Apply Chinese Radicals Into Neural Machine Translation: Deeper Than Character Level

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ADAPT, Dublin City University
Limerick, Ireland, May 24

LPRC 2018: Limerick Postgraduate Research Conference

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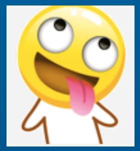
Agenda

- Myself
- Topic intro
- Related work
- Proposed idea/model
- Experiments design
- Evaluation results
- Future work

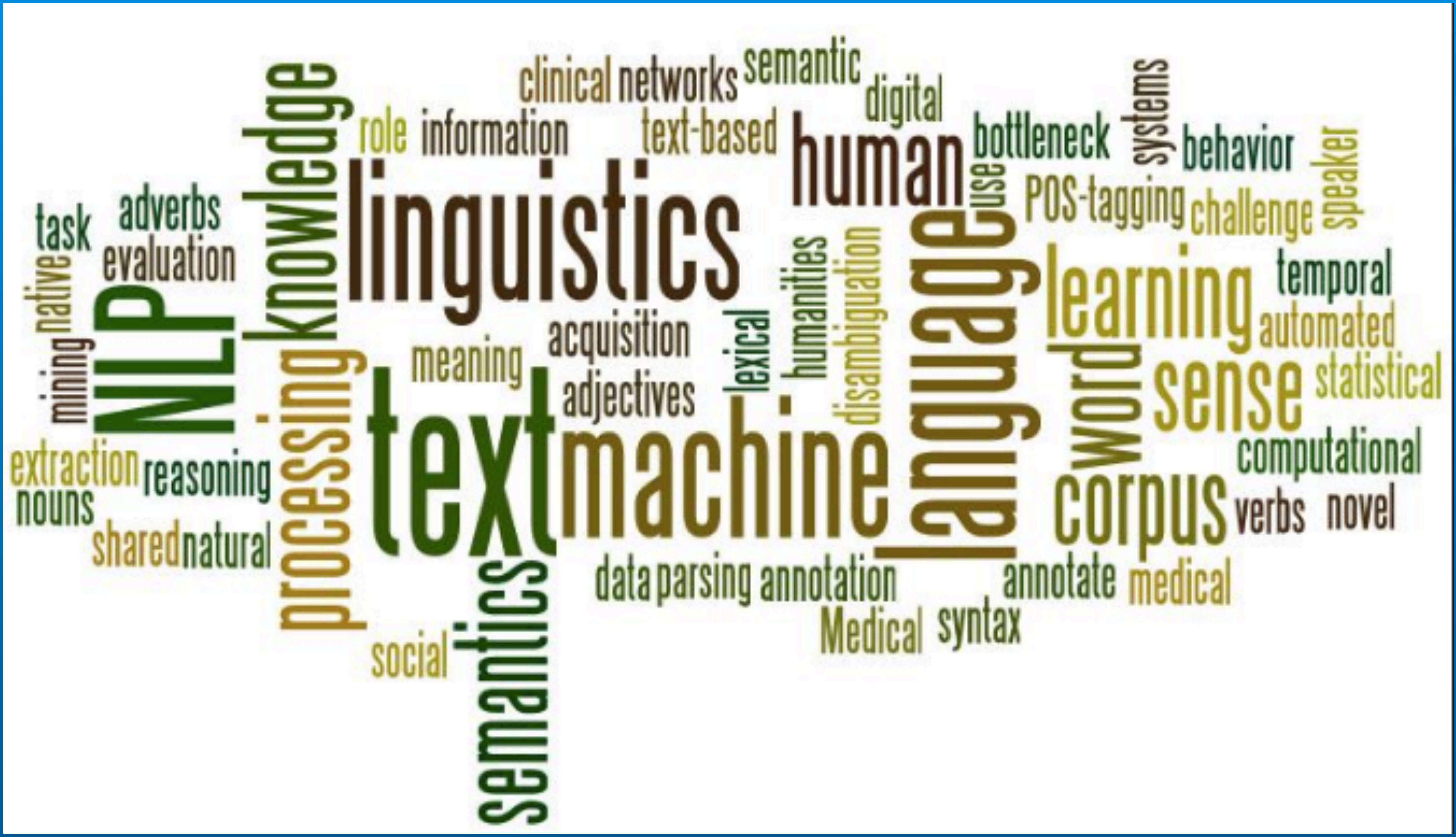
Myself

- PhD student, ADAPT Centre, DCU, Dublin, 2016 on
- Student Researcher, Amsterdam, 2014-16
- Master degree of Sci., Macau, 2011-14
- Bachelor of Maths, Shijiazhuang, 2007-11
- Primary ~ high school, Handan
- No kindergarten 

Intro

- Machine Translation
  - - what I’ m doing. Translate human languages via Machine.
- Natural Language Processing
  - - different processing tasks of human languages
- Artificial Intelligence
  - - teach machine to perform human intelligences

MT-NLP-AI



From: *vikingsna.org*

Related work

- Machine Translation: Rule to Neural
  - - rule, example-based, statistical, phrase-based, hierarchical structure, tree-best, forest, neural models
- Neural MT, sequence to sequence, attention, coverage
  - - word embeddings, sequence to sequence encoding-decoding, attention, coverage, document/discourse level
- Chinese NLP, radical applications
  - - Word Segmentation, Entity recognition, MT, Sentiment Analysis, text mining

Chinese radical: example

Fig. 1: Radical as independent character.

Chinese radical: example

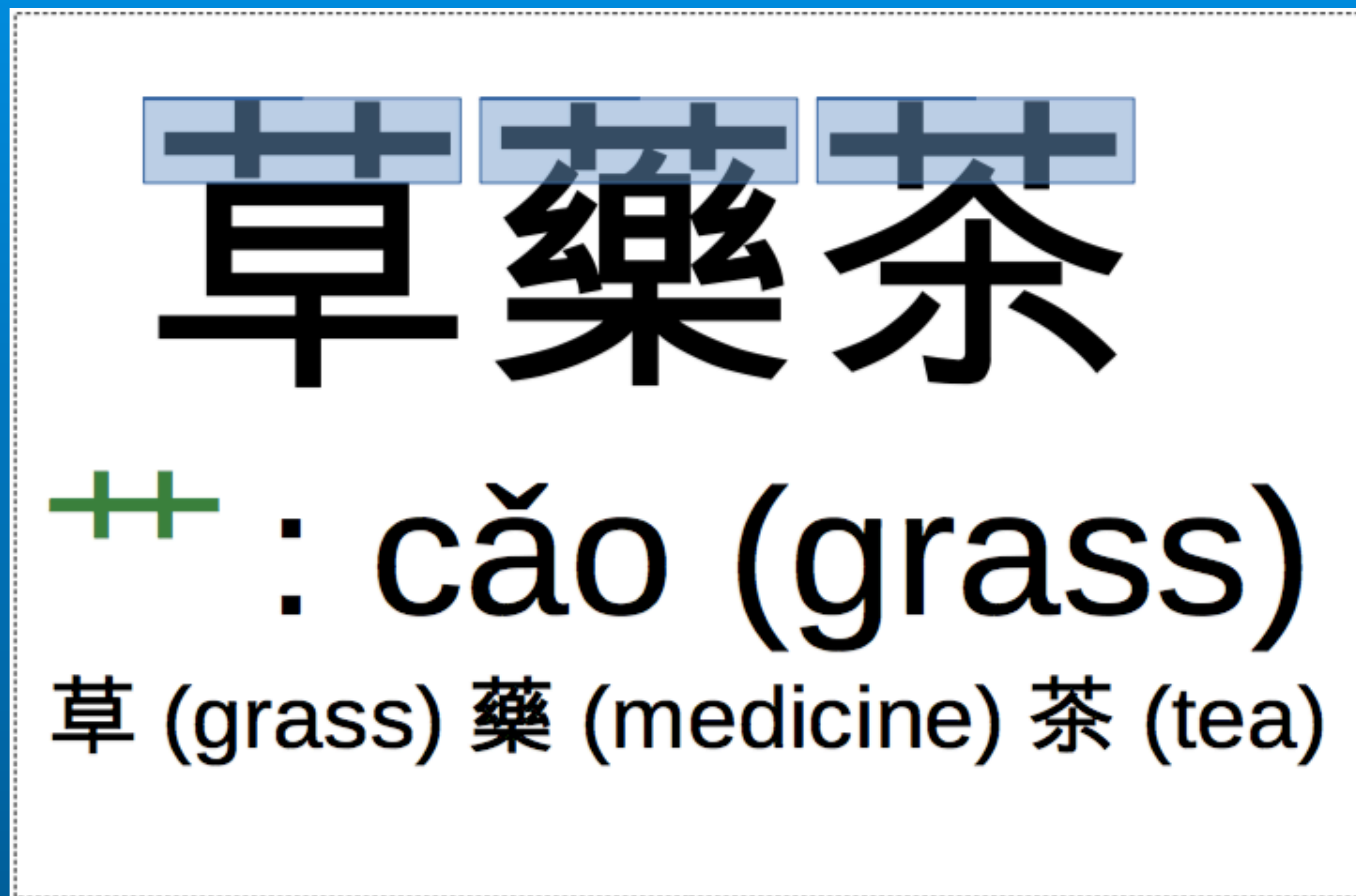


Fig. 2: Radical can not be independent character.

Proposed Model

- Apply Chinese Radical into Translation
  - - how to apply radicals into MT
  - - how to split character into radicals
- Combine radical-level MT with Neural Model
  - - attention-based Neural MT
  - - radical combination into input data

Combinations

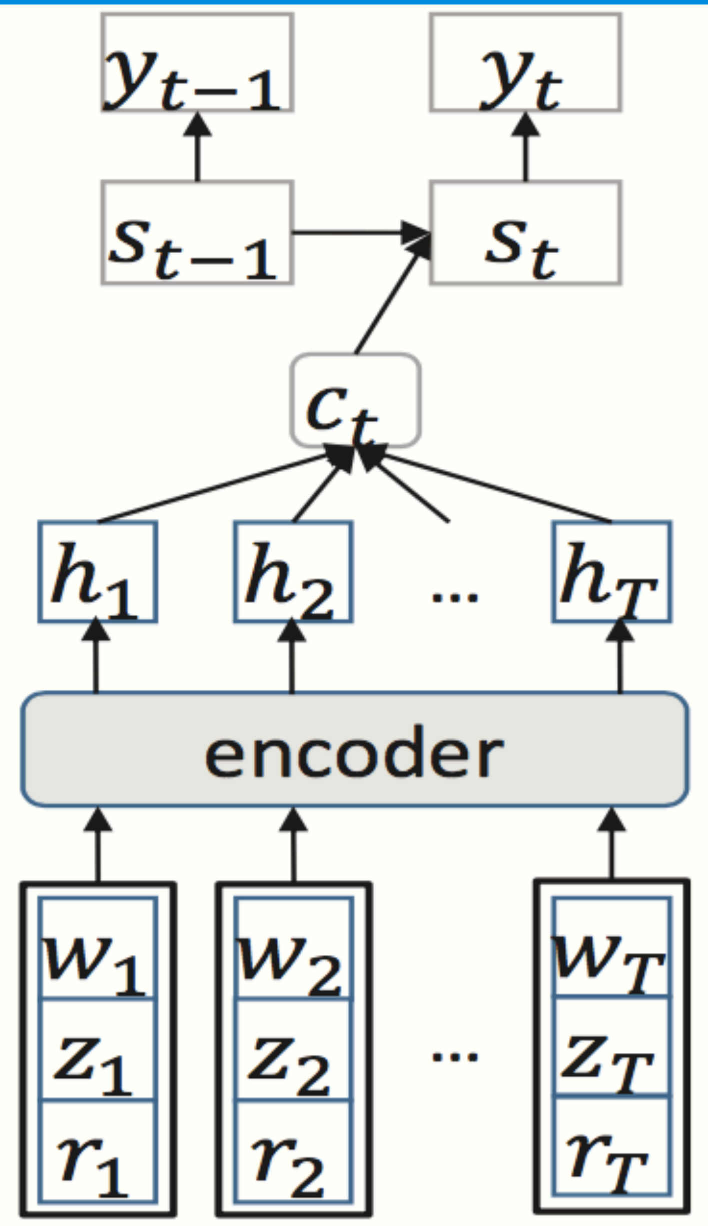


Fig. 3: Architecture of NMT with multi-embedding.

Experiments

- Attention Neural MT
  - Word+Character+Radical
  - Word+Character
  - Character+Radical
  - Word+Radical
- Data prepration
  - Training: 1.25 million parallel Chinese-English sentences / 80.9 millions Chinese words and 86.4 millions English
  - Development / testing: NIST06/NIST08 (National Institute for Standards and Technology, USA)

Settings

Table 1: Model Settings

Settings	Description	abbreviation
Baseline	Words	W
Setting1	Word+Character+Radical	W+C+R
Setting2	Word+Character	W+C
Setting3	Word+Radical	W+R
Setting4	Character+Radical	C+R

Evaluation

- Broader Evaluation Metrics
  - hLEPOR, BEER, CharacTER -> BLEU, NIST
- Evaluation Scores
  - - in-depth analysis

MT evaluation metric LEPOR
Code & WIKI: https://en.wikipedia.org/wiki/LEPOR

Development data BLEU

Table 2: BLEU Scores on NIST06 Development Data

	1-gram	2-gram	3-gram	4-gram
Baseline	.7211	.5663	.4480	.3556
W+C+R	**.7420**	**.5783**	**.4534**	**.3562**
W+C	.7362	.5762	.4524	.3555
W+R	.7346	.5730	.4491	.3529
C+R	.7089	.5415	.4164	.3219

Development data NIST

Table 3: NIST Scores on NIST06 Development Data

	1-gram	2-gram	3-gram	4-gram	5-gram
Baseline	5.8467	7.7916	8.3381	8.4796	8.5289
W+C+R	**6.0047**	**7.9942**	**8.5473**	**8.6875**	**8.7346**
W+C	5.9531	7.9438	8.5127	8.6526	8.6984
W+R	5.9372	7.9021	8.4573	8.5950	8.6432
C+R	5.6385	7.4379	7.9401	8.0662	8.1082

Development data Broader

Table 4: Broader Metrics Scores on NIST06 Development Data

	Metrics on Single Reference		
Models	hLEPOR	BEER	CharacTER
Baseline	.5890	.5112	.9225
W+C+R	.5972	**.5167**	**.9169**
W+C	**.5988**	.5164	.9779
W+R	.5942	.5146	.9568
C+R	.5779	.4998	1.336

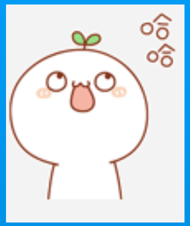
Testing data BLEU 

Table 5: BLEU Scores on NIST08 Test Data

	1-gram	2-gram	3-gram	4-gram
Baseline	.6451	.4732	.3508	.2630
W+C+R	**.6609**	**.4839**	**.3572**	**.2655**
W+C	.6391	.4663	.3412	.2527
W+R	.6474	.4736	.3503	.2607
C+R	.6378	.4573	.3296	.2410

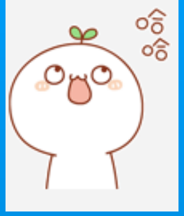
Testing data NIST 

Table 6: NIST Scores on NIST08 Test Data

	1-gram	2-gram	3-gram	4-gram	5-gram
Baseline	5.1288	6.6648	7.0387	7.1149	7.1387
W+C+R	**5.2858**	**6.8689**	**7.2520**	**7.3308**	**7.3535**
W+C	5.0850	6.5977	6.9552	7.0250	7.0467
W+R	5.1122	6.6509	7.0289	7.1062	7.1291
C+R	5.0140	6.4731	6.8187	6.8873	6.9063

Testing data Broader 

Table 7: Broader Metrics Scores on NIST08 Test Data

	Metrics Evaluated on 4-references		
Models	hLEPOR	BEER	CharacTER
Baseline	.5519	.4748	**0.9846**
W+C+R	**.5530**	**.4778**	1.3514
W+C	.5444	.4712	1.1416
W+R	.5458	.4717	0.9882
C+R	.5353	.4634	1.1888

Future work

- Improve parameter optimisation/tuning models
- Include more testing data
- Include different domain data
- Reduce training data and test low-resource scenario
- This paper pre-print: https://arxiv.org/pdf/1805.01565.pdf

Follow the project

- LEPOR: https://github.com/poethan/LEPOR/
- Chinese character decomposition: https://github.com/poethan/MWE4MT/tree/master/radical4mt
- Acknowledgment:

  - The ADAPT Centre for Digital Content Technology is funded under the SFI Research Centres Programme (Grant 13/RC/2106) and is co-funded under the European Regional Development Fund.

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