TITLE: Text, word embeddings, transformers

Roadmap

Outline

Text classification/rating

my wonderful friend took
me to see this movie
for our anniversary.
it was terrible.

→ ☹ : $0 \cdots 1$: ☺

- How to represent the input text ?
- How to make classification ?

Bag of words (BOW)

this movie is just great , with a great music , while a bit long

Bag of words (BOW)

this movie is just great , with a great music , while a bit long

vocabulary	binary bag	count bag	tf.idf bag	...
awesome	0	0	0	...
great	1	2	1.9	...
long	1	1	2.5	...
the	0	0	0	...
this	1	1	0.1	...

A basic vectorial representation of text

$$\mathbf{x} = \begin{pmatrix} 0 \\ 2 \\ 1 \\ 0 \\ 1 \end{pmatrix} \in \mathbb{R}^D \qquad \left.\begin{matrix} \mathit{awesome} \\ \mathit{great} \\ \mathit{long} \\ \mathit{the} \\ \mathit{this} \end{matrix}\right\} D$$

A simple problem

Assumptions

- Let define a finite set of known words: the vocabulary $\mathcal{V}$
- A text is a vector $\mathbf{x}$ of dimension $D = |\mathcal{V}|$
- Each component encodes the presence of a word

Then machine learning

- Naive Bayes
- SVM, Random Forrest, ...
- Logistic Regression

Outline

Back to logistic regression

$$\mathbf{x} = \begin{pmatrix} 0 \\ 2 \\ 1 \\ 0 \\ 1 \end{pmatrix} \in \mathbb{R}^D \qquad \left.\begin{array}{r} \textit{awesome} \\ \textit{great} \\ \textit{long} \\ \textit{the} \\ \textit{this} \end{array}\right\} D$$

For one input text:

$$w_0 + \mathbf{w}^t \mathbf{x} = w_0 + 2 \times w_2 + w_3 + w_5$$

The class is positive $(y = 1)$ if

$$w_0 + 2 \times w_2 + w_3 + w_5 > 0$$

$$2 \times w_{great} + w_{long} + w_{this} + > -w_0$$

A limited representation of words

With the logistic regression model on a bag of words:

$w_{\text{bad}} < 0$ $\qquad\qquad$ $w_{\text{good}} > 0$

☹ $\longrightarrow$ ☺

0

Consider the two following examples:

the end is **really** **bad**	☹ $\Rightarrow$ $w_{\text{bad}} \searrow$
the **bad** guy is *awesome*	☺ $\Rightarrow$ $w_{\text{bad}} \searrow, w_{\text{awesome}} \nearrow$

Multiple dimensions could help to:

- represent different usage
- consider the context
- leverage more from sparse, sometime ambigous observations.

A simple model for document classification - part 1

Idea

- The word representation could be shared among classes
- While their interpretation depends on the class

Input representation and composition

$$\mathbf{R}\times\mathbf{x} = \begin{pmatrix} \vdots & \vdots & \vdots & \vdots & \vdots \\ \mathbf{v}_1 & \mathbf{v}_2 & \mathbf{v}_3 & \mathbf{v}_4 & \mathbf{v}_5 \\ \vdots & \vdots & \vdots & \vdots & \vdots \end{pmatrix} \times \begin{pmatrix} 0 \\ \mathbf{2} \\ \mathbf{1} \\ 0 \\ \mathbf{1} \end{pmatrix} = 2\times\mathbf{v}_2 + \mathbf{v}_3 + \mathbf{v}_5 = \mathbf{d}$$

A simple model for document classification - part 2

Classification

$$P(y|\mathbf{x}) = \text{softmax}(\mathbf{W^o d}) = \text{softmax}(\mathbf{W^o} \times \mathbf{Rx}), \text{ or}$$
$$= \text{softmax}(\mathbf{W^o} \times f(\mathbf{Rx})),$$

with f a non-linear activation function.

Parameters

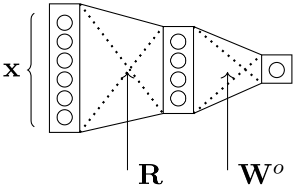
$$\boldsymbol{\theta} = (\mathbf{R}, \mathbf{W^o}) \rightarrow \textbf{to learn !!}$$

Reminder

If $\mathbf{y} = \text{softmax}(\mathbf{a})$, $\mathbf{y}$ is a vector and $\mathbf{a}$ is called the logit vector

$$y_i = \frac{e^{a_i}}{\sum_j e^{a_j}}$$

A first neural network



$$P(y=1|\mathbf{x};\boldsymbol{\theta}) = \sigma(\mathbf{W}^o \times \mathbf{d})$$

- $\mathbf{x}$: $(|\mathcal{V}|, 1)$
- $\mathbf{R}$: $(K, |\mathcal{V}|)$
- $\mathbf{d}$: $(K, 1)$ $\quad\quad \mathbf{d} = \mathbf{R} \times \mathbf{x}$
- $\mathbf{W^o}$: $(1, K)$
- y : $(1, 1)$ $\quad\quad y = \sigma(\mathbf{W^o} \times \mathbf{d})$

Outline

Limitations of BOW classifier

$$\mathbf{h} = \sum_{i=1}^{L} \underbrace{\mathbf{x}_i}_{\text{emb. of word } i}$$

Limitations

- Words are equally important
- Word order independent
- Miss contextual information (local/global)

Local contexts

the	end	is	very	bad	but	what	a	great	music

Local contexts

the	end	is	very	bad	but	what	a	great	music
			$\underbrace{\text{very} \quad \text{bad}}_{very \rightarrow bad++}$						

Local contexts

the	end	is	very	bad	but	what	a	great	music
			$\underbrace{\text{very bad}}_{very \to bad++}$						
			$\underbrace{\text{very bad but}}_{but \text{ will change } bad}$						

Local contexts

the	end	is	very	bad	but	what	a	great	music
			very→*bad*++						
			but will change *bad*						
		bad is for *end* not *music*						*great* is for *music* not fo *end*	

Motivations

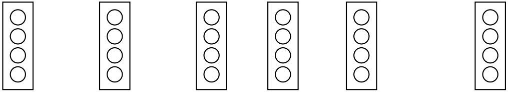
- Local contextualisation
- Global view of the sentence

Another view of a sentence

$$= \quad [\ \text{this},\ \text{movie},\ \text{was},\ \text{a},\ \text{great},\ \text{experience}\ ]$$

$$\downarrow \quad \downarrow \quad \downarrow \quad \downarrow \quad \downarrow \quad \downarrow$$

Look-up



$$\mathbf{v}_{this} \quad \mathbf{v}_{movie} \quad \mathbf{v}_{was} \quad \mathbf{v}_{a} \quad \mathbf{v}_{great} \quad \mathbf{v}_{experience}$$

$$\downarrow$$

$$\begin{bmatrix} 1.7 & -0.3 & -0.5 & -2.7 & -0.0 & -0.3 \\ -0.5 & 0.3 & 0.4 & -1.1 & -0.9 & -0.5 \\ 0.7 & 0.6 & -1.3 & -1.1 & 0.7 & 1.6 \\ -0.0 & -0.7 & 1.1 & -0.3 & 0.7 & 1.5 \end{bmatrix}$$

Outline

Draw attention for classification

Remind CBOW classifier

The classifier output:

$$\text{softmax}(\mathbf{W}^o\mathbf{h}) \text{ (multiclass) or } \sigma(\mathbf{w}^o\mathbf{h}) \text{ (binary)}$$

- What does represent a row of $\mathbf{W}^o$?
- The product $\mathbf{W}^o\mathbf{h}$?
- The softmax ?

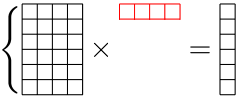
Draw attention

Is a word vector related to the classification task ?

$$\mathbf{h} = \sum_{i=1}^{L} \underbrace{\mathbf{x}_i}_{\text{emb. of word } i} \longrightarrow \mathbf{h} = \sum_{i=1}^{L} \underbrace{\lambda_i}_{???} \mathbf{x}_i$$

Draw attention for classification (binary task)

$$\mathbf{X}\mathbf{q} = L$$



$$\in \mathbb{R}^L$$

$$(\mathbf{X}\mathbf{q})_i = \mathbf{x}_i^t\mathbf{q} \quad \text{(dot product)}$$

$$\mathbf{a} = \mathrm{softmax}(\mathbf{X}\mathbf{q})$$

- $\mathbf{a} = (a_i)$, $\sum_{i=1}^{L} a_i = 1$ and $0 \leq a_i \leq 1$
- $\mathbf{a}$: attention vector for the "query" $\mathbf{q}$ and the "keys" $\mathbf{X}$.
- $\mathbf{q}$ is a vector to be learnt [11, 7]

Attention to weight inputs (binary task)

- $\mathbf{a} = \mathrm{softmax}(\mathbf{X}\mathbf{q})$ is the attention vector

$$\mathbf{h} = \sum_{i=1}^{L} a_i \mathbf{x}_i = \mathbf{a}^t \mathbf{X}$$

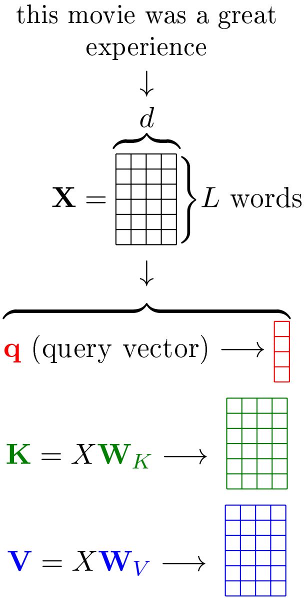
- A new vector, focused on the classification task ($\mathbf{q}$)
- To summarize:

$$\mathbf{h} = \mathrm{softmax}(\mathbf{X}\mathbf{q})^t \mathbf{X} \rightarrow \text{ classification}$$

Issues:

- Scale the dot product
- X is involved everywhere !

Basic attention mechanism for classification (binary task)



$$\mathbf{h} = \mathrm{softmax}\left(\frac{\mathbf{Kq}}{\sqrt{d}}\right)^t \mathbf{V}$$

- X can be static emb.
- or contextualized embedding
- $\mathbf{q}$ is learnt as a target for selection
- $\mathbf{a} = \mathbf{Kq}$: selection in $\mathbf{V}$

Outline

Contextualized word embeddings

Consider the word driver:

the	audio	driver	is	really	outdated
the	driver	exceeded	the	speed	limit

The context

The	The	$\lambda_{2,1}$
audio	driver	$\lambda_{2,2}$
driver	exceeded	$\lambda_{2,3}$
is	the	$\lambda_{2,4}$
really	speed	$\lambda_{2,5}$
outdated	limit	$\lambda_{2,6}$

Self attention: a first idea

Look at the "correlation" between words (embeddings)

- $\mathbf{X}\mathbf{X}^t$ is a $L \times L$ matrix, stores $(\mathbf{x}_i^t \mathbf{x}_j)$
- The i^{th} row stores the "correlation between" $\mathbf{x}_i$ and all the other words in the sentence
- For $i = 2$, we have the correlations with driver
- We can use this correlation as a weight

$$\mathbf{z}_2 = \mathbf{z}_{driver} = \sum_{j=1}^{L} \underbrace{\lambda_{2,j}}_{\mathbf{x}_2^t \mathbf{x}_j} \mathbf{x}_j$$

More (linear) transformations

Two different Transformations on $\mathbf{X}$

$$\mathbf{X} \longrightarrow \mathbf{X}\mathbf{W}_Q = \mathbf{Q}$$

$$\mathbf{X} \longrightarrow \mathbf{X}\mathbf{W}_K = \mathbf{K},$$

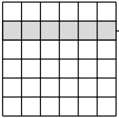
- with $\mathbf{W}_Q$ and $\mathbf{W}_K \in \mathbb{R}^{d \times d}$
- $\mathbf{Q}$ and $\mathbf{K}$ have the same dimensions as $\mathbf{X}$

$$\mathbf{A} = \mathbf{Q}\mathbf{K}^t = \underbrace{(\mathbf{Q}_{i,*}\mathbf{K}^t_{j,*})_{i,j}}_{L \times L} = (\mathbf{q}_i^{\mathbf{k}j}) = (\lambda_{i,j}),$$

with $\lambda_{i,j}$ the attention on "word" j to generate $\mathbf{z}_i$

Normalization of attention

Take the row-wise softmax:

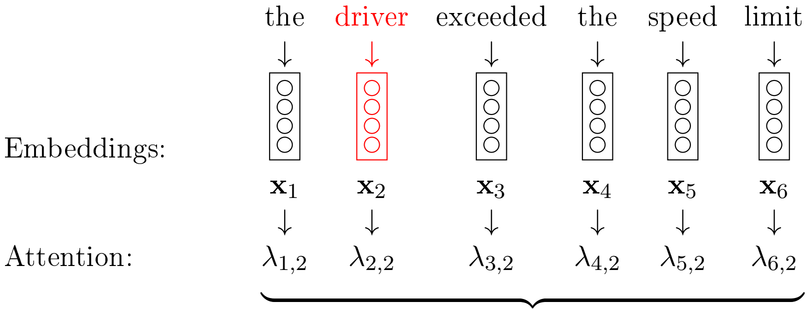


$$\sum_j \underbrace{\lambda_{i,j}}_{\text{or } a_{i,j}} = 1 \text{ and } \lambda_{i,j} \geq 0$$

Each row of $\mathbf{A}$ gives a convex combination

Self attention (overview)

Consider the word driver:



Output:

$$\mathbf{z}_2 = f\Big(\sum_j [\lambda_{2,j} \times g(\mathbf{x}_j)]\Big)$$

- $(\lambda_{i,j})$ are the attention coefficients, $\sum_j \lambda_{i,j} = 1$, and
- Reflects the influence of $\mathbf{x_j}$ on $\mathbf{x_i}$ (transformed version)

Transformer : Queries, Keys, Values

the driver exceeded the speed limit

$$\downarrow$$

$$\mathbf{X} = \underbrace{\quad}_{d} \Big\} L \text{ words}$$

$$\downarrow$$

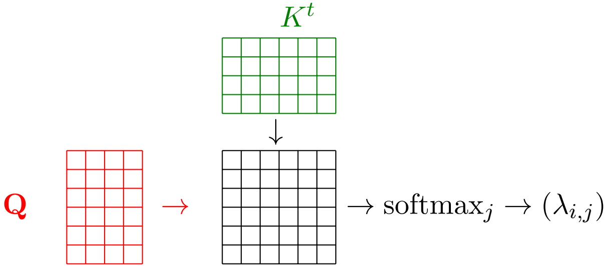
$$\mathbf{Q} = X\mathbf{W}_Q \longrightarrow$$

$$\mathbf{K} = X\mathbf{W}_K \longrightarrow$$

$$\mathbf{V} = X\mathbf{W}_V \longrightarrow$$

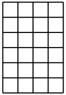
Tranformer : Attention matrix

The distance matrix between Q and K

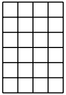


Scaled Dot-Product Attention

$$\mathbf{Z} = \mathrm{softmax}\left(\frac{\mathbf{Q}\mathbf{K^t}}{\sqrt{d}}\right)\mathbf{V} =$$



Multi-head attention (with 2 heads)

$\mathbf{X} =$ 

$$\downarrow$$

$$\mathbf{W}_Q^{(1)}, \mathbf{W}_K^{(1)}, \mathbf{W}_V^{(1)} \qquad \mathbf{W}_Q^{(2)}, \mathbf{W}_K^{(2)}, \mathbf{W}_V^{(2)}$$

$$\downarrow \qquad \downarrow$$

$$\mathbf{Q}^{(1)}, \mathbf{K}^{(1)}, \mathbf{V}^{(1)} \qquad \mathbf{Q}^{(2)}, \mathbf{K}^{(2)}, \mathbf{V}^{(2)}$$

$$\downarrow \qquad \downarrow$$

$$\mathbf{Z}^{(1)} \qquad \mathbf{Z}^{(2)}$$

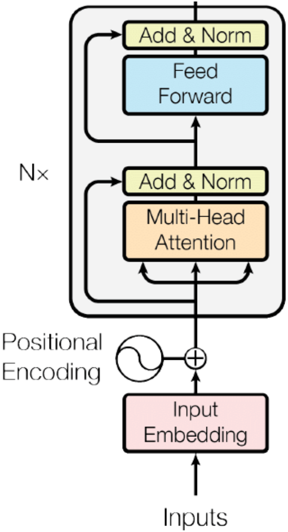
$$\mathbf{Z} = (\mathbf{Z}^{(1)}; \mathbf{Z}^{(2)})\mathbf{W_o}$$

Putting all together (with more tricks)

Transformer block

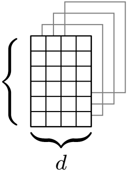
From [10]

- Inputs is $\mathbf{X}$
- Positional embeddings
- Multihead attention
- Residual connections [6]
- Layer Normalization [2]
- Final filtering

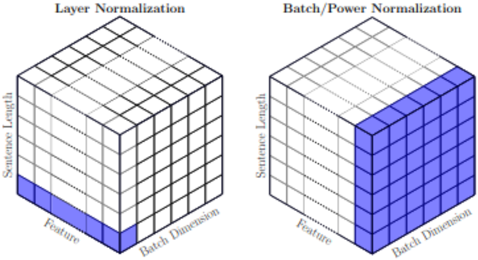


Layer norm

Assume $\mathbf{Z}$ a minibatch of sequences (B, L, D): $\mathbf{Z} = L$

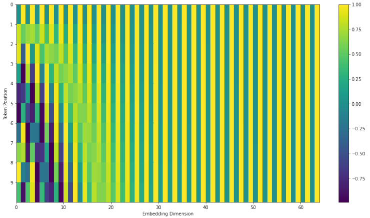


Batch or Layer norm



[9]

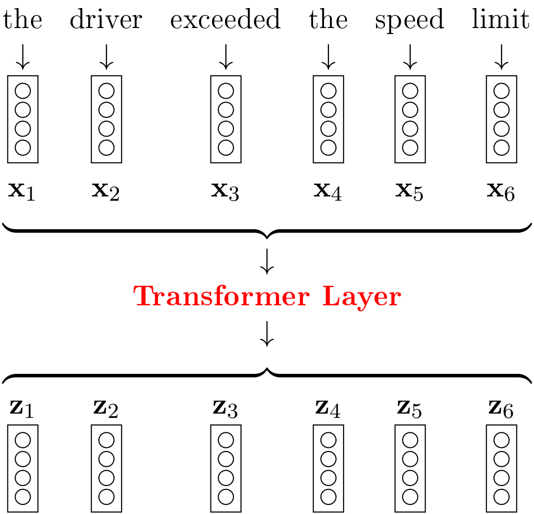
Positional embeddings



- Originally "absolute"
- Can be learnt [5, 1]
- Or relative [8]

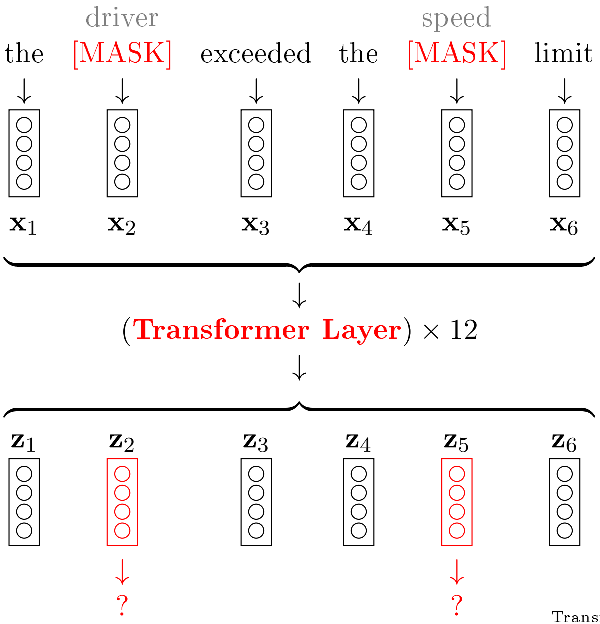
(figure generated by the following code `https://github.com/jalammar/jalammar.github.io/blob/master/notebookes/transformer/transformer_positional_encoding_graph.ipynb`)

A Transformer layer

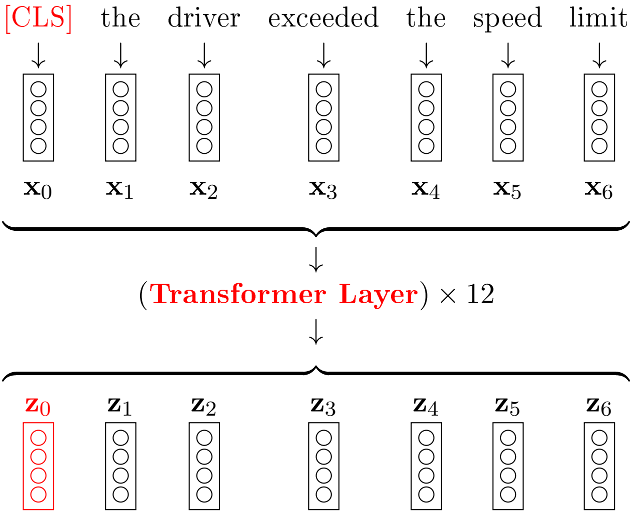


Transformer layers can be stacked !

Pre-training as a (Masked) language model



BERT Encoder for text classification



Outline

Summary

Attention, attention

- This mechanism allows the model to efficiently handle different kind of structure.
- Originally for machine translation, and with BI-GRU [4, 3].

Transformers

- Architecture proposed in [10]
- Nowadays state of the art component

Transformers are everywhere

State of the art encoder

- For text ! (BERT)
- And also for speech, DNA, vision, ...

Also a powerful generator

- For text (GPT, ...)
- Speech, ... sequences

Outline

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[11] Zichao Yang et al. "Hierarchical Attention Networks for Document Classification". In: *Proceedings of the North American Chapter of the Association for Computational Linguistics (NAACL)06*. 2016.