by	a	red	bus	in
----	---	-----	-----	----

If we do this, the dataset we're virtually building and training the model against would look like this:

input 1	input 2	input 3	input 4	output
by	a	bus	in	red



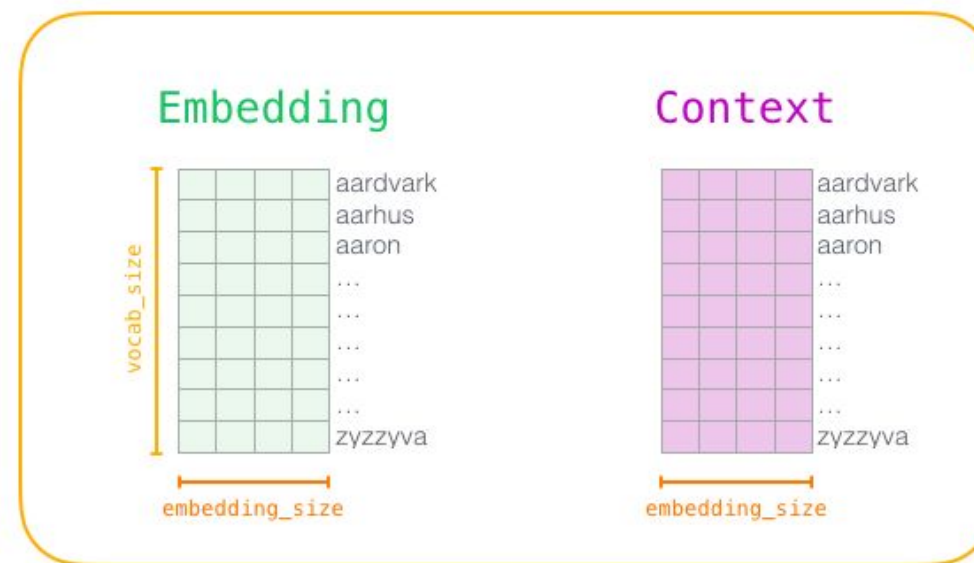
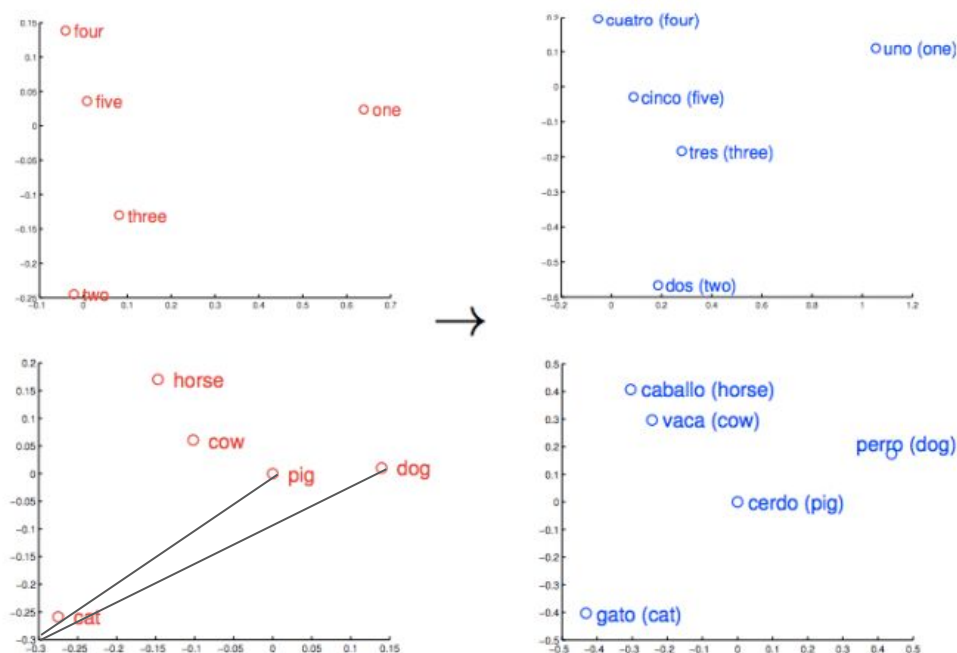
<https://jalammarr.github.io/illustrated-word2vec/>
 Word2vec paper <https://arxiv.org/pdf/1301.3781.pdf>

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Recurrent neural nets, LSTM para

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Utilizar word2vec: Embedding para representar las supervisado.



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Recurrent neural nets, ejemplo

Ajuster en las series de tiempo

Definir window size: Tamaño de la secuencia
Cuántas palabras se utilizaran para prede

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Definir arquitectura: Cuantas capas y neuro

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