A Case Study on

Neural Headline Generation

for Editing Support

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Summary

Our work

Address "short title" generation for a news aggregation service,
 where editors create short titles to introduce important articles

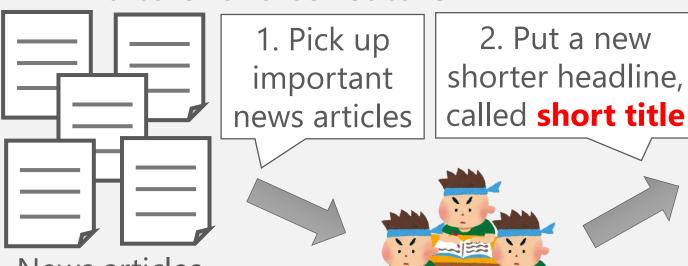
Contributions

- Show a practical use case of neural headline generation
 - Most news articles basically already have headlines
- Propose an encoder-decoder model with multiple encoders
- Deploy our model to an editing support tool and show the results of comparing the editors' behavior



Yahoo! News

- Biggest news portal in Japan
 - PV/month: 15,000,000,000+
 - Editors' choice feature ->



News articles delivered by providers

Professional editors

Pros:

- Quick understandability
- Saving display space



Editor's choice feature



Short title generation as editing support

- Purpose: To generate short title candidates to help editors
- Task: Translation from (headline, lead) to short title
 - Lead is a short version (summary) of the article





List of news articles



Example of (short title, headline, lead)

Phrase order is changed Japanese /

Short title

Headline

首相 忖度ないと言い切れず

忖度なかったと言い切ることはできない=加

計問題で安倍首相

Lead

安倍晋三首相は14日午後行われた参院予算 委員会の集中審議で、加計疑惑などを巡り、 官僚側から首相に対する忖度(そんたく)が あったのではとの指摘に対して「忖度があっ たかどうか、忖度される側には分かりにくい 面もある」と述べた。「忖度がなかったと言 い切ることはできない」としつつ、「ごまを <u>する</u>ための忖度は求めていない」などと説明 Lengths are 。塚田一郎委員(自民)への答弁。

English translation

The prime minister cannot say that there is no surmise It cannot be said that there is no "sontaku (surmise)" with absolute certainty. The prime minister Abe said about the problem of "Kake Gakuen (Kake school)".

Prime Minister Shinzo Abe said, in an intensive deliberation with the House of Councilors Budget Committee held on the afternoon of the 14th, as an answer to a question about whether bureaucrats surmised to the prime minister regarding the Kake suspicion, "It is difficult to understand whether there is a sontaku (surmise)". He said "It cannot be said that there was nothing wrong," while explaining that "I do not need to be obsequious". An answer to Ichiro Tsukada (LDP).

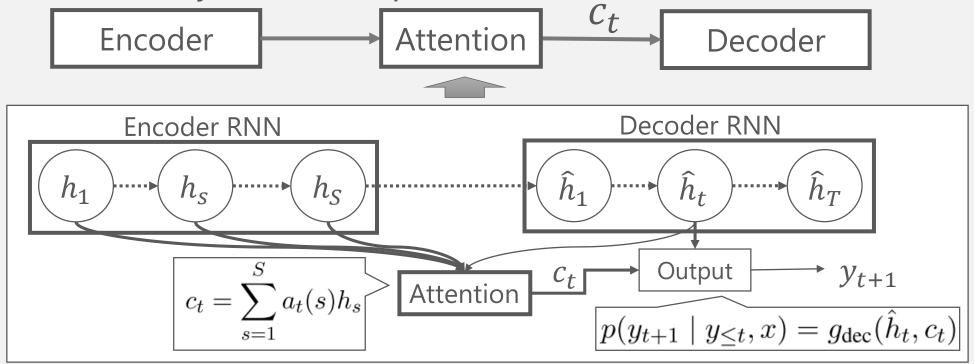
Short title generation task is not so easy



different

Encoder-decoder model with attention

- Conditional language model consisting of two RNNs
 - Described by three components (encoder, attention, decoder)

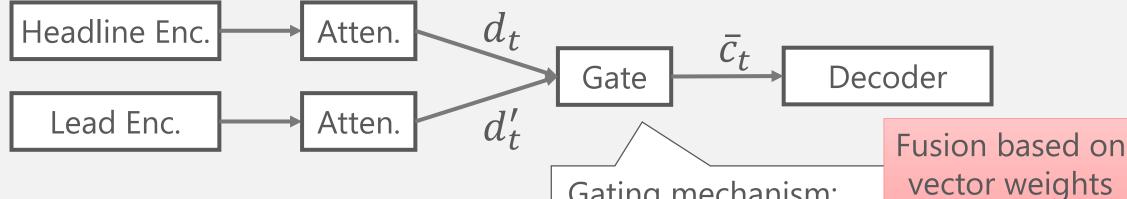


Attention calculates a context c_t from the encoder's states h_s



Proposed method: GateFusion

Combine headline and lead contexts w/ gating mechanism



Existing work (Hori+ 2017) used an attention mechanism

$$\overline{c}_t = \alpha d_t + \beta d_t'$$

Fusion based on scalar weights



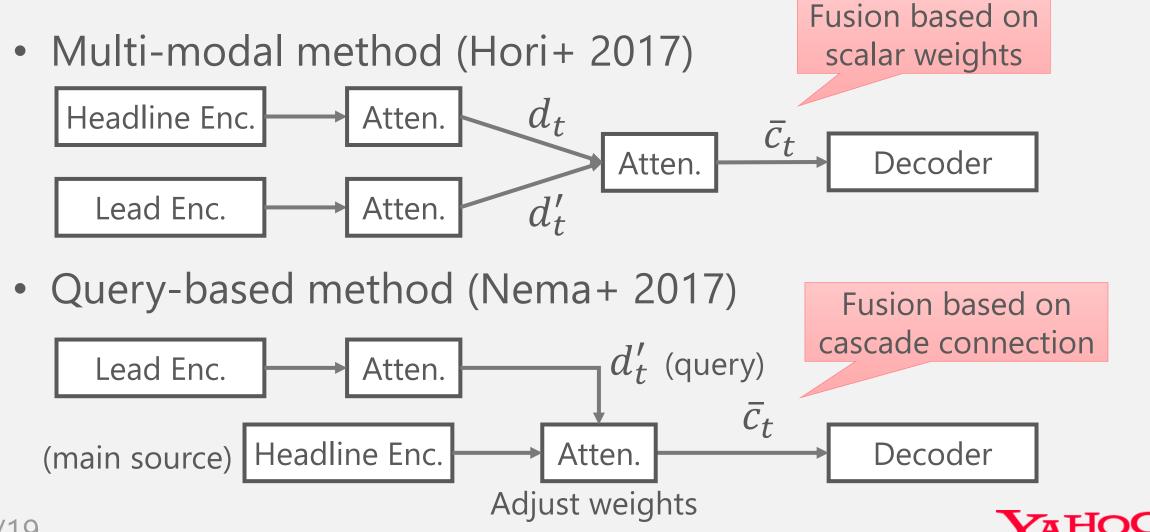
$$w_t = \sigma(W[d_t; d'_t; \hat{h}_t]),$$

$$w'_t = \sigma(W'[d_t; d'_t; \hat{h}_t]),$$

$$\bar{c}_t = w_t \odot d_t + w'_t \odot d'_t,$$



Baselines with multiple encoders



Training dataset

- 263K triples of (headline, lead, short title) in Yahoo! News
 - Training (90%), validation (5%), testing (5%)
- Statistics:

	Headline	Lead	Short title
Average length	24.87	128.49	13.05
Character type	3618	4226	3156

- Extractively solvable instances: 20%
 - Characters in each short title are completely covered by the headline
- Edit distance of headlines and short titles: 23.74
 - Short titles cannot be easily created only from headlines



Model and training settings

- Implemented on OpenNMT
- Headline encoder: BiLSTM
- Lead encoder: CNN (Kim, 2014)
 - To reduce the computational time
- Ensemble of 10 models
- Hyper-parameter settings are listed in the right table

Hyper-parameter	Value
# of layers (RNN, CNN)	3
# of units (embedding)	200
# of units (RNN, CNN)	400
# of units (context)	400
Window width of CNN	7
Dropout rate	0.3
Learning rate	0.05
Momentum rate	0.8
Learning_decay rate	0.85
# of epochs	20
Batch size	64
Beam width	5



Human evaluation by crowdsourcing

- Two crowdsourcing tasks for readability and usefulness
 - Average score of 10 workers for each of 1,000 outputs

- Readability (four-point scale)
 - How readable a short title was
- Usefulness (four-point scale)
 - How useful a short title was compared to the headline



Evaluation results (1/2)

Our model performed well for the usefulness measure

		Readablity	Usefulness	Average =	=(R+U)/2
Correct titles	Editor	3.62	3.18	3.40	
First 13 chars	Prefix	2.72	2.38	2.55	
Single enc.	OpenNMT	3.53	3.16	3.35	
Multi enc.	MultiModal QueryBased	3.51	3.12	3.32	
	QueryBased	3.52	3.11	3.32	
Our model	GateFusion	3.50	↑3.22	3.36	

Complicated expressions

Aggressively copy characters



Evaluation results (2/2)

Our model performed well for the usefulness measure

		Readablity	Usefulness	Average	=(R+U)/2
Correct titles	Editor	3.62	3.18	3.40	
First 13 chars	Prefix	2.72	2.38	2.55	
Single enc.	OpenNMT	3.53	3.16	3.35	
Multi enc.	MultiModal	3.51	3.12	3.32	
	QueryBased	3.52	3.11	3.32	Close to
Our models -	GateFusion	3.50	†3.22	3.36	Editor
Gate+Query	HybridFusion	†3.55	†3.22	†3.39	

QueryBased helped GateFusion generate headline-style outputs

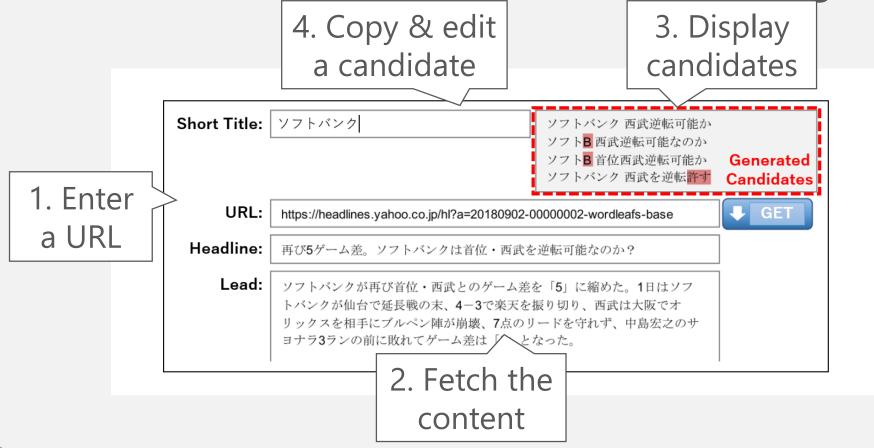


	Input and generated title (Japanese)			
	Headline	逆境をチャンスに変えた <mark>ダルビッシュ</mark> の進化く	Last word	
	Lead	レンジャーズの <u>ダルビッシュ</u> 有(29)が 28	tends to k	
		日、本拠地で行われたパイレーツ戦で[]	importar	
Best	Editor	術前より進化 ダルの肉体改造		
baseline	ackslash OpenNMT	逆境をチャンスに変えた <mark>進化</mark>		
Our best	>HybridFusion	ダル 逆境をチャンスに変えた		
model				
		English translation		
	Headline	Evolution of Darvish turning adversity into opportunity. Yu Darvish (29) in Rangers took a mound for the first time		
	Lead			
	in 1 year and 9 months with Pirates []			
	Editor	Dar sculpted his body better than before surgery.		
	OpenNMT Evolution; turning adversity into opportunity.			
	HybridFusion	Dar turned adversity into opportunity.		



Editing support tool

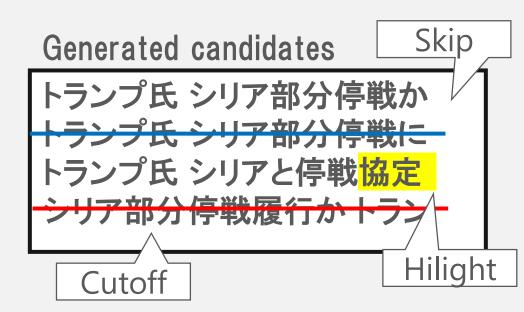
Editors can check candidates when creating short titles





Functionalities in the tool

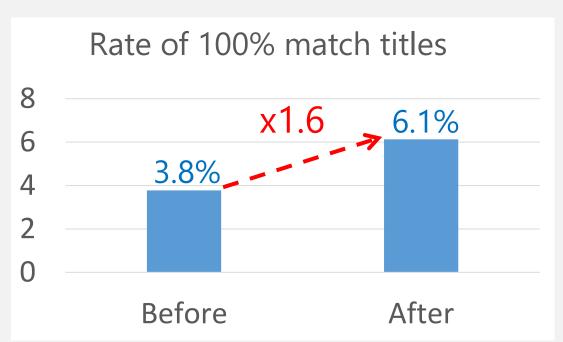
- Cutoff unpromising candidates
 - If perplexity>x
 - To keep the system quality
- Skipping redundant candidates
 - If edit distance<y
 - To display various outputs
- Highlighting unknown characters
 - If not in the article
 - To encourage fact checking

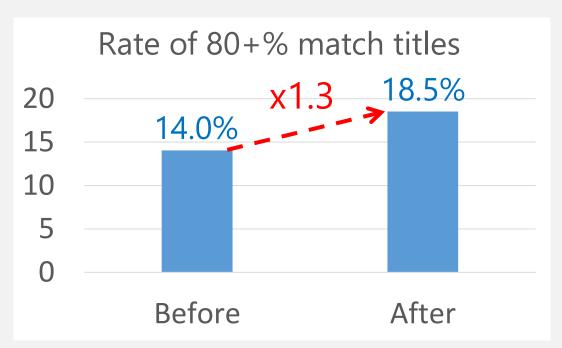




Effect of the tool release

- Editors' behavior in three weeks before/after the release
 - Rate at which an editor's title matches the generated one by X%





Editors began to refer to generated outputs after the release

Conclusion

- Short titles were successfully generated for editing support
- Editors began to refer to generated titles of our system
- Future work
 - Verify how much our model can affect click-through rate
 - Need a much safer model to avoid generating fake titles
- Acknowledgements
 - We would like to thank editors and engineers in the news service who continuously supported our experiments



Thank you for your attention!

