Hierarchical Attention Networks for Sentence Ordering

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Outline

- Introduction
- Prior methods
- Our approach
- Experiment & Result

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Introduction

- What's Sentence Ordering?
  - organize a given set of sentences into a coherent text in a clear and consistent manner
  - learn which ordering of sentences is likely to enhance understanding and avoid confusion
- Why do this?
  - modeling discourse coherence
  - help downstream tasks
    - multi-doc summarization
    - question answering
    - text planning

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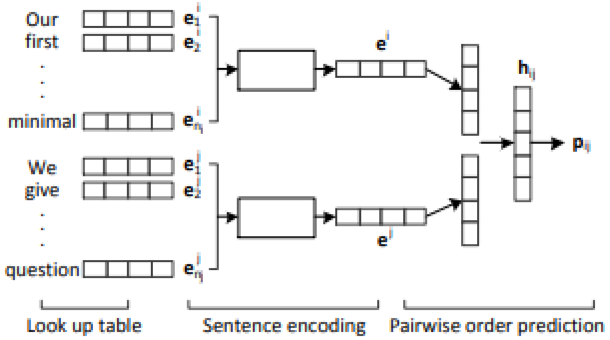
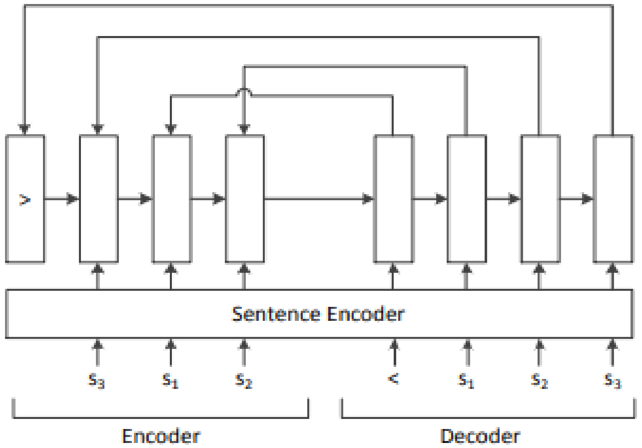
Prior methods

- Pair-wise
  - Classification
    - only consider local coherence
    - no contextual information



- End-to-end
  - RNN based pointer network
    - treats the out-of-order set of sentences as a sequential input



Chen, X.; Qiu, X.; and Huang, X. 2016. Neural sentence ordering. arXiv: Computation and Language.

Agrawal, H.; Chandrasekaran, A.; Batra, D.; Parikh, D.; and Bansal, M. 2016. Sort story: Sorting jumbled images and captions into stories. empirical methods in natural language processing 925–931.

Gong, J.; Chen, X.; Qiu, X.; and Huang, X. 2016. End-to-end neural sentence ordering using pointer network. arXiv: Computation and Language.

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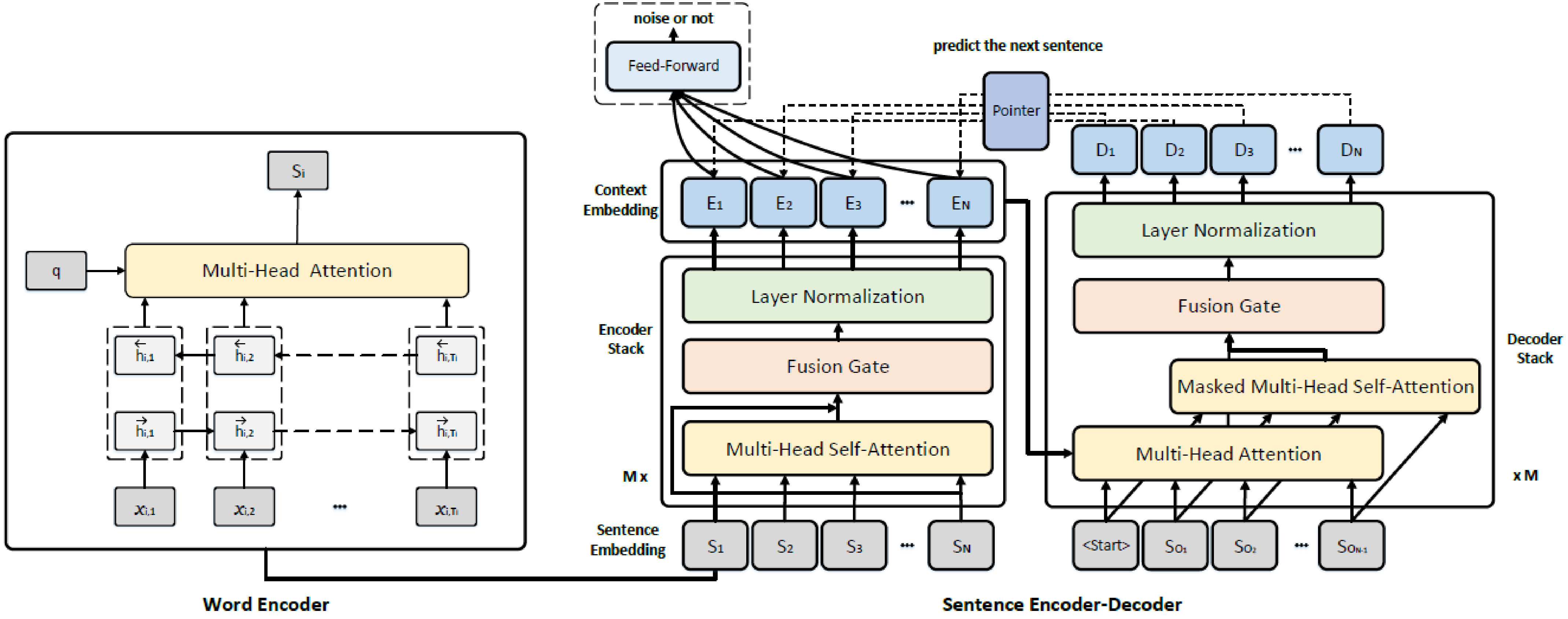
Our approach

- Hierarchical attention networks



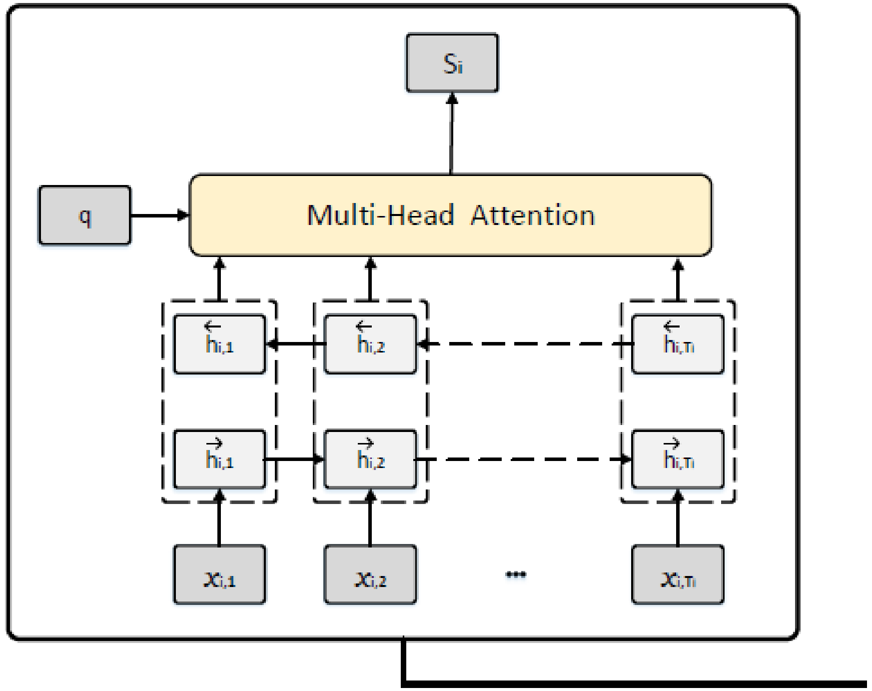
Word attention

- Word clues
  - keywords like “first” and “then” provide clues for ordering

- Multi-head attention(Transformer)

$$\hat{Q}^j = ReLU(QW_Q^j)$$
$$\hat{K}^j = ReLU(KW_K^j)$$
$$\hat{V}^j = ReLU(VW_V^j)$$
$$\hat{C}^j = softmax(\frac{\hat{Q}^j \hat{K}^{j\top}}{\sqrt{d/H}})\hat{V}^j$$
$$C = [\hat{C}^1; \hat{C}^2; ...; \hat{C}^H]$$

where Q, K, V are the packages of a set of queries, keys and values, $W_Q^j, W_K^j, W_V^j \in \mathbb{R}^{d \times d/H}$ are parameter matrices,



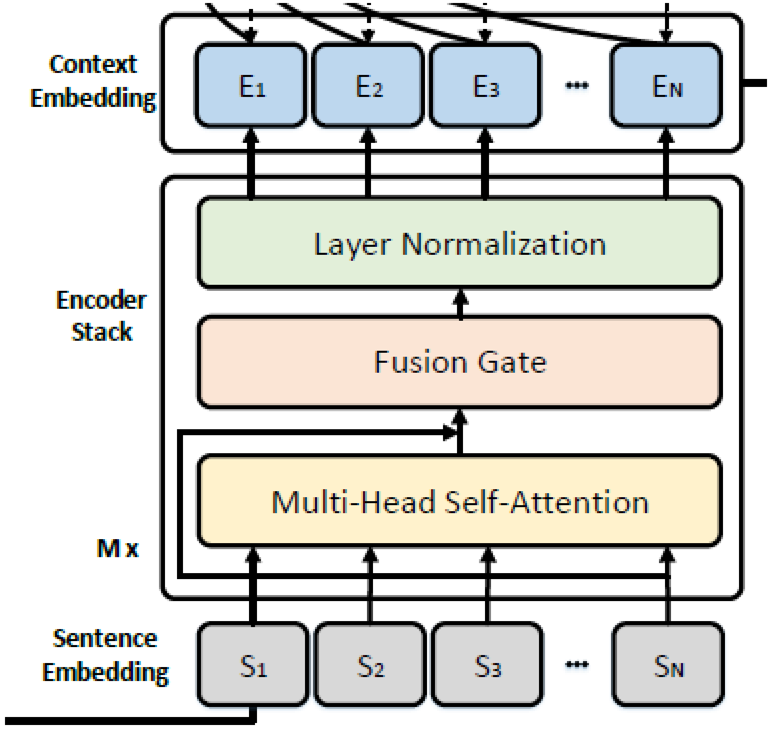
Word Encoder

Sentence encoder

- Recode sentence
  - capture global dependencies
  - adjust representations of sentences in context
- Encoder stack

$$E_{in}^j = E_{out}^{j-1}$$
$$C = MultiHead(E_{in}^j, E_{in}^j, E_{in}^j)$$
$$G = sigmoid(E_{in}^j W_{in}^j + C W_{out}^j)$$
$$F = G E_{in}^j + (1-G)C$$
$$E_{out}^j = LayerNorm(F)$$

where $W_{in}^j, W_{out}^j \in \mathbb{R}^{d\times 1}$ are parameter matrices



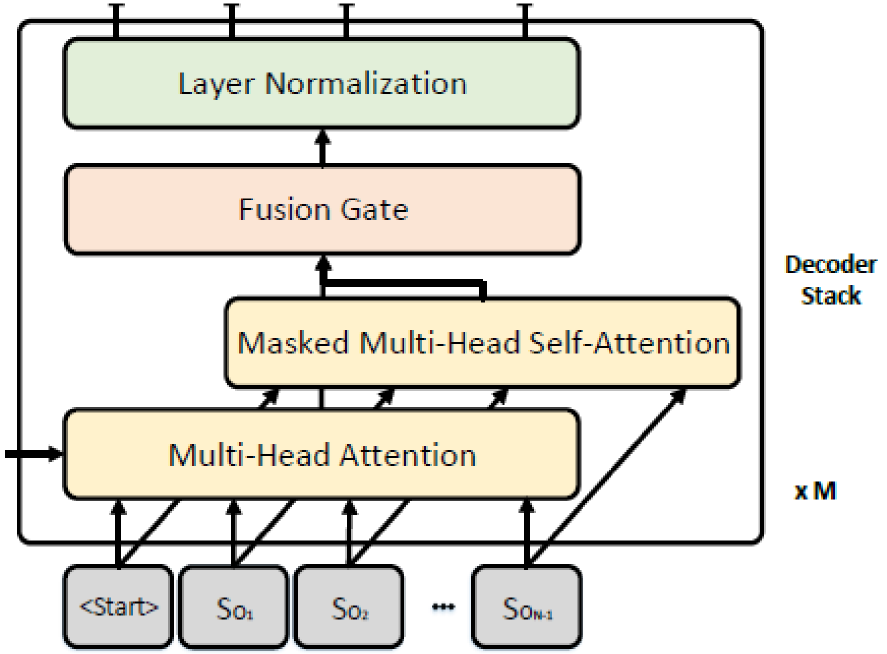
Sentence Decoder

- Masked multi-head attention
  - prevent earlier decoding steps from accessing information from later steps
  - utilize the information of ordered subsequence and construct a context for predicting the next sentence

$$Mask_{x,y} = \begin{cases} 0 & x <= y \\ -\infty & otherwise \end{cases}$$

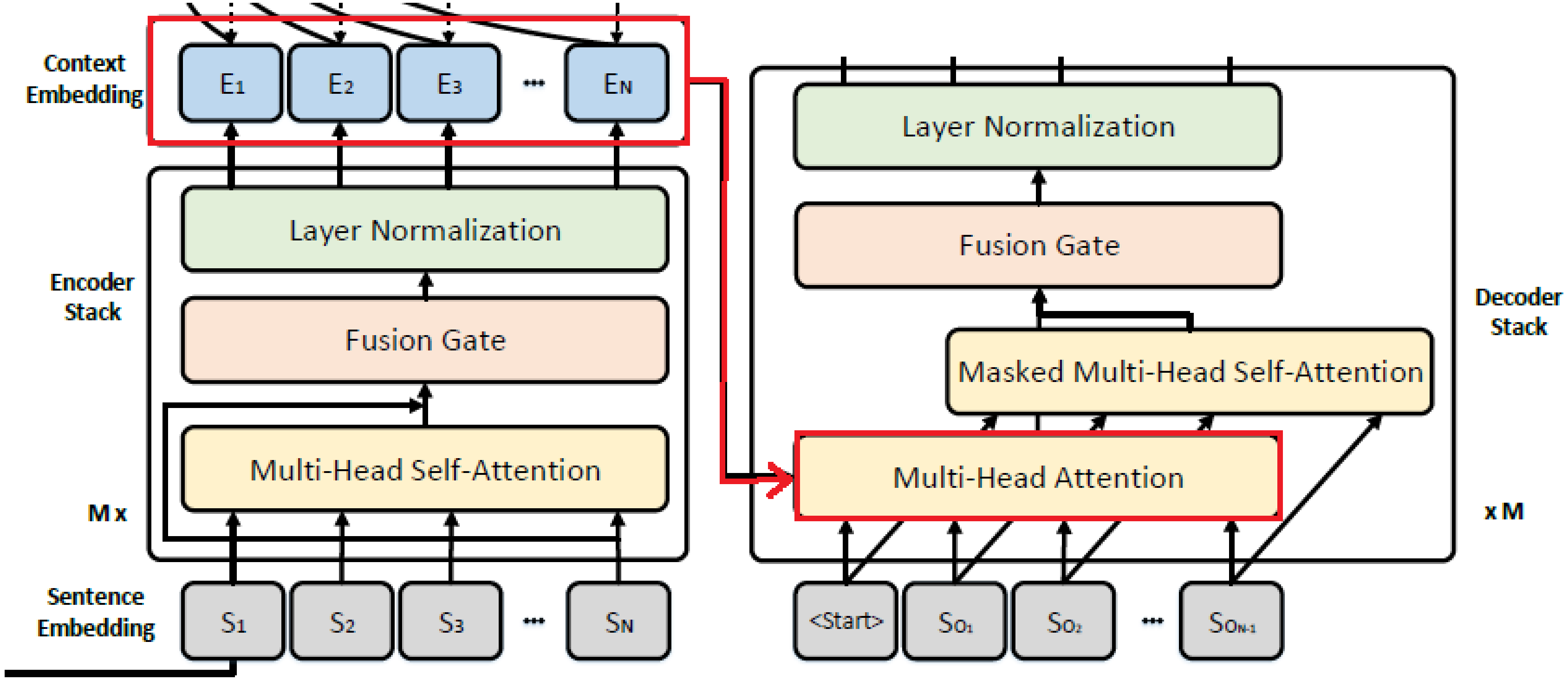
$$\hat{C}^j = softmax(\frac{\hat{Q}^j \hat{K}^{j\top} + Mask}{\sqrt{d/H}})\hat{V}^j$$

$$C = [\hat{C}^1; \hat{C}^2; ...; \hat{C}^H]$$



Sentence Decoder

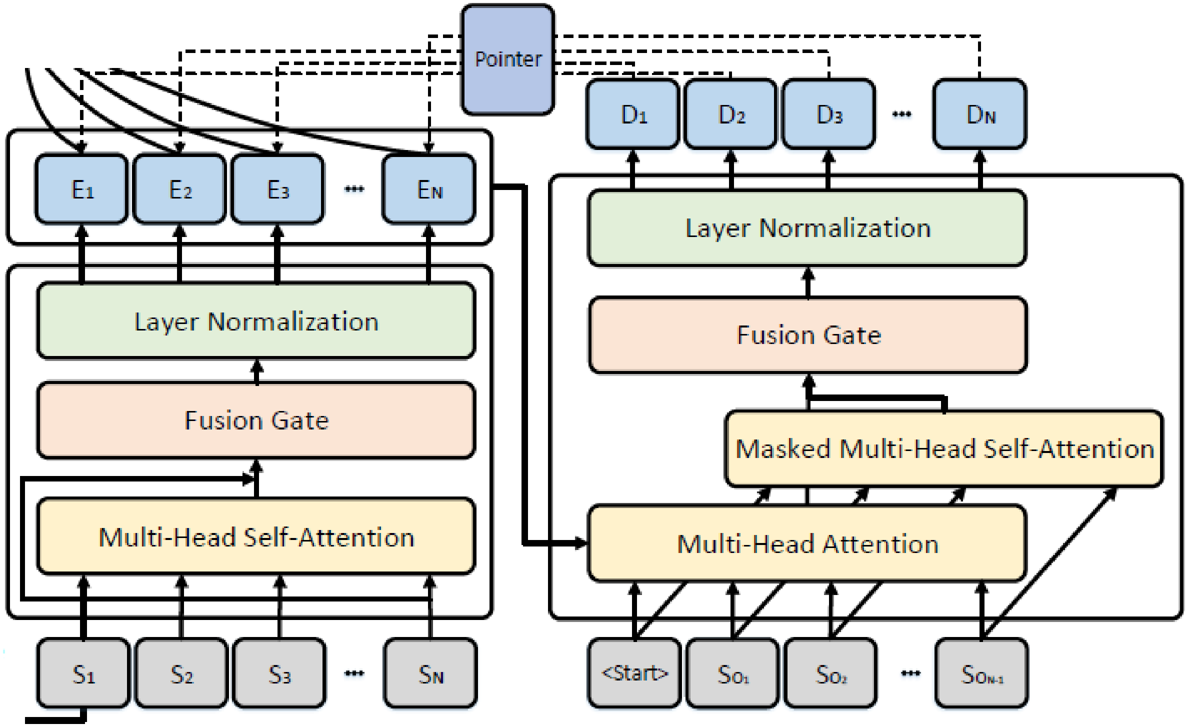
- global attention
  - utilizes the global information captured by the encoder



Sentence Decoder

- Pointer
  - predicting the next sentence
  - Inference
    - beam search

$$Q = ReLU(D^{M}_{out}W_Q)$$
$$K = ReLU(E^{M}_{out}W_K)$$
$$P = softmax(\frac{QK^{\top}}{\sqrt{d}})$$



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Experiment

- Dataset
  - arXiv
    - 884912 training abstracts, 110614 validation abstracts and 110615 testing abstracts of papers on arXiv website
    - composed of 2 to 20 sentences
  - VIST
    - 40155 training stories, 4990 validation stories and 5055 testing stories
    - composed of 5 sentences
  - ROCStory
    - 78529 training stories, 9816 validation stories and 9817 testing stories
    - composed of 5 sentences

Experiment

- Metrics
  - Kendall's tau

$$\tau = 1 - \frac{2(InvertPairs)}{N(N-1)/2}$$

where N is the number of sentences being ordered and $(InvertPairs)$ is the number of interchanges of consecutive elements necessary to arrange them in their natural order.

  - Perfect Match Ratio
    - the ratio of cases of exact match of the whole sequence

Result

Table 1: Comparison of results on three datasets

Methods	arXiv		VIST		ROCStory	
	τ	PMR	τ	PMR	τ	PMR
random	0	0.0827	0	0.0083	0	0.0083
LSTM+Pairwise (Chen, Qiu, and Huang 2016)	0.6594	0.3343	-	-	-	-
SkipThought+Pairwise (Agrawal et al. 2016)	-	-	0.4640	-	-	-
LSTM+PtrNet (Gong et al. 2016)	0.7158	0.4044	0.4842	0.1234	-	-
Seq2Seq+Pairwise (Li and Jurafsky 2017)	0.0593	0.1370	0.1892	0.1250	0.3419	0.1793
LSTM+Set2Seq (Logeswaran, Lee, and Radev 2018)	0.7281	0.4157	0.4919	0.1380	0.7112	0.3581
WordAtt+PtrNet	0.7367	0.4210	0.4925	0.1346	0.7024	0.3285
Our	**0.7536**	**0.4455**	**0.5021**	**0.1501**	**0.7322**	**0.3962**

- Parameter study on the arXiv dataset

	M	H	P_{drop}	WordAtt	τ	PMR
base	3	4	0.05	yes	**0.7536**	**0.4455**
(A)	2				0.7484	0.4419
	4				0.7515	0.4409
(B)		1			0.7437	0.4368
		2			0.7496	0.4420
		8			0.7481	0.4407
(C)			0		0.7475	0.4413
			0.1		0.7526	0.4442
(D)				no	0.7399	0.4301

Experiment with noise

- Noise
  - Randomly chosen from another abstract or story
  - Why?
    - to test the robustness and effectiveness
    - For example, if the model arranging sentence only according to words clues like “First” and “Then”, we can add a noisy sentence like “First, we…”, which is irrelevant to the abstract to cheat the model
- Strategy
  - add 1 noisy sentence (1 noise)
  - add 1 noisy sentence with a probability of 50% (0/1 noise)

Experiment with noise

- Discrimination

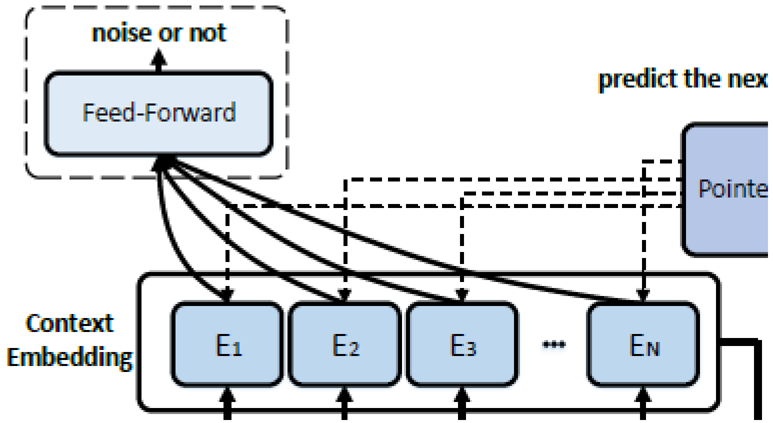
Table 3: Performance of noise discrimination.

Strategy	Methods	arXiv	VIST	ROCStory
		acc	acc	acc
1 noise	random	0.1819	0.1667	0.1667
	Our	0.9664	0.8462	0.9382
0/1 noise	random	0.2955	0.5833	0.5833
	Our	0.9330	0.9151	0.9698

- Sentence ordering

Table 4: Performance of sentence ordering on three datasets with noise.

Strategy	Methods	arXiv		VIST		ROCStory	
		PM_F	PMR	PM_F	PMR	PM_F	PMR
0 noise	random	0.5000	0.0827	0.5000	0.0083	0.5000	0.0083
	LSTM+PtrNet (Gong et al. 2016)	0.8579	0.4044	-	-	-	-
	WordAtt+PtrNet	0.8683	0.4210	0.7463	0.1346	0.8512	0.3285
	Our	**0.8768**	**0.4455**	**0.7510**	**0.1520**	**0.8661**	**0.3962**
1 noise	random	0.3178	0.0238	0.3357	0.0011	0.3326	0.0010
	LSTM+PtrNet (Gong et al. 2016)	0.8228	0.3733	-	-	-	-
	WordAtt+PtrNet	0.8271	0.3805	0.6432	0.0980	0.7852	0.2930
	Our	**0.8586**	**0.4325**	**0.6992**	**0.1283**	**0.8376**	**0.3883**
0/1 noise	random	0.3830	0.0259	0.4096	0.0049	0.4227	0.0069
	LSTM+PtrNet (Gong et al. 2016)	0.8344	0.3675	-	-	-	-
	WordAtt+PtrNet	0.8407	0.3740	0.6706	0.1064	0.7967	0.3055
	Our	**0.8516**	**0.4094**	**0.6974**	**0.1300**	**0.8293**	**0.3879**



Visualization

- Word clues
  - Darker shades correspond to higher attention weights

$$\alpha = \frac{1}{H}\sum_{j=1}^{H} softmax(\frac{\hat{Q}^j \hat{K}^{j\top}}{\sqrt{d/H}})$$

In this paper some important inequalities are revisited . First , as motivation , we give another proof of the Hardy 's inequality applying convenient vector fields as introduced by Mitidieri , see [6] . Then , we investigate a particular case of the Caffarelli-Kohn-Nirenberg 's inequality . Finally , we study the Rellic 's inequality .
Wireless microsensor networks , which have been the topic of intensive research in recent years , are now emerging in industrial applications . An important milestone in this transition has been the release of the IEEE 802.15.4 standard that specifies interoperable wireless physical and medium access control layers targeted to sensor node radios . In this paper , we evaluate the potential of an 802.15.4 radio for use in an ultra low power sensor node operating in a dense network . Starting from measurements carried out on the off-the-shelf radio , effective radio activation and link adaptation policies are derived . It is shown that , in a typical sensor network scenario , the average power per node can be reduced down to 211m mm mW . Next , the energy consumption breakdown between the different phases of a packet transmission is presented , indicating which part of the transceiver architecture can most effectively be optimized in order to further reduce the radio power , enabling self-powered wireless microsensor networks .
Jimmy needed to break up with his girlfriend . He drove to her house and knocked on her door . She answered a minute later and they began to talk . Jimmy told her the bad news and she began to cry . Jimmy left the scene and felt very bad about himself .

Thanks