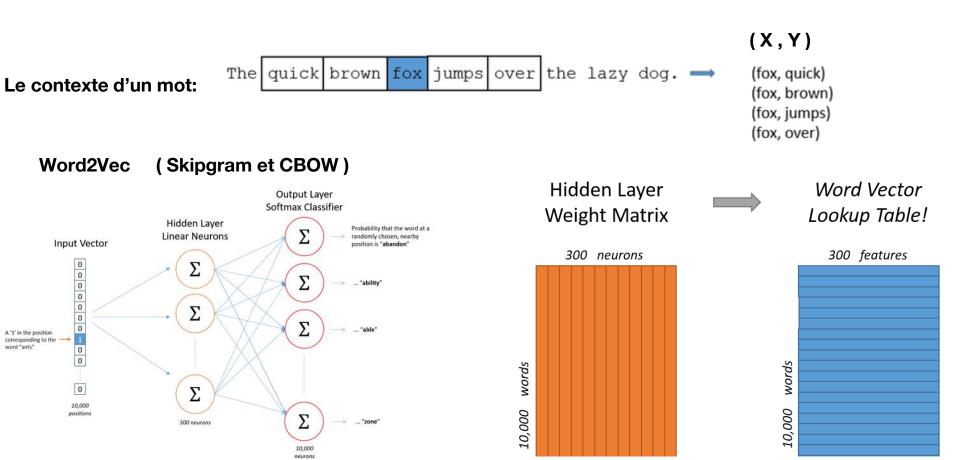
Word representations

PSTALN

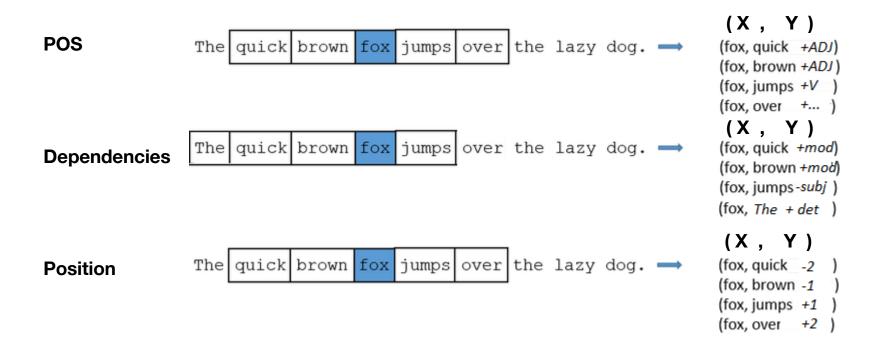


Word2Vec



Source: http://mccormickml.com/2016/04/19/word2vec-tutorial-the-skip-gram-model/

Word2Vec



Contextualized Word Representations (ELMo)

Each word representation should be a function of its context

Solves Polysemy

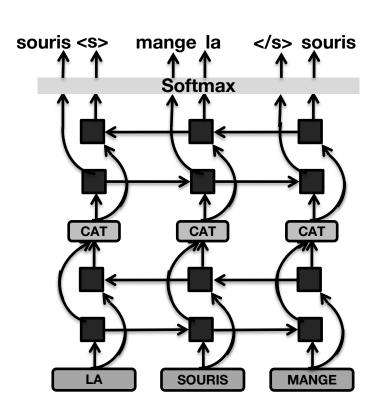
How?

Train a Neural Language model

$$p(t_1, t_2, \dots, t_N) = \prod_{k=1}^{N} p(t_k \mid t_{k+1}, t_{k+2}, \dots, t_N)$$
$$p(t_1, t_2, \dots, t_N) = \prod_{k=1}^{N} p(t_k \mid t_1, t_2, \dots, t_{k-1}).$$

Use its hidden states as word embeddings

$$\begin{split} R_k &= \{\mathbf{x}_k^{LM}, \overrightarrow{\mathbf{h}}_{k,j}^{LM}, \overleftarrow{\mathbf{h}}_{k,j}^{LM} \mid j = 1, \dots, L\} \\ \mathbf{ELMo}_k^{task} &= E(R_k; \Theta^{task}) = \gamma^{task} \sum_{j=0}^L s_j^{task} \mathbf{h}_{k,j}^{LM}. \end{split}$$



Contextualized Word Representations (ELMo)

Task	Previous SOTA		Our baseline	ELMo + Baseline	Increase (Absolute/Relative)
SQuAD	SAN	84.4	81.1	85.8	4.7 / 24.9%
SNLI	Chen et al (2017)	88.6	88.0	88.7 +/- 0.17	0.7 / 5.8%
SRL	He et al (2017)	81.7	81.4	84.6	3.2 / 17.2%
Coref	Lee et al (2017)	67.2	67.2	70.4	3.2 / 9.8%
NER	Peters et al (2017)	91.93 +/- 0.19	90.15	92.22 +/- 0.10	2.06 / 21%
Sentiment (5-class)	McCann et al (2017)	53.7	51.4	54.7 +/- 0.5	3.3 / 6.8%