



Neural Machine Translation with Word Predictions

Rongxiang Weng, Shujian Huang, Zaixiang Zheng, Xinyu Dai and Jiajun Chen State Key Laboratory for Novel Software Technology Nanjing University

Nanjing 210023, China

{wengrx, huangsj, zhengzx, daixy, chenjj}@nlp.nju.edu.cn





Outline



- Background
- Motivation
- Approach
- Experiment
- Conclusion



Outline



- Background
- Motivation
- Approach
- Experiment
- Conclusion



Neural Machine Translation







Neural Machine Translation







Encoder-Decoder Framework



• Decoder: decode target sentence start from this fragmentation of the start from the start from







• Encoder and Decoder are connected by Initial State





Encoder-Decoder Framework



- Initial State has all target information
- Hidden States of Decoder have target information which have hot been generated **For Sequence Learning**





Outline



- Background
- Motivation
- Approach
- Experiment
- Conclusion







- Initial State does not have a direct control
- Hidden States of Decoder are just supervised by current word For









- The initial state and hidden state plays an important role of translation, but it does not have a good control in the durrently researcher
 - **To Sequence Learning**
- Propagating translation errors through the end-to-end recurrent structures is not enough of control the hidden states



Outline



- Background
- Motivation
- Approach
- Experiment
- Conclusion



Word Prediction



- Translation task to generate an ordered sequence
- The goal of word prediction is to generate several words which is no order







Word Prediction



- Words in the target sentence could be viewed as a natural annotation
- Initial State and Hidden States should containing factor about words in target sentence
 To Sequence Learning



Word Prediction



- For the Initial State (WP_E)
- For Decoder's Hidden States (WP_D) sed Pretraining For To Sequence Learning



WP for the Initial State



• Initial State is responsible for the translation of whole target sentence, it should contain information of each word in the target sentence retraining For **For Sequence Learning**





WP for the Initial State



• Initial State is responsible for the translation of whole target sentence, it should contain information of each word in the target sentence retraining For **For Sequence Learning**

















Make use of word predictor



- Using large vocabulary will reduce decoding efficiency
- Exact small vocabulary will produce better translation effects Io Sequence Learning
- In the testing stage, word prediction mechanism can predict a small vocabulary to decode



Make use of word predictor



- Predicting top-k words as new vocabulary
 - sed Pretraining For Using the new vocabulary to decode **To Sequence Learning** Vocabulary Decoder $\mathcal{V}1$ $\mathcal{V}2$ Vi $y_1y_2\cdots y_j\cdots$ Initial State Encoder $\overrightarrow{h_2}$ $\overrightarrow{h_i}$ $\overrightarrow{h_1}$ \dot{h}_1 h_2 $h_{\rm i}$ x_1 x_2 x_i



 $WP_E + WP_D (WP_{ED})$



- Training stage
 - WP_E mechanism
 - WP_D mechanism
- Testing stage
 - WP_E as word predictor





Outline



- Background
- Motivation
- Approach
- Experiment
- Conclusion



Data and Setting



- Chinese-English (CH-EN)
 - 8M LDC data set as training set
 - MT02 as validation set
 - MT03, MT04 and MT05 as test sets
 - Both validation set and test sets have 4 references
- German-English (DE-EN)
 - WMT14 as training set
 - Newstest 2012 as validation set
 - Newstest 2013 as test set
 - Both validation set and test set have 1 reference







- The source and target vocabularies are limited to the most frequent 30K words sed Pretraining For
- The out-of-vocabulary words mapped searspected lokanting.
- Using *EOS* as the end-of-sentence symbol
- Sentences were encoded using byte-pair encoding (BPE) on DE-EN experiments







• Using WP_{ED} technique improves the baseline by **4.53** BLEU on the CH-EN experiment and **1.3** BLEU on the DE-EN experiment **Experiment For**

Models	MT02(dev)	MT03C	MF64u	enges1	-qest Aves	IMP
baseNMT	34.04	34.92	36.08	33.88	34.96	
WPE	39.36	37.17	39.11	36.20	37.49	+2.53
WPD	40.28	38.45	40.99	37.90	39.11	+4.15
WP _{ED}	40.25	39.50	40.91	38.05	39.49	+4.53

Chinese-English

Models	NST13(dev)	NST14	IMP
baseNMT	23.56	20.68	_
WP _E	24.44	21.09	+0.41
WPD	25.31	21.54	+0.86
WP _{ED}	25.97	21.98	+1.3







• Using WP_{ED} technique improves the baseline by **4.53** BLEU on the CH-EN experiment and **1.3** BLEU on the DE-EN experiment in the DE-EN experiment in the technique improves the baseline by **4.53** BLEU on the CH-EN

Models	MT02(dev)	MT030	MF64u	enges I	- qastaves	IMP
baseNMT	34.04	34.92	36.08	33.88	34.96	
WPE	39.36	37.17	39.11	36.20	37.49	+2.53
WPD	40.28	38.45	40.99	37.90	39.11	+4.15
WP _{ED}	40.25	39.50	40.91	38.05	39.49	+4.53

Chinese-English

Models	NST13(dev)	NST14	IMP
baseNMT	23.56	20.68	—
WP _E	24.44	21.09	+0.41
WPD	25.31	21.54	+0.86
WP _{ED}	25.97	21.98	+1.3





• Along with ensemble method, the improvement could be up to **5.79** BLEU on the CH-

EN and 1.79 BLEU on the DE-EN

sed Pretraining For To Sequence Learning

Models	Test	IMP
baseNMT	34.86	_
WP _{ED}	39.49	+4.53
baseNMT-dropout	37.02	+2.06
WP _{ED} -dropout	39.25	+4.29
baseNMT-ensemble(4)	37.71	+2.75
WP _{ED} -ensemble(4)	40.75	+5.79

Models	Test	IMP
baseNMT	20.68	_
WP _{ED}	21.98	+1.3
baseNMT-dropout	21.62	+0.94
WP _{ED} -dropout	21.71	+1.03
baseNMT-ensemble(4)	21.58	+0.9
WP _{ED} -ensemble(4)	22.47	+1.79

Chinese-English





• Along with ensemble method, the improvement could be up to **5.79** BLEU on the CH-

EN and 1.79 BLEU on the DE-EN

sed Pretraining For To Sequence Learning

Models	Test	IMP
baseNMT	34.86	—
WP _{ED}	39.49	+4.53
baseNMT-dropout	37.02	+2.06
WP _{ED} -dropout	39.25	+4.29
baseNMT-ensemble(4)	37.71	+2.75
WP _{ED} -ensemble(4)	40.75	+5.79

Models	Test	IMP
baseNMT	20.68	_
WP _{ED}	21.98	+1.3
baseNMT-dropout	21.62	+0.94
WP _{ED} -dropout	21.71	+1.03
baseNMT-ensemble(4)	21.58	+0.9
WP _{ED} -ensemble(4)	22.47	+1.79

Chinese-English





• Along with ensemble method, the improvement could be up to **5.79** BLEU on the CH-

EN and 1.79 BLEU on the DE-EN

sed Pretraining For To Sequence Learning

Models	Test	IMP
baseNMT	34.86	—
WP _{ED}	39.49	+4.53
baseNMT-dropout	37.02	+2.06
WP _{ED} -dropout	39.25	+4.29
baseNMT-ensemble(4)	37.71	+2.75
WP _{ED} -ensemble(4)	40.75	+5.79

Models	Test	IMP
baseNMT	20.68	_
WP _{ED}	21.98	+1.3
baseNMT-dropout	21.62	+0.94
WP _{ED} -dropout	21.71	+1.03
baseNMT-ensemble(4)	21.58	+0.9
WP _{ED} -ensemble(4)	22.47	+1.79

Chinese-English



Precision and Recall



• The initial state in WP_E contains more specific information about target words

	sed Pretraining For					
top	base	NMT	uence W	Learning P _E		
top-11	Prec.	Recall	Prec.	Recall		
top-10	45%	17%	73%	30%		
top-20	33%	21%	63%	43%		
top-50	21%	30%	41%	55%		
top-100	14%	39%	28%	68%		
top-1k	2%	67%	4%	89%		
top-5k	0.7%	84%	0.9%	95%		
top-10k	0.4%	90%	0.5%	97%		



Precision and Recall



• The initial state in WP_E contains more specific information about target words

	sed Pretraining For					
	hase	NMT Sec	uence]	earning		
top-n	Prec.	Recall	Prec.	Recall		
top-10	45%	17%	73%	30%		
top-20	33%	21%	63%	43%		
top-50	21%	30%	41%	55%		
top-100	14%	39%	28%	68%		
top-1k	2%	67%	4%	89%		
top-5k	0.7%	84%	0.9%	95%		
top-10k	0.4%	90%	0.5%	97%		



Decoding Efficiency



• With a 6k predicted vocabulary, the cost is about 60% of a full-vocabulary; the performance is comparable fixed-vocabulary **Pstetraining For**



sentence.

Decoding time with different vocabulary sizes for each sentence.



Decoding Efficiency



• With a 6k predicted vocabulary, the cost is about 60% of a full-vocabulary; the performance is comparable fixed-vocabulary **Pstemaining For**



BLEU scores with different vocabulary sizes for each sentence.

Decoding time with different vocabulary sizes for each sentence.



Translation Example



 WP_{ED} carries the exact information during translation, most of errors no longer exist sed Pretraining For

source	时代华纳公司的网络公司美国线 Lo 说 它预期nce 。 Leathing 商业销售将由 二。。一年的二十七亿美元减少到十五亿美元。
reference	america online, the internet arm of time warner conglomerate, said it expects
	advertising and commerce revenue to decline from us \$ 2.7 billion in 2001 to us \$ 1.5
	in 2002 .
baseNMT	in the us line, the internet company 's internet company said on the internet that it
	expected that the business sales in 2002 would fall from \$ UNK billion to \$ UNK billion
	in 2001.
WP _{ED}	the internet company of time warner inc., the us online, said that it expects that the
	advertising and commercial sales in 2002 will decrease from \$ UNK billion in 2001
	to us \$ 1.5 billion .



Translation Example



WP_{ED} carries the exact information during translation, most of errors no longer exist
sed Pretraining For

source	时代华纳公司的网络公司美国线 Loix 它预期 noce Lot 的前先 商业销售将由 二 o o 一年的二十七亿美元减少到十五亿美元。
reference	america online, the internet arm of time warner conglomerate, said it expects
	advertising and commerce revenue to decline from us \$ 2.7 billion in 2001 to us \$ 1.5
	in 2002 .
baseNMT	in the us line, the internet company 's internet company said on the internet that it
	expected that the business sales in 2002 would fall from \$ UNK billion to \$ UNK billion
	in 2001.
WP _{ED}	the internet company of time warner inc., the us online, said that it expects that the
	advertising and commercial sales in 2002 will decrease from \$ UNK billion in 2001
	to us \$ 1.5 billion.



Outline



- Background
- Motivation
- Approach
- Experiment
- Conclusion







- The backpropagation provides no direct control of the information carried by the hidden states. sed Pretraining For
 - **To Sequence** Learning
- Word prediction mechanism can enhance the initial state and hidden states of decoder as well.





sed Pretraining For To Sequence Learning

Thanks