Neural networks

Natural language processing - word representations



NATURAL LANGUAGE PROCESSING

Topics: one-hot encoding

- The major problem with the one-hot representation is that it is very high-dimensional
 - the dimensionality of e(w) is the size of the vocabulary
 - a typical vocabulary size is $\approx 100\ 000$
 - a window of 10 words would correspond to an input vector of at least 1 000 000 units!
- This has 2 consequences:
 - vulnerability to overfitting
 - millions of inputs means millions of parameters to train in a regular neural network
 - computationally expensive
 - not all computations can be sparsified (ex.: reconstruction in autoencoder)

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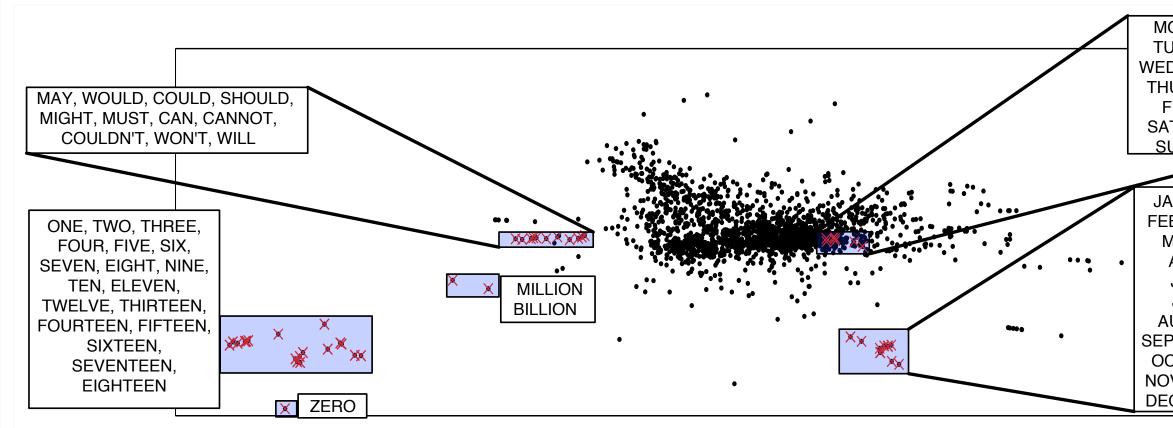
Topics: continuous word representation

- Idea: learn a continuous representation of words
 - each word w is associated with a real-valued vector C(w)

Word	w	C(w)
"the "	1	[0.6762, -0.9607, 0.3626, -0.2410, 0.6636]
"a"	2	[0.6859, -0.9266, 0.3777, -0.2140, 0.6711]
" have "	3	[0.1656, -0.1530, 0.0310, -0.3321, -0.1342]
" be "	4	[0.1760, -0.1340, 0.0702, -0.2981, -0.1111]
" cat "	5	$[\ 0.5896, \ 0.9137, \ 0.0452, \ 0.7603, \ -0.6541 \]$
" dog "	6	$[\ 0.5965, \ 0.9143, \ 0.0899, \ 0.7702, \ -0.6392 \]$
"car"	7	[-0.0069, 0.7995, 0.6433, 0.2898, 0.6359]

Topics: continuous word representation

- Idea: learn a continuous representation of words
 - we would like the distance ||C(w) C(w')|| to reflect meaningful similarities between words



(from Blitzer et al. 2004)

MONDAY TUESDAY WEDNESDAY THURSDAY FRIDAY SATURDAY SUNDAY JANUARY **FEBRUARY** MARCH APRIL JUNE JULY AUGUST SEPTEMBER OCTOBER **NOVEMBER** DECEMBER

Topics: continuous word representation

- Idea: learn a continuous representation of words
 - we could then use these representations as input to a neural network
 - to represent a window of 10 words $[w_1, \ldots, w_{10}]$, we concatenate the representations of each word

$$\mathbf{x} = \left[\mathit{C}(\mathit{w_1})^{ op}, \, ... \, , \, \mathit{C}(\mathit{w_{10}})^{ op}
ight]^{ op}$$

- We learn these representations by gradient descent
 - we don't only update the neural network parameters
 - we also update each representation C(w) in the input x with a gradient step

$$C(w) \longleftarrow C(w) - \alpha \nabla_{C(w)} l$$

where l is the loss function optimized by the neural network



Topics: word representations as a lookup table

- Let C be a matrix whose rows are the representations C(w)
 - obtaining C(w) corresponds to the multiplication $e(w)^{\top} C$
 - view differently, we are projecting e(w) onto the columns of C
 - this is a reduction of the dimensionality of the one-hot representations e(w)
 - this is a continuous transformation, through which we can propagate gradients

- In practice, we implement C(w) with a lookup table, not with a multiplication
 - C(w) returns an array pointing to the w^{th} row of \mathbf{C}

