The *NiuTrans* System for NTCIR-9 PatentMT

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Outline

- Our NiuTrans System
- Improvements for Patent MT
- Evaluation Results
- Future Work

Our Submissions

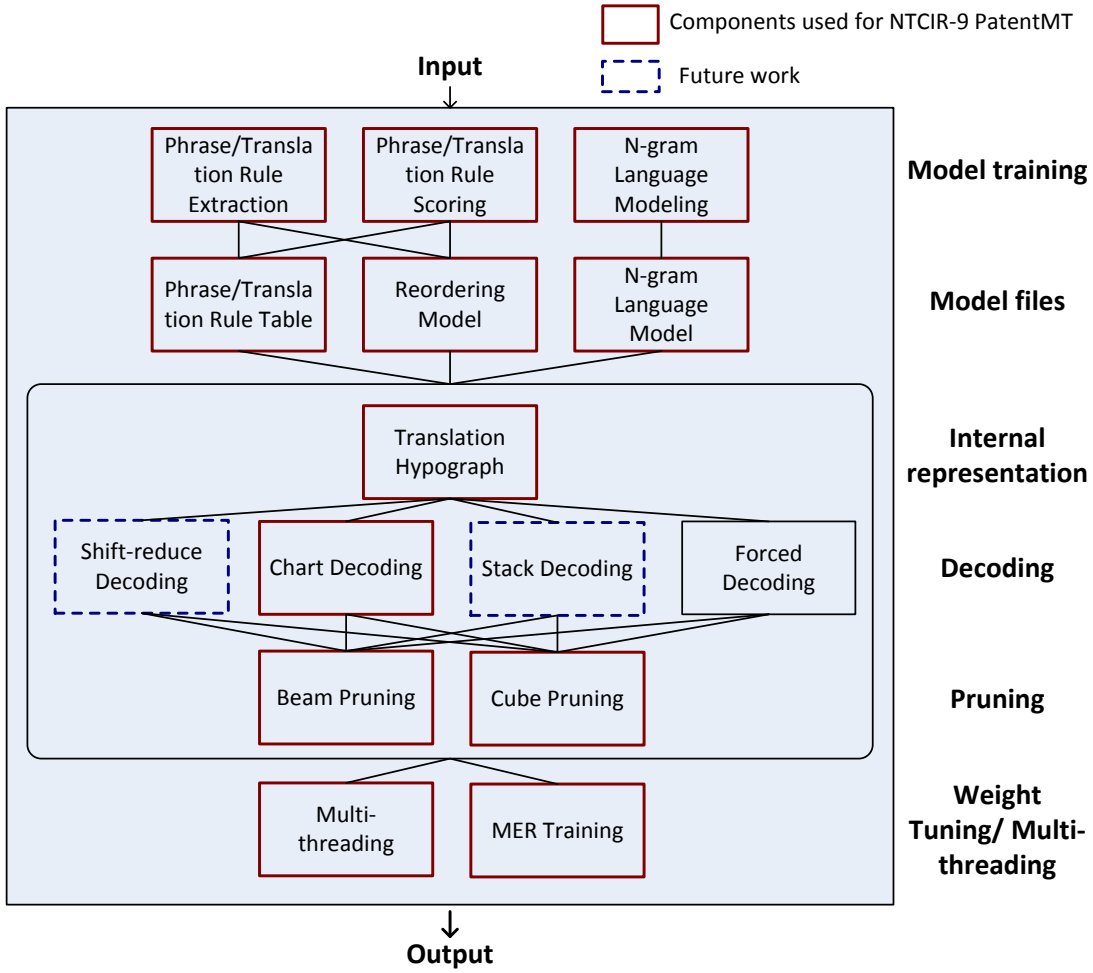
- Patent MT Tasks
  - Chinese-English (2 submissions)
  - Japanese-English (2 submissions)
  - *English-Japanese* (*no submission*)

NiuTrans

- NiuTrans is an open-source Statistical Machine Translation (SMT) system which is developed by our group - NLP Lab at Northeastern University.
  - Publicly released on this July, and so far shared by more than 200+ research groups all over the world.
- Features
  - Written in C++. It is fast, easy to install and use.
  - Multi-thread supported
  - Competitive performance for Chinese-Foreign translation
  - A compact but efficient n-gram language model is embedded.
  - Support multiple SMT models
    - Phrase-based model
    - Hierarchical phrase-based model
    - Syntax-based model (string-to-tree/tree-to-string/tree-to-tree) (coming soon)
- Available at http://www.**nlplab**.com

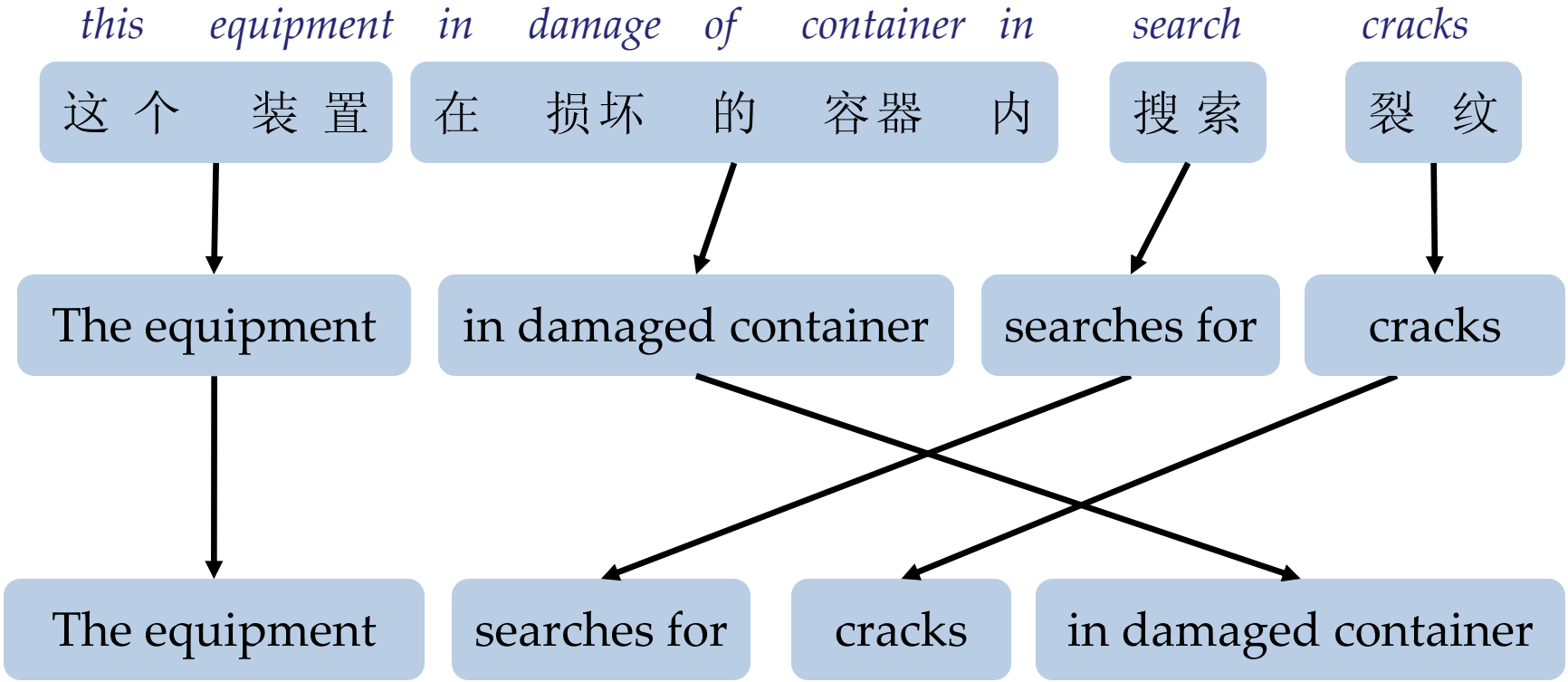
NiuTrans for NTCIR-9 PatentMT

- All of the SMT models are implemented in the same framework
  - We chose the phrase-based engine for NTCIR-9
- Note that we did not use the syntax-based engine in this task because current parsing accuracy is far from satisfactory on non-news domain technical documents.



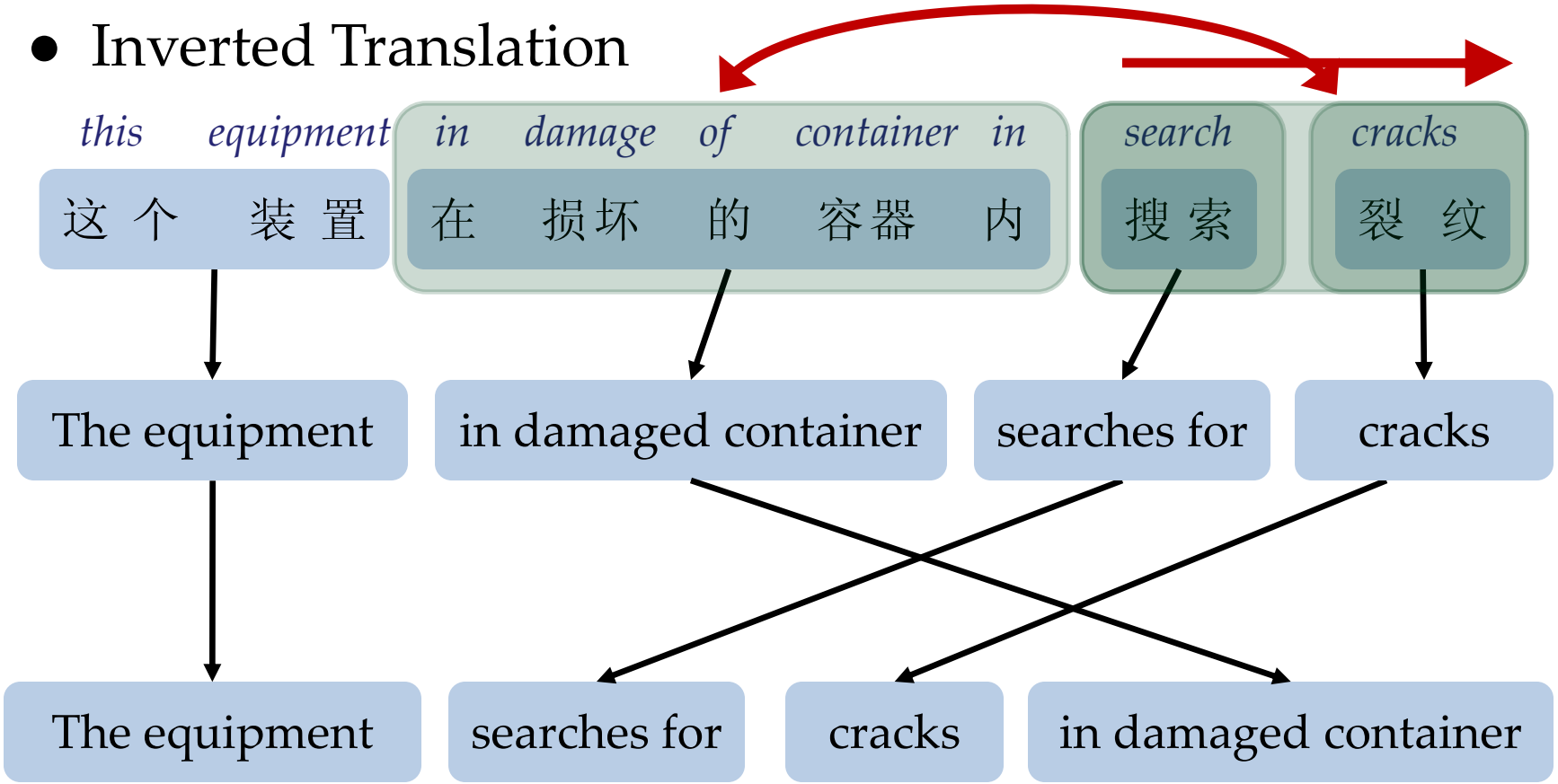
NiuTrans.Phrase

- NiuTrans.Phrase system follows the general framework of Inversion Transduction Grammar (ITG)

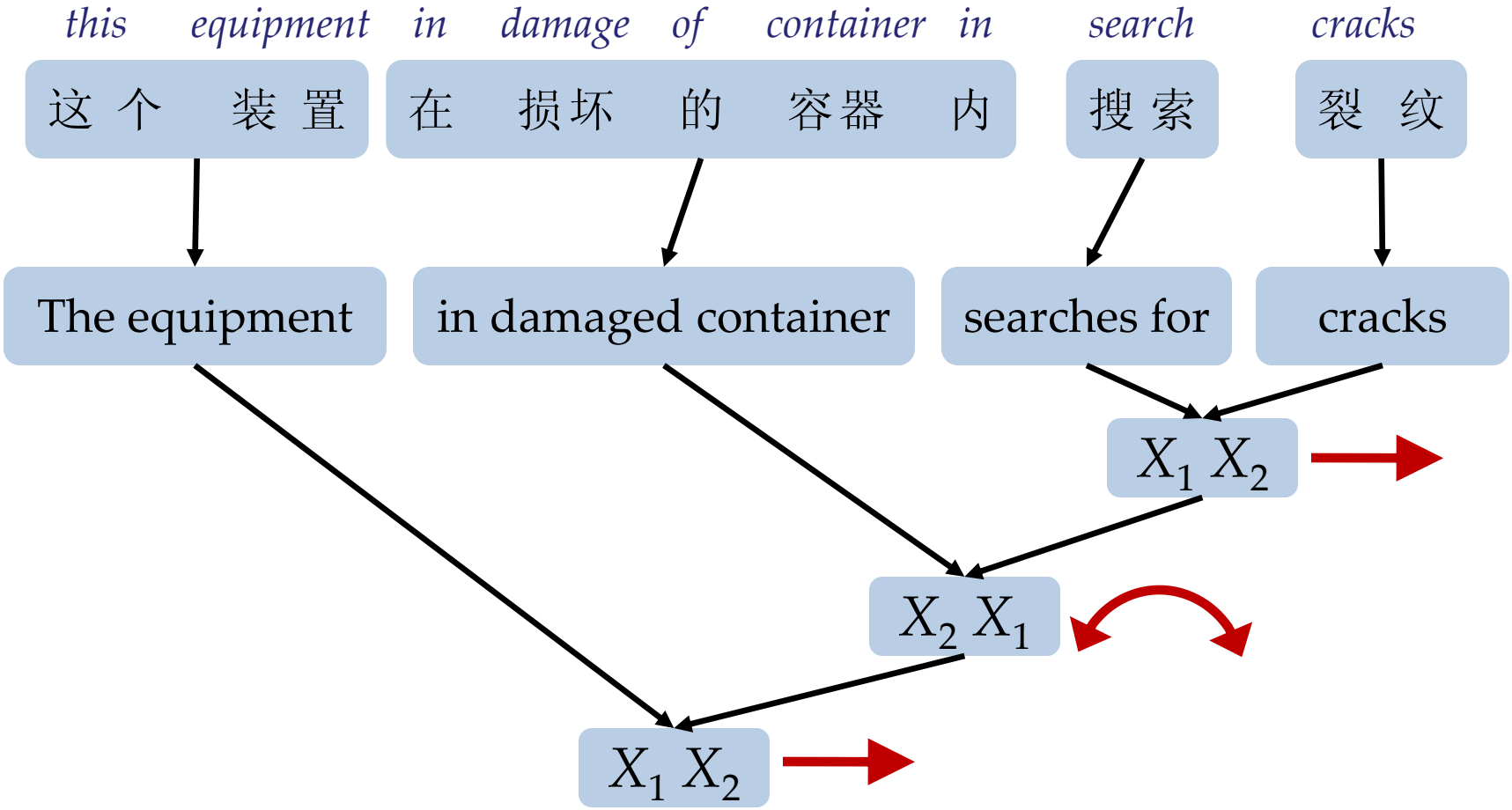


NiuTrans.Phrase

- Monotone Translation
- Inverted Translation



NiuTrans.Phrase



Improvements for Patent Translation

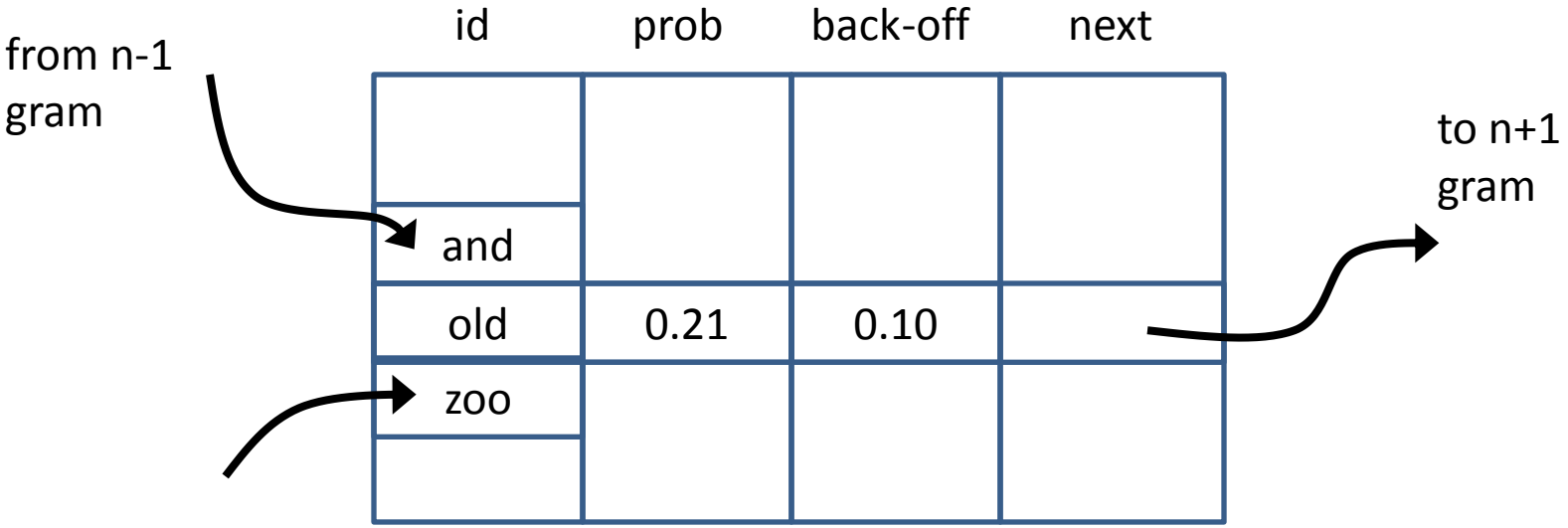
- Hybrid Reordering Model for Phrase-based SMT
- Large-scale N-gram Language Modeling
- Combining SMT and EBMT

A hybrid reordering model

- Many reordering models are available
  - competitive translation quality
  - different strengths and weaknesses
    - ME ordering: characterizes the movement of hierarchical structures by phrase boundary features
    - MSD ordering: powerful in local reordering that is inherent in the phrase translations
- It is natural to explore approaches that use or combine multiple reordering models
  - Our Solution: jointly use them during decoding

Large-Scale N-gram Language Modeling

- Our LM builder is basically a "sorted" Trie structure (Pauls and Klein, 2011)



- Pruning
  - Vocabulary filtering
  - N-gram filtering
- 57GB raw text → 6.1GB (5-gram) LM file (binary format)

Combining SMT and EBMT

- Combination is a desirable way to achieve higher translation accuracy than any individual approach does.
  - SMT: NiuTrans.Phrsae
  - EBMT: a naïve word-based EBMT system
    - Longest Common Subsequences
    - Delete unexpected target words
  - Select EBMT output only when very similar sentences are found
- Problem
  - Noisy data
  - Needs a better combination strategy

Features

- These improvements result in 17 features for our submitted (SMT) system

	Feature	Description	Weight (*ch-en*)	Weight (*jp-en*)
1	$\Pr(t \mid s)$	Phrase trans-probability	0.089	0.107
2	$\Pr_{lex}(t \mid s)$	Lexical weight	0.043	0.034
3	$\Pr(s \mid t)$	Inverted $\Pr(t \mid s)$	0.017	0.050
4	$\Pr_{lex}(s \mid t)$	Inverted $\Pr_{lex}(t \mid s)$	0.033	0.039
5	$\Pr_{\mathrm{LM5}}(t)$	5-gram language model	0.157	0.063
6	Length(t)	# of target words	0.095	0.154
7	Count(Phr)	# of phrases	0.111	0.104
8	WD	# of word deletions	-0.006	-0.018
9	Bi-Lex	# of bi-lex links	0.082	0.051
10	Count(low-freq)	# of low-frequency rules	-0.040	-0.031
11	$f_{BTG\text{-}ME}$	ME-based reordering feature	0.193	0.201
12	$f_{M\text{-}previous}$	M orientation (previous)	0.037	0.024
13	$f_{S\text{-}previous}$	S orientation (previous)	0.017	0.014
14	$f_{D\text{-}previous}$	D orientation (previous)	0.018	0.030
15	$f_{M\text{-}following}$	M orientation (following)	0.017	0.031
16	$f_{S\text{-}following}$	S orientation (following)	0.036	0.011
17	$f_{D\text{-}following}$	D orientation (following)	0.002	0.028

Evaluation (formal run)

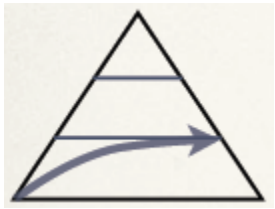
- The recourses we used were constrained to those provided for NTCIR-9 PatentMT
  - Chinese-English: 38M/43M words
  - Japanese-English: 116M/110M words
  - English (USPTO): 10,882M words
- Results

Entry	Chinese-English			Japanese-English		
	adequacy	accept	BLEU4	adequacy	accept	BLEU4
NiuTrans.Phrase	**3.51**	**0.543**	0.3229	2.37	0.416	0.2440
NiuTrans.Phrase + EBMT	N/A	N/A	**0.3273**	N/A	N/A	0.2488
Baseline 1 – Moses' hiero	3.29	0.476	0.3072	2.61	0.474	**0.2895**
Baseline 2 – Moses' phrasal	2.89	N/A	0.2932	2.42	0.447	0.2861
Baseline 3 – A rule-based system	2.27	N/A	0.1075	**3.53**	**0.674**	0.1885
Baseline 4 – Google's online translation	2.96	0.42	0.2569	2.27	0.417	0.1873

- NiuTrans.Phrase outperforms all five baselines on CE MT
- EBMT is useful in enhancing SMT output
- Maybe there is something wrong with the use of the open-source Japanese segmentation tool for our task.

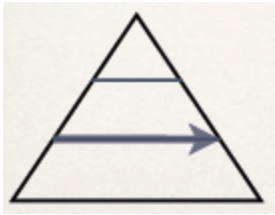
Future work:
NiuTrans will support more features

string-to-string



string-to-tree

tree-to-string



tree-to-tree

Current Version (v0.3.0)
- (Hierarchical) Phrase-based models

Standard Version (v1.0.0)
- Various syntax-based models
- Tree-parsing and parsing-based decoding

Coming soon!

Thank you!

Google *NiuTrans* to find it

Welcome