Structure, Attention, and BERT

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Roadmap

Outline

The simplest classifier based on word embeddings

Input text is now a sequence of vectors (embeddings)

$$\mathbf{X} \text{ or } \mathbf{X}^t = \overbrace{\begin{array}{|c|c|c|c|}\hline \; & \; & \; & \; \\ \hline & & & \\ \hline & & & \\ \hline & & & \\ \hline & & & \\ \hline & & & \\ \hline \end{array}}^{d}\left.\vphantom{\begin{array}{c} \\ \\ \\ \\ \\ \\ \end{array}}\right\} L \text{ words}$$

Derive a vector of features that represent the text

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

Classification

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

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	$\underbrace{\text{very} \mid \text{bad}}_{very \rightarrow bad{+}{+}}$	but	what	a	great	music

Local contexts

the	end	is	very	bad	but	what	a	great	music

$$\underbrace{\text{very bad}}_{very \rightarrow bad{+}{+}}$$

$$\underbrace{\text{very bad but}}_{but\ \text{will change}\ bad}$$

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

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

Look-up

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

$$\downarrow$$

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

Propose 2 solutions for an improved text classification

. . .

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)

$$\mathbf{X}\mathbf{q} = L\left\{\begin{array}{|c|c|c|c|}\hline \; & \; & \; & \; \\ \hline & & & \\ \hline & & & \\ \hline & & & \\ \hline & & & \\ \hline & & & \\ \hline \end{array}\right. \times \begin{array}{|c|c|c|c|}\hline \; & \; & \; & \; \\ \hline \end{array} = \begin{array}{|c|}\hline \; \\ \hline \\ \hline \\ \hline \\ \hline \\ \hline \\ \hline \end{array} \in \mathbb{R}^L$$

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

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

- $\mathbf{a} = (a_i)$, $\sum_{i=1}^{L} a_i = 1$ 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 [9, 5]

Attention to weight inputs (binary task)

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

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

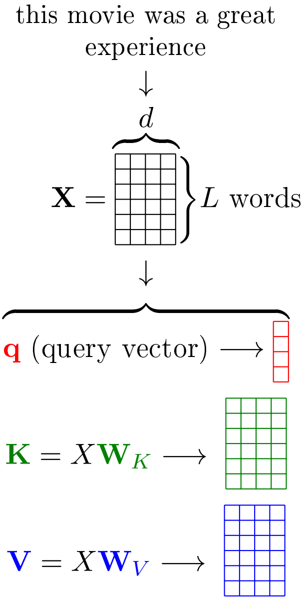
- A new vector, focused on the classification task ($\mathbf{q}$)
- To summarize:

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

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 $\mathbf{V}$

Attention classifier: Going to multiclass

Exercise

- How to modify (parametrize) the model for multiclass classification ?
- Can we add more transformations ?

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 $\mathbf{X}$

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

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

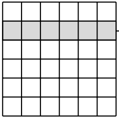
- with $\mathbf{W}_Q$ and $\mathbf{W}_K \in \mathbb{R}^{d \times d}$
- $\mathbf{Q}$ and $\mathbf{K}$ have the same dimensions as $\mathbf{X}$

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

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

Normalization of attention

Take the row-wise softmax:



$\longrightarrow \mathrm{softmax}_j(\mathbf{A}_{i,*})$

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

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

Self attention (overview)

Consider the word driver:

	the	driver	exceeded	the	speed	limit
	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$
Embeddings:	$\mathbf{x}_1$	$\mathbf{x}_2$	$\mathbf{x}_3$	$\mathbf{x}_4$	$\mathbf{x}_5$	$\mathbf{x}_6$
	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$
Attention:	$\cancel{\lambda_{1,2}}$	$\cancel{\lambda_{2,2}}$	$\cancel{\lambda_{3,2}}$	$\cancel{\lambda_{4,2}}$	$\cancel{\lambda_{5,2}}$	$\cancel{\lambda_{6,2}}$

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

$$\downarrow$$

$$\mathbf{X} = \overbrace{\qquad\qquad}^{d} \Big\} L \text{ words}$$

$$\downarrow$$

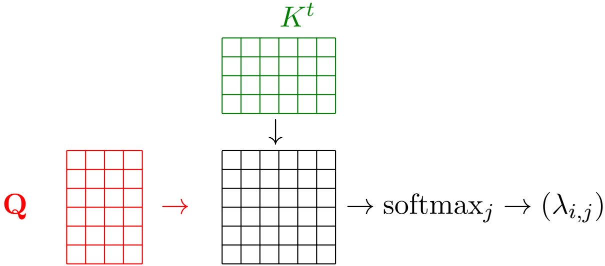
$$\mathbf{Q} = X\mathbf{W}_Q \longrightarrow$$

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

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

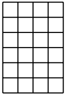
Tranformer : Attention matrix

The distance matrix between Q and K



Scaled Dot-Product Attention

$$\mathbf{Z} = \text{softmax}\left(\frac{\mathbf{QK^t}}{\sqrt{d}}\right)\mathbf{V} =$$



Q,K,V and Metric Learning

$$
\begin{aligned}
\mathbf{Q}\mathbf{K}^t &= \mathbf{X}\mathbf{W}_Q \times (\mathbf{X}\mathbf{W}_K)^t = \mathbf{X}\mathbf{W}_Q \times (\mathbf{W}_K^t \mathbf{X}^t) \\
&= \mathbf{X}\mathbf{M}\mathbf{X}^t
\end{aligned}
$$

- If $\mathbf{M}$ would be PSD, it is a metric.
- Otherwise, it is a transformed similarity (bilinear similarity)

$\mathbf{M}$ is learnt: a transformer block learns its own similarity.

Multi-head attention (with 2 heads)

$$\mathbf{X} = \begin{array}{|c|c|c|c|}\hline \, & \, & \, & \, \\ \hline \, & \, & \, & \, \\ \hline \, & \, & \, & \, \\ \hline \, & \, & \, & \, \\ \hline \, & \, & \, & \, \\ \hline \, & \, & \, & \, \\ \hline \end{array}$$

$$\downarrow$$

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

$$\downarrow \qquad\qquad \downarrow$$

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

$$\downarrow \qquad\qquad \downarrow$$

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

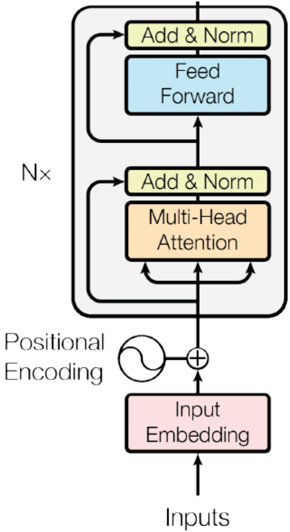
$$\mathbf{Z} = (\mathbf{Z}^{(1)}; \mathbf{Z}^{(2)})\mathbf{W_o}$$

Putting all together (with more tricks)

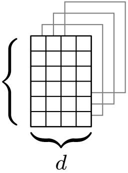
Transformer block

From [8]

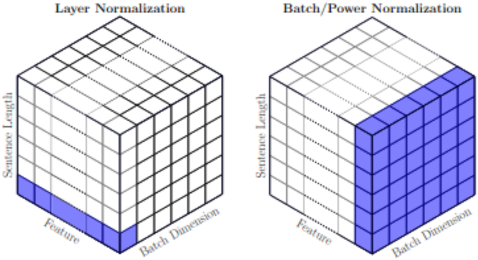
- Inputs is $\mathbf{X}$
- Positional embeddings
- Multihead attention
- Residual connections [4]
- Layer Normalization [2]
- Final filtering



Layer norm

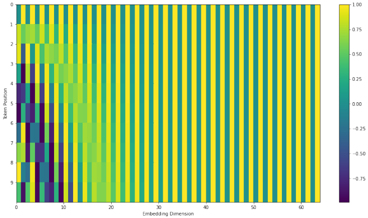
Assume $\mathbf{Z}$ a minibatch of sequences (B, L, D): $\mathbf{Z} = L$ 

Batch or Layer norm



[7]

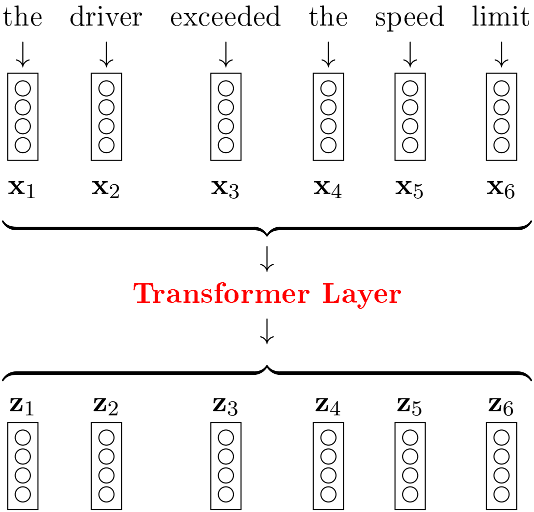
Positional embeddings



- Originally "absolute"
- Can be learnt [3, 1]
- Or relative [6]

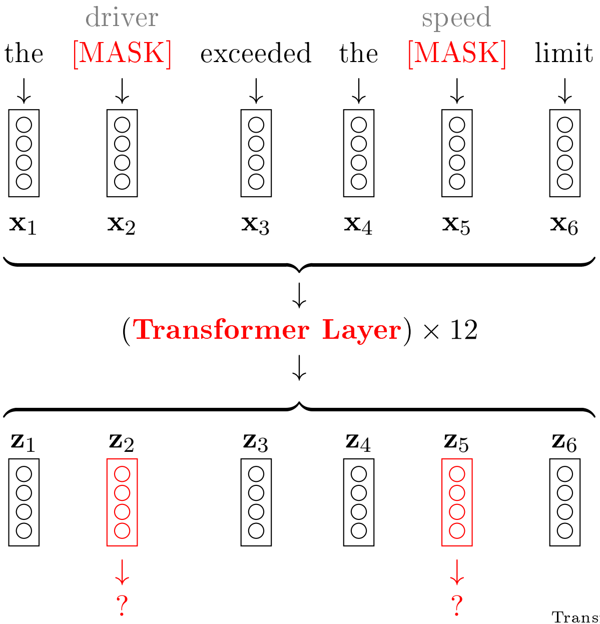
(figure generated by the following code `https://github.com/jalammar/jalammar.github.io/blob/master/notebookes/transformer/transformer_positional_encoding_graph.ipynb`)

A Transformer layer

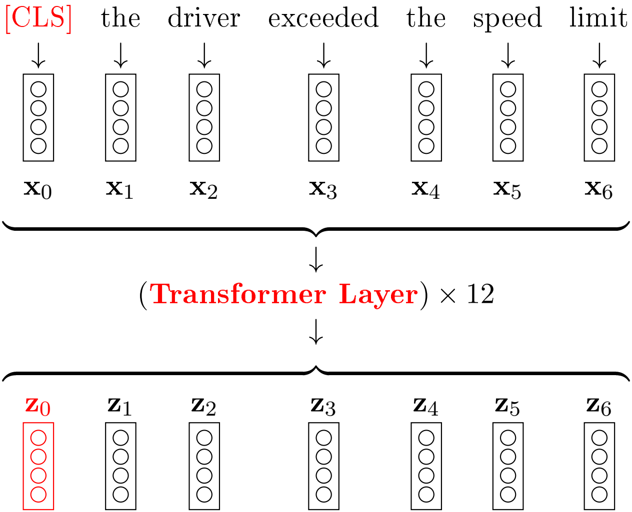


Transformer layers can be stacked !

Pre-training as a (Masked) language model



BERT Encoder for text classification



Outline

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

[1] Rami Al-Rfou et al. *Character-Level Language Modeling with Deeper Self-Attention*. 2018. arXiv: 1808.04444 [cs.CL].

[2] Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E. Hinton. *Layer Normalization*. 2016. arXiv: 1607.06450 [stat.ML].

[3] Jonas Gehring et al. “Convolutional Sequence to Sequence Learning”. In: *CoRR* abs/1705.03122 (2017). arXiv: 1705.03122. URL: http://arxiv.org/abs/1705.03122.

[4] Kaiming He et al. “Deep Residual Learning for Image Recognition”. In: *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 2016, pp. 770–778. arXiv: 1512.03385 [cs.CV].

[5] Zhouhan Lin et al. “A STRUCTURED SELF-ATTENTIVE SENTENCE EMBEDDING”. In: *International Conference on Learning Representations*. 2017. URL: https://openreview.net/forum?id=BJC_jUqxe.

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[7] Sheng Shen et al. “PowerNorm: Rethinking Batch Normalization in Transformers”. In: *Proceedings of the 37th International Conference on Machine Learning*. Ed. by Hal Daumé III and Aarti Singh. Vol. 119. Proceedings of Machine Learning Research. PMLR, 2020, pp. 8741–8751. URL: https://proceedings.mlr.press/v119/shen20e.html.

[8] Ashish Vaswani et al. "Attention is All you Need". In: *Advances in Neural Information Processing Systems 30*. Ed. by I. Guyon et al. Curran Associates, Inc., 2017, pp. 6000–6010. URL: http://papers.nips.cc/paper/7181-attention-is-all-you-need.pdf.

[9] 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.