BBN's Systems for the Chinese-English Sub-task of the NTCIR-10 PatentMT Evaluation

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Speech, Language, and Multimedia
Raytheon BBN Technologies
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Overview

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- Statistical machine translation framework
- Building patent machine translation systems
- Official evaluation results
- Summary

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Part I:
Statistical Machine Translation Framework

Statistical Machine Translation (MT) Framework

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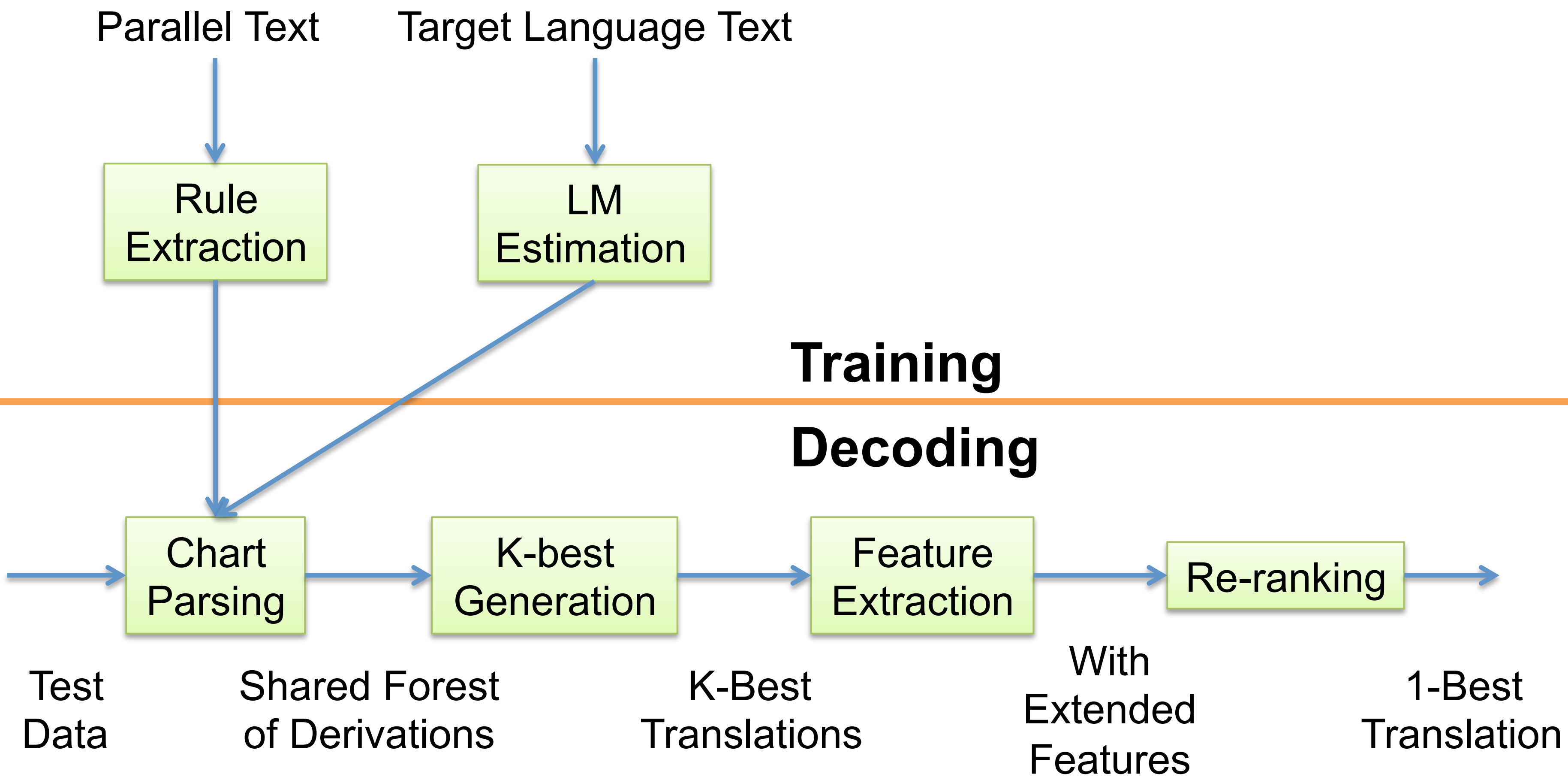

String-to-Dependency Translation Model

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- Modified version of Chiang's Hiero algorithm
- Extract hierarchical rules with well-formed dependencies on the target side
  - Well-formed dependency structure:
    - Single rooted tree, with each child being a complete sub-tree
    - Sequence of siblings, each being a complete sub-tree
  - Use POS tag of head word as non-terminal labels on the target side

X : X_1 出发 去 X_2 → VB : NR_1 leaves for NN_2

- Extract all phrasal rules, ignoring dependency
- Features:
  - 10+ core features
  - ~50K sparse binary features

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Part II:
Building Patent Machine Translation Systems

BBN Patent MT systems - Overview

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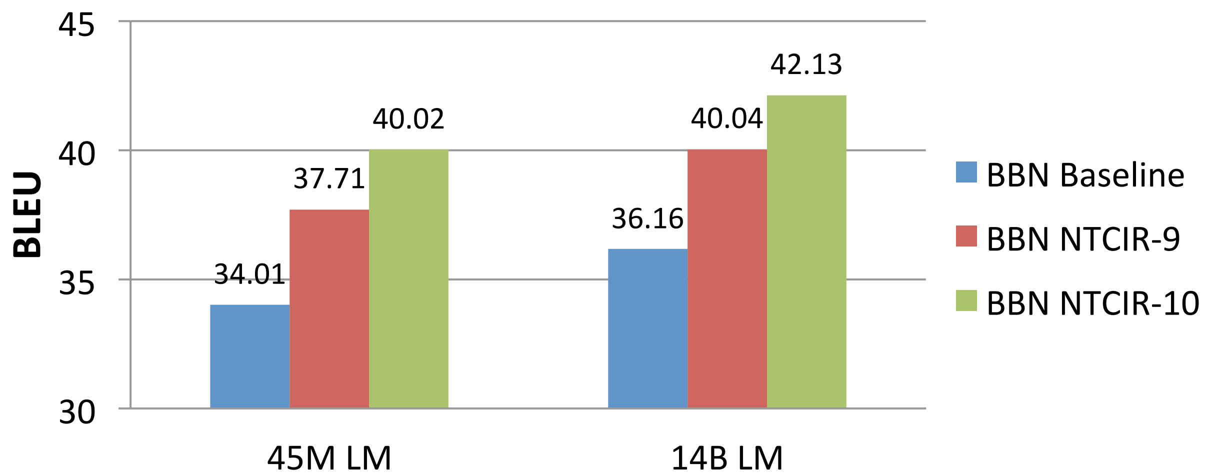
- Data released by the NTCIR-10 organizers
  - Parallel data: 45M words of Chinese-English sentence pairs
  - Extra LM data: 14B words of US patents in English
  - Development data: 2K Chinese-English sentence pairs, split into tuning and test set
- Model training
  - Translation Model: trained on the 45M parallel corpus
  - Language Models:
    - 45M LM: trained on the target side of the 45M parallel corpus
    - 14B LM: trained on the 45M words plus the 14B US patent words
- Summary of results on the test set (development)



Review of Work for BBN NTCIR-9

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- Consistent tokenization
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  - Replace special tokens with a common token for each type in translation and language model
    - Numbers: e.g., 2,596, -123.321
    - Patent IDs: e.g., No.5,400,788, No. 5,405,753
    - Math expressions: e.g., p=0.004, Sine(45)=0.7071
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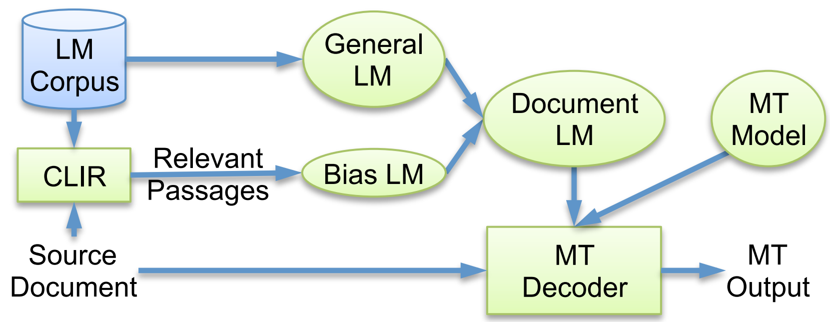
  - Find documents in monolingual English patent corpus that are similar to test document
  - Estimate a separate LM and interpolate with the general LM



$$P_{LM}(s) = (1-\alpha)P_{generalLM}(s) + \alpha P_{biasLM}(s)$$

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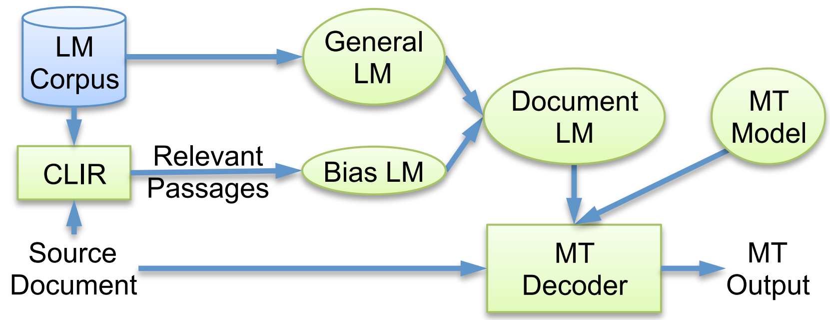

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System	BLEU
BBN Baseline with 45M LM	**34.01**
+ consistent tokenization	34.56
+ more token sharing	34.97
+ patent case-LM	36.47
+ optimized word segmenter	36.95
+ top 100 features	**37.71**
+ 14B LM	39.14
+ document-level LM adaptation	**40.04**

Development for NTCIR-10 Evaluation

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- Overview
  - Miscellaneous additional features
  - Sentence-level LM adaptation
  - Robust context dependent translation
  - Recurrent neural network LM
  - Translation-based caser

Miscellaneous Additional Features

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- Bigram lexical translation model
  - Extension of context-based lexical probabilities to model joint likelihood of target bigrams given source context

$$\mathrm{P}\left(t_{s_i}, t_{s_{i-1}} \mid s_i, s_{i-1}, s_{i+1}, s_{i-2}\right)$$

  - Apply chain rule and use simple back-off smoothing
  - Similarly for the backward direction

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  - Percent of NULL source content words
  - Percent of words that re-order
  - Percent of low-frequency n-grams
  - Source-to-target length ratio

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+ miscellaneous features	**38.06**
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+ miscellaneous features	**39.51**

Sentence-level LM adaptation

- Patent documents tend to use well-structured sentence and re-use n-grams in other patent documents

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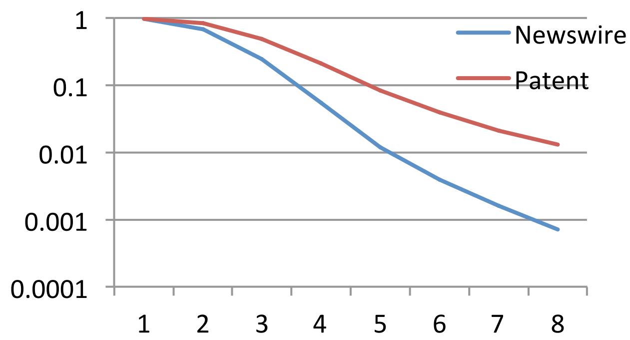

Percentage of source n-grams (tokens) in the test sentences that are observed in the parallel training for newswire (GALE) and patent (NTCIR-10)

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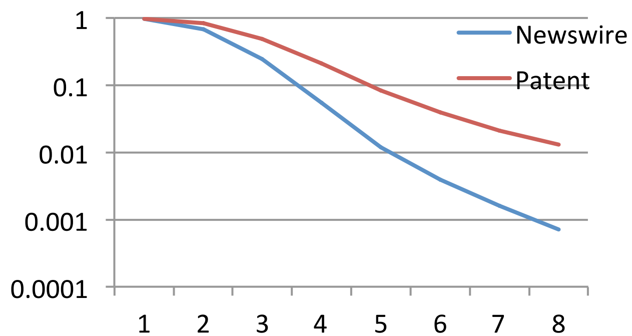

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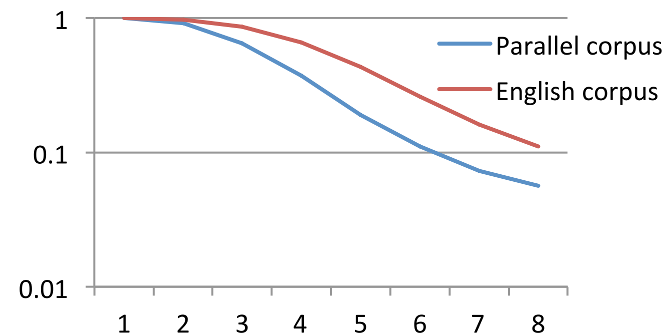

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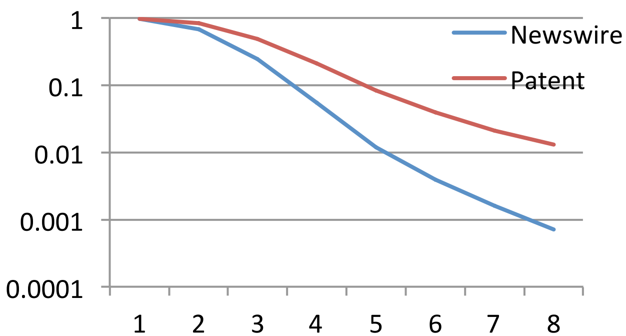

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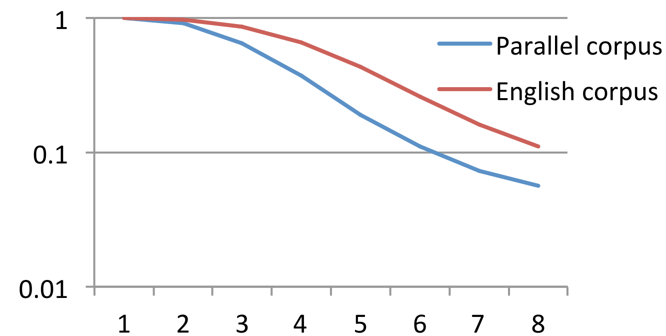

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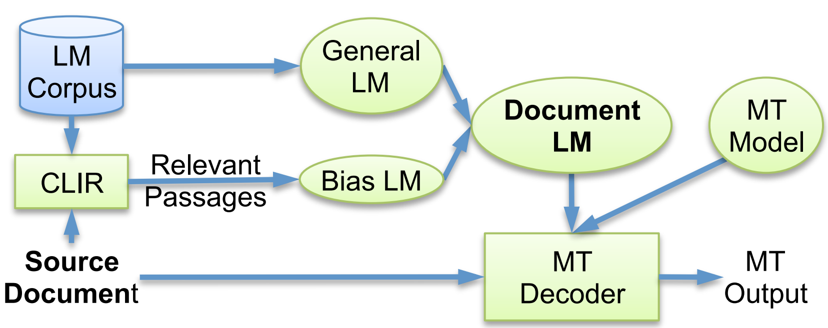

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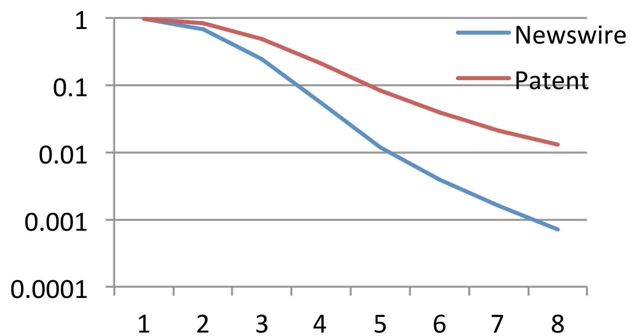

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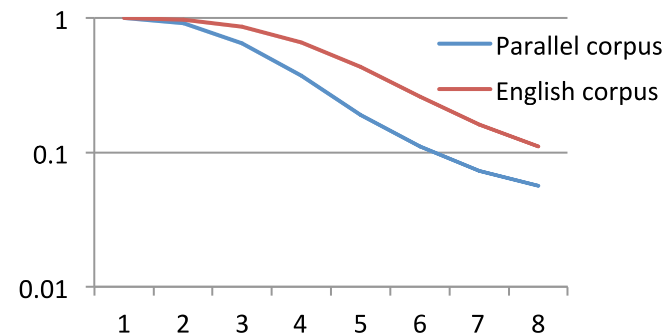

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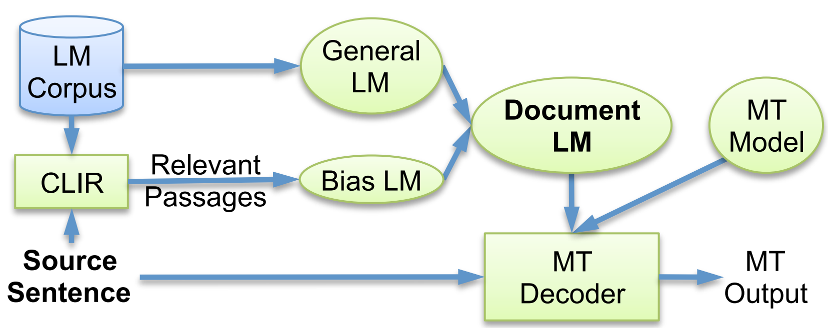

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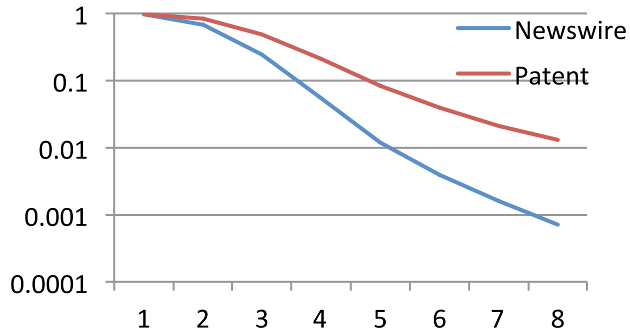

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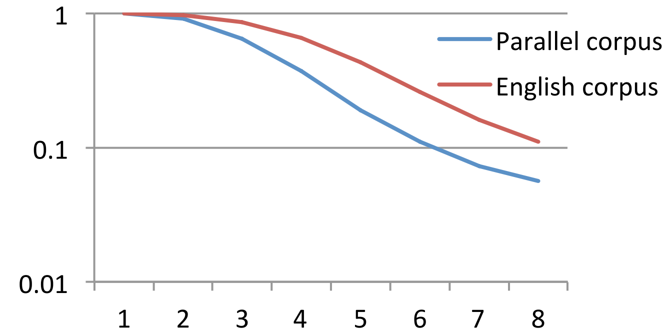

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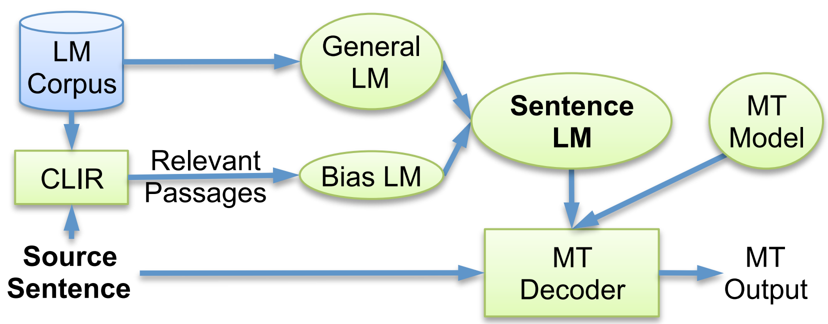

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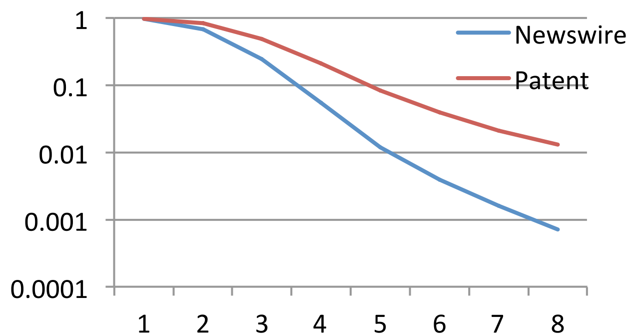

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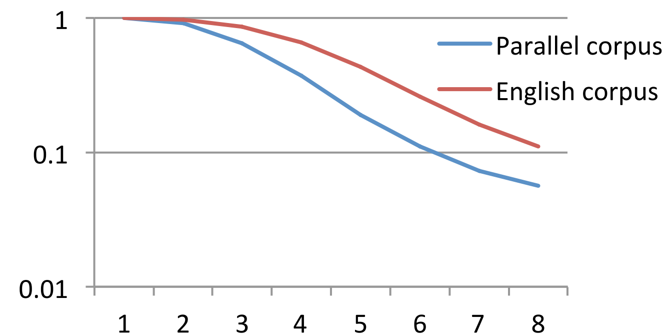

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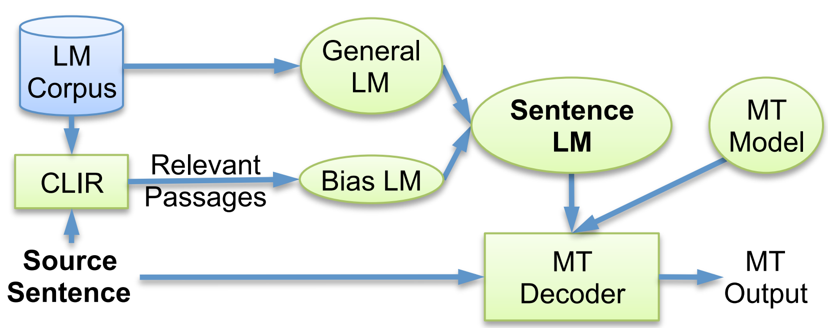

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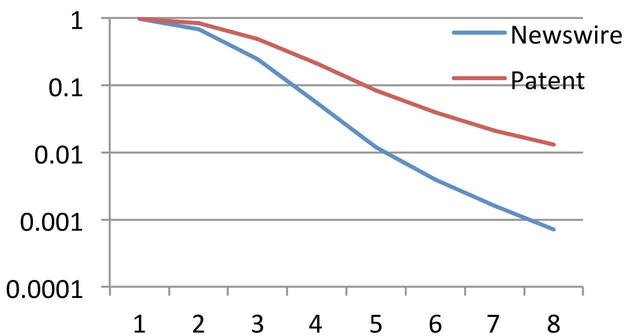

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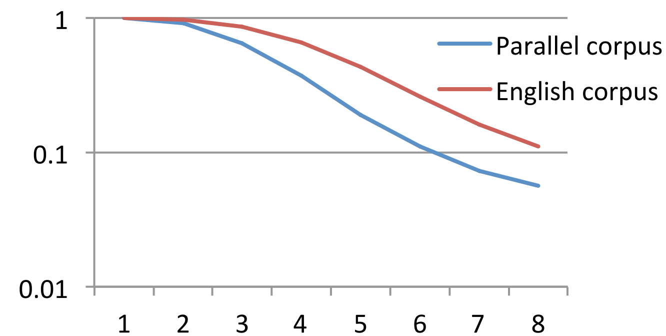

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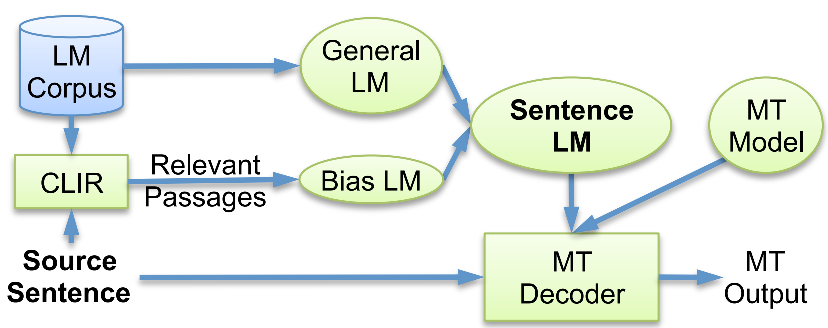

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Robust Context-Dependent Modeling

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- High order context-dependent translation models may be very sparse

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  - First, apply the chain rule

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  - Back-off each probability independent
- But, unlike LM, there is no clear back-off ordering
  - Is $P\left(t_{s_{i-1}} \mid t_{s_i}, s_{i-1}\right)$ "better" than $P\left(t_{s_{i-1}} \mid s_i, s_{i-1}\right)$?

Robust Context-Dependent Modeling

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- Our solution: interpolate all possible back-off components
  - Sparse context types can be added independently of one another

$$\mathrm{P}\left(t_{s_{i-1}} \mid t_{s_i}, s_i, s_{i-1}, s_{i+1}, s_{i-2}\right) = \omega_0 \mathrm{P}\left(t_{s_{i-1}} \mid t_{s_i}, s_i, s_{i-1}, s_{i+1}, s_{i-2}\right) + \omega_1 \mathrm{P}\left(t_{s_{i-1}} \mid t_{s_i}, s_i, s_{i-1}, s_{i+1}\right) + \cdots + \omega_{30} \mathrm{P}\left(t_{s_{i-1}} \mid t_{s_i}\right)$$

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- Each weight ω is a function of the marginal count

$$\omega_j \mathrm{P}\left(t_{s_i} \mid s_i, s_{i-1}\right) = \frac{1}{Z} \alpha_j \log\left(C\left(s_i, s_{i-1}\right)\right) \frac{C\left(t_{s_i}, s_i, s_{i-1}\right)}{C\left(s_i, s_{i-1}\right)}$$

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- Weights α are optimized to maximize likelihood on a held-out set
  - Least useful components are thrown out for efficiency

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$$P\left(t_{s_{i-1}} \mid t_{s_i}, s_i, s_{i-1}, s_{i+1}, s_{i-2}\right) = \omega_0 P\left(t_{s_{i-1}} \mid t_{s_i}, s_i, s_{i-1}, s_{i+1}, s_{i-2}\right) + \omega_1 P\left(t_{s_{i-1}} \mid t_{s_i}, s_i, s_{i-1}, s_{i+1}\right) + \cdots + \omega_{30} P\left(t_{s_{i-1}} \mid t_{s_i}\right)$$

- Each weight ω is a function of the marginal count

$$\omega_j P\left(t_{s_i} \mid s_i, s_{i-1}\right) = \frac{1}{Z} \alpha_j \log\left(C\left(s_i, s_{i-1}\right)\right) \frac{C\left(t_{s_i}, s_i, s_{i-1}\right)}{C\left(s_i, s_{i-1}\right)}$$

- Weights α are optimized to maximize likelihood on a held-out set
  - Least useful components are thrown out for efficiency

System	Test
NTCIR-9 system with 45M LM	37.71
+ miscellaneous features	38.06
+ robust context dependent translation	**38.72**
NTCIR-9 system with 14B LM	39.14
+ miscellaneous features	39.51
+ sentence-level LM adaptation	40.95
+ robust context dependent translation	**41.09**

Neural Net LM

Raytheon
BBN Technologies

- Trained a recurrent neural net LM for rescoring
  - Mikolov's toolkit: http://www.fit.vutbr.cz/~imikolov/rnnlm/
  - Interpolated with 5-gram KN Smoothing LM

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+ miscellaneous features	39.51
+ document-level LM adaptation	39.94
+ sentence-level LM adaptation	40.95
+ robust context dependent translation	41.09
+ recurrent neural network LM	**41.43**

Translation-based Caser

- Treats casing as a translation problem
  - Similar to (Hassan, et al. 2006)'s MaTrEx system
  - Trained on 45M LM training data
  - Use rule probabilities, case LM probability, and sparse features, e.g., *Is the target word upper cased and does it follow a period? Is the target word upper cased and a proper noun?*

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System	Test
NTCIR-9 system with 45M LM	37.71
+ miscellaneous features	38.06
+ robust context dependent translation	38.72
+ recurrent neural network LM	39.35
+ translation-based caser	**40.02**
NTCIR-9 system with 14B LM	39.14
+ miscellaneous features	39.51
+ document-level LM adaptation	39.94
+ sentence-level LM adaptation	40.95
+ robust context dependent translation	41.09
+ recurrent neural network LM	41.43
+ translation-based caser	**42.13**

Part III:
Official Evaluation Results

Official Automatic (BLEU) Results

Raytheon
BBN Technologies

- The two BBN systems
  - BBN-1 : the primary system, trained on 45M parallel corpus plus 14B English patent corpus
  - BBN-2: the secondary system, trained on 45M parallel corpus only
- NCTIR Official Baseline systems
  - Baseline1– Moses phrase-based hierarchical SMT system
  - Baseline2– Moses phrase-based SMT system

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  - Baseline2– Moses phrase-based SMT system

System	Intrinsic evaluation	Chronological evaluation	Multilingual evaluation
BBN-1	42.68	39.44 ⟶ 41.09	27.62
BBN-2	39.98	36.69 ⟶ 38.93	N/A
Baseline1	32.52	30.74	17.96
Baseline2	31.34	29.34	18.05

* ⟶ indicates the change in BLEU from NTCIR-9 evaluation to NTCIR-10 evaluation

Official Manual Evaluation Results

Raytheon BBN Technologies

- Adequacy: scores from 5 (best) to 1 (worst)

System	Average adequacy	Allocation of scores				
		5	4	3	2	1
BBN-1	42.68	156	66	44	34	0
Baseline1	32.52	46	73	91	84	6
Baseline2	31.34	38	34	75	141	12

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- Acceptability: scores in AA (best), A, B, C, and F (worst)
- Pairwise acceptability: percentage of wins and ties when comparing acceptability score with other submissions

System	Pairwise score	Allocation of scores				
		AA	A	B	C	F
BBN-1	0.69	81	36	50	35	98

Official Manual Evaluation Results

Raytheon BBN Technologies

- Adequacy: scores from 5 (best) to 1 (worst)

System	Average adequacy	Allocation of scores 5	4	3	2	1
BBN-1	42.68	156	66	44	34	0
Baseline1	32.52	46	73	91	84	6
Baseline2	31.34	38	34	75	141	12

- Acceptability: scores in AA (best), A, B, C, and F (worst)
- Pairwise acceptability: percentage of wins and ties when comparing acceptability score with other submissions

System	Pairwise score	Allocation of scores AA	A	B	C	F
BBN-1	0.69	81	36	50	35	98

- Patent examination evaluation: scores in S (perfect), A, B, C, D, and F (worst)

System	Allocation of scores S	A	B	C	D	F
BBN-1	6	19.5	3.5	0	0	0

Translation Examples

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BBN Technologies

Source: 对于每一像素，着色引擎210使用在以上等式(2)-(4)中陈述的边等式来确定所述像素是否在三角形中。

MT output: For each pixel, the rendering engine 210 uses the edge equation set forth in equations (2) to (4) above to determine whether the pixels in a triangle.

Reference: For each pixel, the shading engine 210 determines whether the pixel is in the triangle using the edge equations set forth in equations (2) - (4) above.

Source: 上述说明书全面描述了根据本发明原理的改进型可穿透膜片的成分、制造和用途。

MT output: The above description fully describes the composition, manufacture and use of improved penetrable diaphragm in accordance with the principles of the present invention.

Reference: The above specification provides a complete description of the composition, manufacture and use of the improved penetrable membrane in accordance with the principles of the present invention.

Summary

Raytheon
BBN Technologies

- It was relatively straightforward to port BBN's MT system to work on patents
  - 4-5 weeks of efforts in NTCIR-9 evaluation
  - 3-4 weeks of efforts in NTCIR-10 evaluation
  - All techniques initially developed for other domains work well on patents
- Special attention to patents helps
  - Better tokenization, special token sharing, optimizing word segmentation
  - Sentence-level LM adaptation
  - Further improvement is possible by exploring special properties of patents
- Lots of potential
  - Patents are easier to translate
  - State-of-the-art accuracies in both automatic and manual evaluations
  - Helpful in real patent examination and possibly other tasks

Related MT Research at BBN

Raytheon
BBN Technologies

Leading performer in DARPA's MT programs

- Text-to-text translation (GALE, BOLT)
  - Arabic and Chinese to English. newswire, weblogs, web forums, SMS/chat
- Speech-to-text translation (GALE)
  - Arabic and Chinese to English. broadcast news and broadcast conversation
- Speech-to-speech translation (TransTac, BOLT)
  - English to/from Iraqi Arabic, Farsi, Dari, Pashto, Malay, and Spanish
  - TransTalk: portable (Android), two-way translation device; deployed by US Army
- Image to text translation (MADCAT)
  - Foreign text (Arabic, Chinese and Korean) in images (through OCR) to English
- Multilingual broadcast/web monitoring
  - Continuous searchable archive of international television broadcasts and web sites
  - Automatic translation to English for deep analysis

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