Binaural Speech Enhancement Based on Deep Attention Layers

Tom Gajecki & Waldo Nogueira

Auditory Prosthetic Group, Department of Otolaryngology, Hannover Medical School, Cluster of Excellence, Hannover, Germany

Submission to the Clarity Challenge

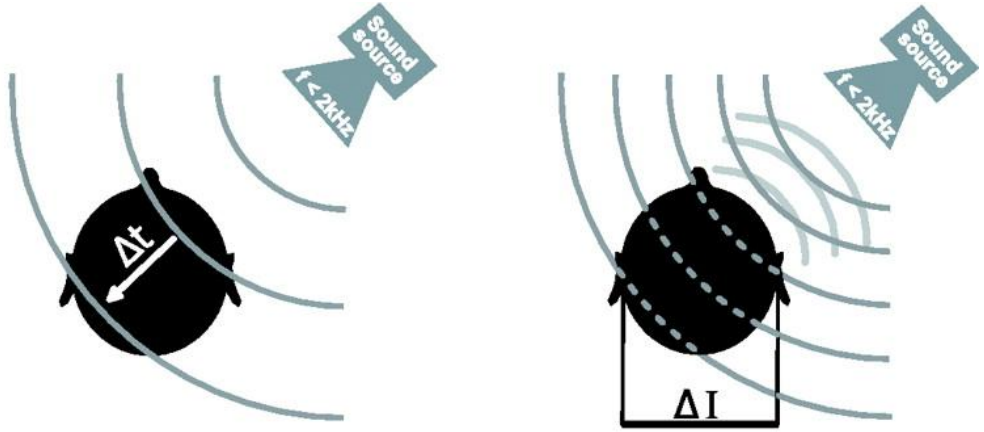
Introduction

- The speech enhancement system is a binaural end-to-end audio source separation framework that connects information between hearing aids

- We investigate the effect of applying attention mechanisms to improve binaural audio source separation

Binaural Hearing

- The ability to process the information available in pressure waves arriving at the two ears is called binaural hearing
- Binaural unmasking is the ability that the binaural hearing system has to enhance target sound sources when spatially separated from interferers [Ira J. Hirsh, 1948]
- The binaural system exploits two binaural cues:
  - Interaural time differences (ITDs)
  - Interaural level differences (ILDs)



Binaural Impairment

- Hearing loss can cause a degradation in the ability of exploiting binaural cues [S. C. Hogan, D. R. Moore, 2003]
- Binaural impairment can cause :
  - Poor speech intelligibility performance in noisy conditions when compared with a healthy hearing system
  - Poor sound localization abilities when compared to a healthy hearing system

Motivation

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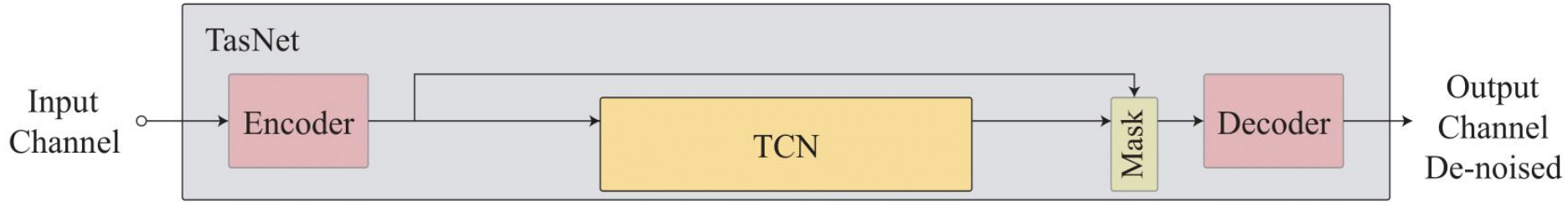
- We aim at developing a speech enhancement system that uses inputs from both hearing sides
- The system should share information between sides, inspired by the binaural system, to exploit binaural cues
- We propose a deep neural network architecture which shares information between sides through intermediate layers that we will refer to as “attention layers“, inspired by other successful attention mechanisms used in other domains [A. Vaswan, 2017]
- We hypothesize that an algorithm that uses attention layers will yield better objective performance compared to a system that does not use them

Methods: The architecture

- We propose a binaural speech enhancement system built upon a well known single-channel speech separation algorithm: TasNet [Y. Luo and N. Mesgarani, 2019]



- The encoder maps a segment of the mixture waveform to a high-dimensional representation
- The temporal convolution network (TCN) calculates a multiplicative function (i.e., a mask) for the desired target source
- The decoder decoder reconstructs the source waveforms from the masked features

Methods: The architecture

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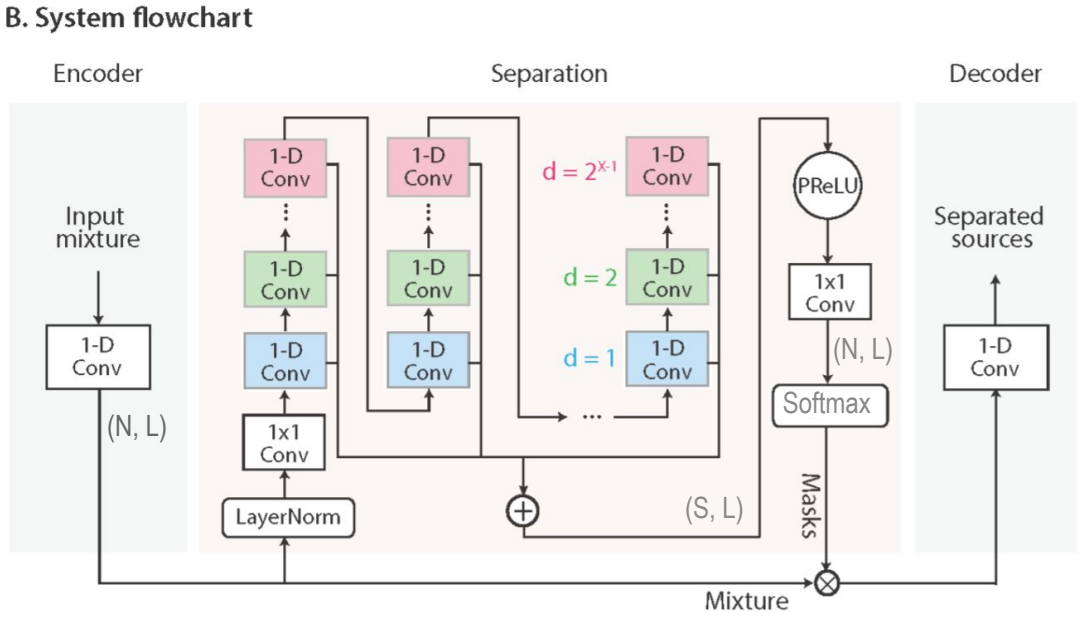
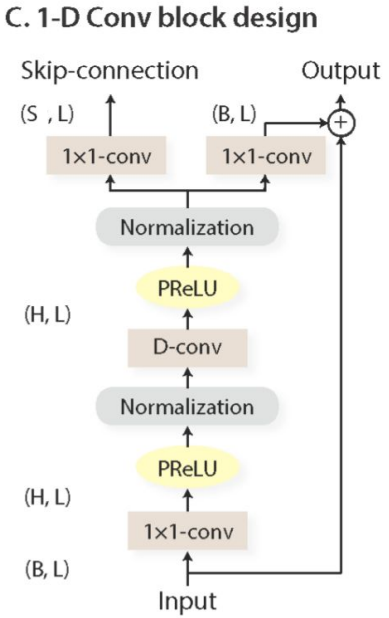
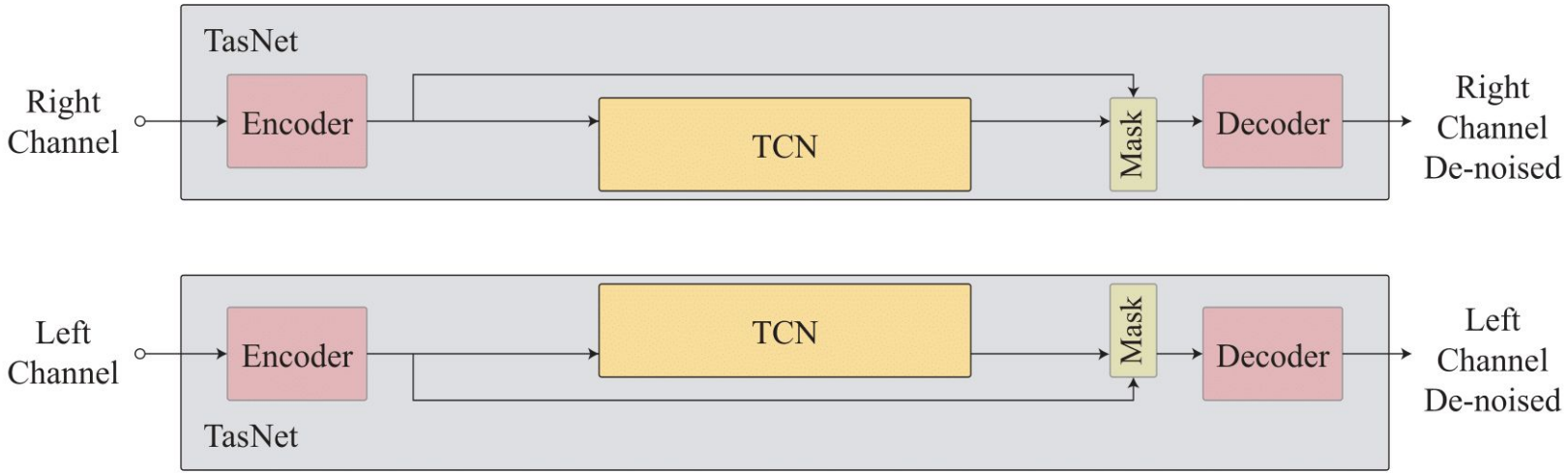
Symbol	Description
N	Number of filters in autoencoder
L	Length of the filters (in samples)
B	Number of channels in bottleneck and the residual paths' 1×1-$conv$ blocks
S	Number of channels in skip-connection paths' 1×1-$conv$ blocks
H	Number of channels in convolutional blocks
P	Kernel size in convolutional blocks
X	Number of convolutional blocks in each repeat
R	Number of repeats





Methods: The architecture

Independent model



Methods: The architecture

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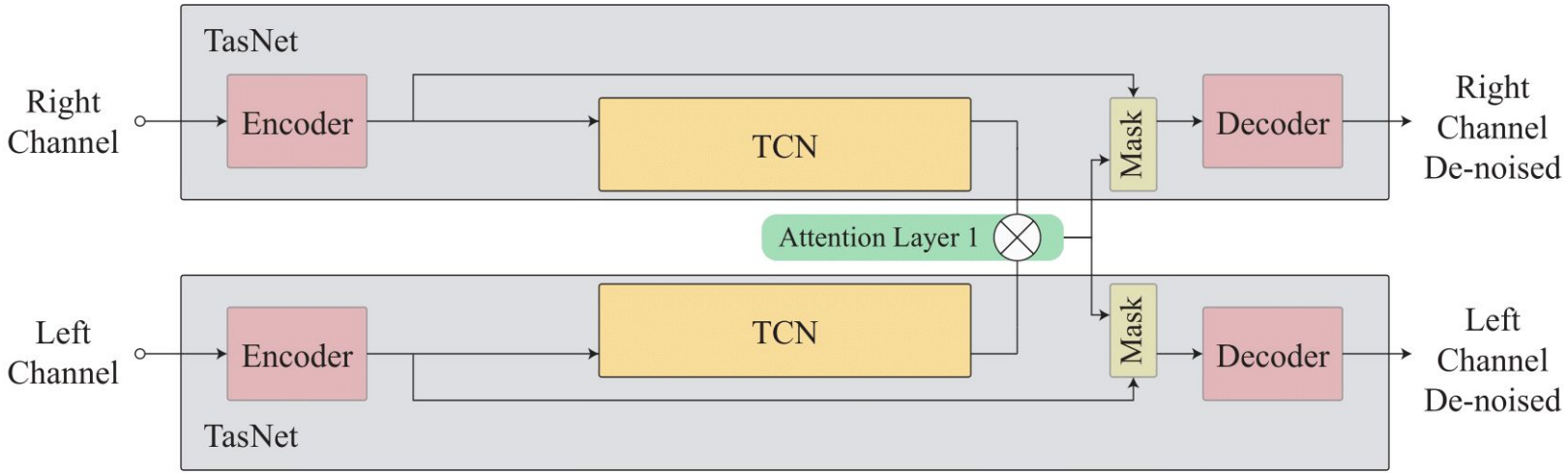
Single Attention model



Methods: The architecture

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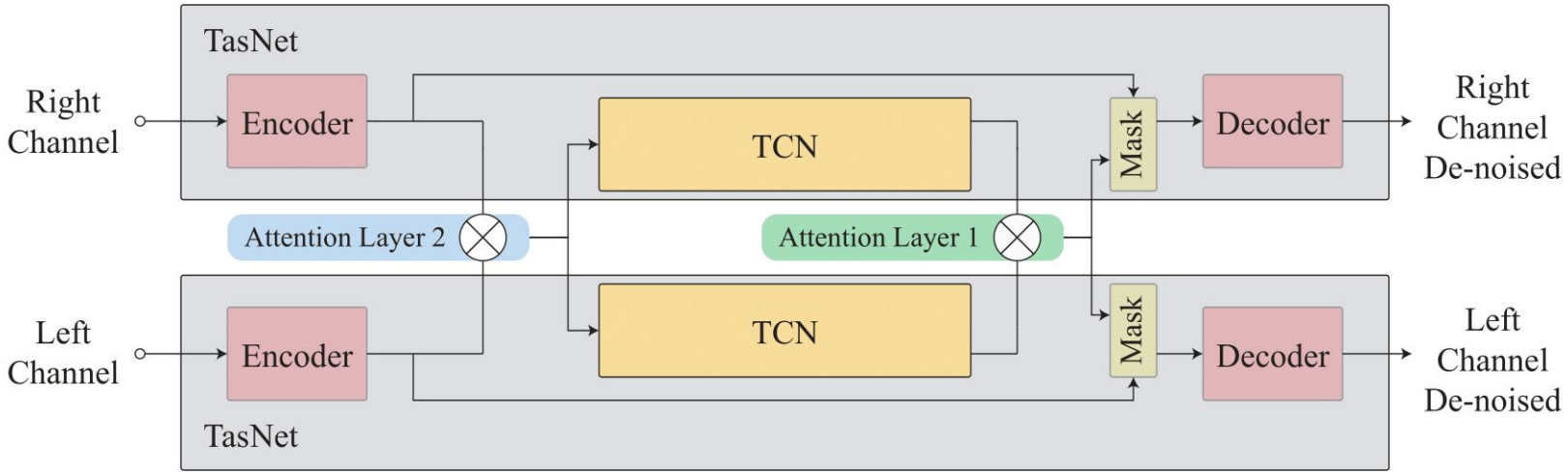
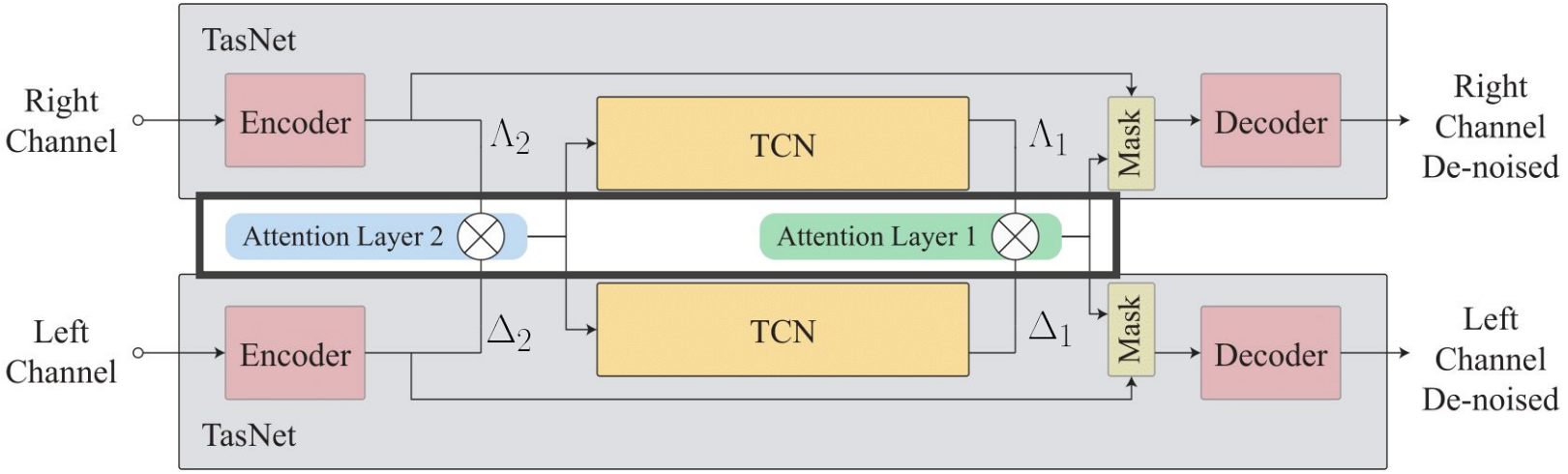
Double Attention model



Methods: Attention layers

- Intermediate layers that perform element wise dot product to the latent representations of the signals in each side: $Attention(\Lambda, \Delta) = \Lambda \otimes \Delta$
- They do not introduce trainable parameters



Source code implemented in TensorFlow [M. Abadi et.al., 2015] available online at: https://github.com/APGDHZ/BinAttSE

Methods: Hyperparameters

Description	Value
Number of filters in autoencoder	64
Length of the filters	16
Number of channels in the bottleneck blocks	64
Number of channels in the skip-connections	S
Number of channels in the convolutional blocks	64
Kernel size in convolutional blocks	128
Number of convolutional blocks in each repeat	2
Number of repeats	2

Table 1: *Hyperparameters used for training the models. The parameter that corresponds to the size of the attention layers (S) is a factor that is investigated in this work and its value is variable (refer to sections 2.2 and 3).*

Methods: Hyperparameters

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The input filter size of 16 samples causes an algorithmic latency of 2ms for an input signal sampled at 8kHz

Methods: Training

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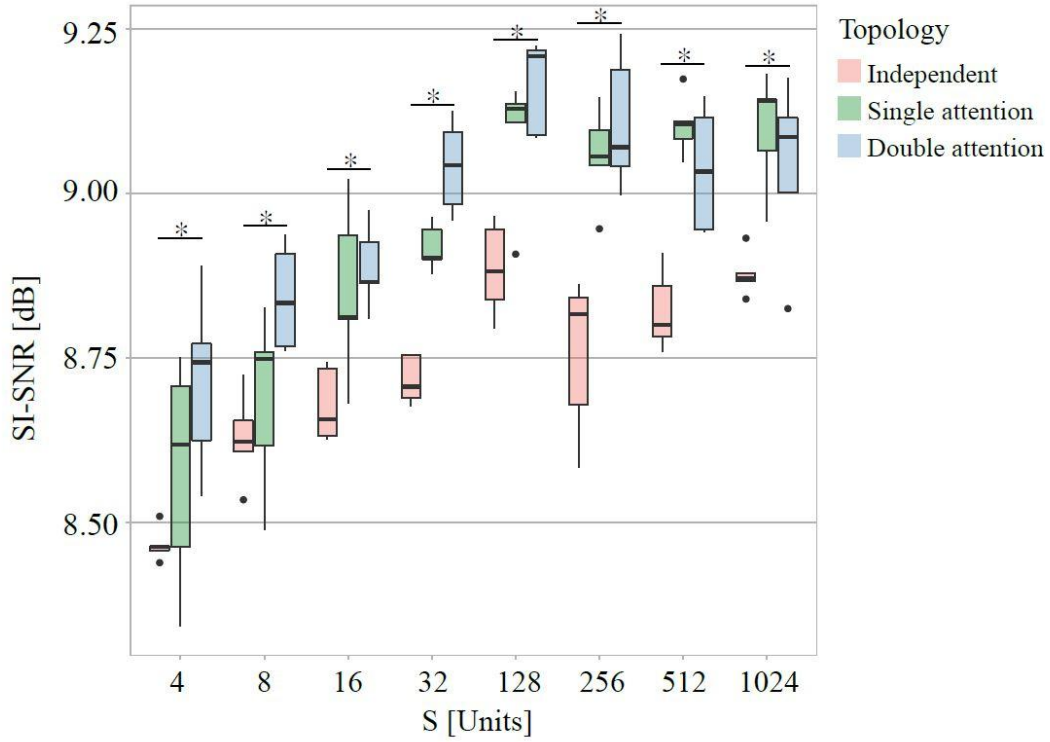
- 8 Model sizes were selected for training (S = {4,8,16,32,128,256,512,1024}) to investigate the effect of the attention/skip connection size
- Each model was trained 5 times to account for variance related to random initialization
- The models were trained for a maximum of 100 epochs using early stopping with a patient of 5 epochs looking at the validation set
- 4-second long audio sections corresponding to the front mic, sampled at 8kHz were used for training
- The learning rate was halved if the accuracy of the validation set did not improve during 3 consecutive epochs
- For the optimization, Adam [D. P. Kingma et.al., 2015] was used to maximize the scale invariant source-to-noise-ratio (SI-SNR) [J. L. Roux et.al., 2019]

Results: SI-SDR

- SI-SNR as a function of the number of attention layers and attention size



Results: Validation MBSTOI

- MBSTOI [A. H. Andersen et.al., 2018] scores as a function of the number of attention layers and attention size for the validation dataset

S	Validation MBSTOI			
	Baseline	Ind.	Single att.	Double att.
-	0.41	-	-	-
4	-	0.70	0.61	0.71
8	-	0.63	0.65	0.71
16	-	0.61	0.65	0.68
32	-	0.67	0.62	0.61
128	-	0.61	0.57	0.62
256	-	0.64	0.65	0.65
512	-	0.64	0.66	**0.77**
1024	-	0.65	0.65	0.69

Table 2: *Maximum validation MBSTOI for all of the tested algorithms. Bold value indicates the best performing algorithm configuration.*

Results: Evaluation MBSTOI

- MBSTOI [A. H. Andersen et.al., 2018] scores as a function of the number of attention layers and attention size for the evaluation dataset, for different interferer types [I. Demirsahin et.al., 2020]

Interferer	Evaluation MBSTOI	
	Baseline	Submitted Algorithm
Speech	0.34	**0.55**
Noise	0.29	**0.48**

Table 3: *Evaluation MBSTOI for the baseline system and the submitted algorithm, for different interferer types.*

Results: Speech Tests

- Due to a suboptimal individualized hearing loss compensation our algorithm obtained worse performance than the baseline provided

Conclusions

- In this work we present a binaural speech enhancement method based on deep binaural attention layers
- Noise reduction amount seems to be proportional to the number of attention layers, being significantly higher using a double attention system when compared to a non-attentive one
- We observed a threshold above which larger attention size yields poorer performance
- Future work should investigate other attention mechanisms such a additive attention to reduce computational cost

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Questions?

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