NICT-2 Translation System for WAT2016: **Applying Domain Adaptation** to Phrase-based Statistical Machine Translation

Summary

- Domain adaptation method of Imamura+ (2016) was applied to WAT2016 data.
- ◆ Japan Patent Office Corpus (JPC) was regarded as a mixture of four domain corpora.
- > Domain adaptation was effective on the patent data even if the domains are different.
- We added ASPEC as the fifth domain, but there were no effects. > The patent data was not effective to the scientific paper domain.
- Google n-gram language models are added as external knowledge.
- Our domain adaptation can easily incorporate such knowledge.

Domain Adaptation (Imamura+ 2016)

Adaptation of Weight Vector

- Feature weights are optimized using feature augmentation (Daumé 2007).
- A feature space is expanded to common and domain-specific spaces.
- All domains are simultaneously optimized/adapted.



3. During search of the best hypothesis, the likelihoods are computed using only the common space and domain-specific space of the input sentence.

Domain/Corpora

- Japan Patent Office Corpus (JPC) was regarded as a mixture of four domains.
- Asian Scientific Paper Excerpt Corpus (ASPEC) was used as the fifth domain corpus.
- The language pairs: Japanese-English (Ja-En) and Japanese-Chinese (Ja-Zh).

		#training sents.	
Corpus	Domain	Ja-En pair	Ja-Zh pair
JPC	Chemistry	250k	250k
	Electricity	250k	250k
	Machine	250k	250k
	Physics	250k	250k
ASPEC	ASPEC	1,000k	672k

Implementation Notices

Empty Value

• A value of feature functions when phrases appear only one of the corpus-concatenated or single domain models (unknown probability).

	Common	Domain i
	Φ_c (translation, 翻訳)	Φ _i (translation, 翻訳)
(-:	/ 1.7, -6.3, -2.2, -7.6)	?? if the pair does not exist in the phrase table.

- We experimentally set to maximize the BLEU score of the development set.
- This time, empty= -7 (i.e., exp(-7) = 0.0009).

Large Monolingual Corpora

- External knowledge such as language models constructed from large monolingual corpora is located to the common space while increasing the dimension.
- Language models are constructed from Google n-gram, and added as the external knowledge.
- The back-off models are estimated using maximum likelihood.
- English Data : Web 1T 5-gram Version 1 (LDC2006T13) Japanese Data: Web Japanese N-gram Version 1 (http://www.gsk.or.jp/catalog/gsk2007-c/)

Optimization

- Independent optimization of Imamura+ (2016) was used.
- Each domain is optimized one-by-one.
- Optimization algorithm: K-best Batch MIRA.

Translation System

- Phrase-based SMT with preordering.
- Two preorderers:
- (1) Top-Down BTG (w/o external knowledge), and (2) In-house preorderer tuned to patents
- (w/ external knowledge, using Berkeley Parser).
- Moses clone decoder.

Domain Adaptation vs. {Single-Domain / Corpus Concatenation} Evaluation Metric: BLEU Statistical Testing: MultEval (p<0.05). The scores are different from the official scores. JPO Corpus (w/o External Knowledge) Corpus Concatenation: JPC was regarded as one domain corpus. Single Domain Model: If we divided JPC into 4 domains, the translation guality decreased because the number of the training sentences in each domain is reduced. Domain Adaptation: The BLEU scores were the highest. Method Corpus Concatena Single-Domain Mo Domain Adaptatio JPO and ASPEC Corpus (w/ External Knowledge) • On JPC, Google n-gram the language models and domain adaptation were both effective. They can be combined. On ASPEC, domain adaptation was not effective. This might be because the corpus size of ASPEC is large. Metho w/o Corpus Concat GN Single-Domain Domain Adapta Corpus Concat w/ GN Single-Domain Domain Adapta Method w/o Corpus Concate GN Single-Domain Domain Adapta w/ Corpus Concate GN Single-Domain Domain Adapta References Hal Daumé III. 2007. Frustratingly Easy Domain Adaptation. In Proc. of ACL-2007, pp. 256-263. • Kenji Imamura and Eiichiro Sumita. 2016. Multi-domain Adaptation for Statistical Machine Translation Based on Feature Augmentation. In Proc. o AMTA-2016. pp. 79-92.

Experimental Results

Settings

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	JPC			
	Ja-En	En-Ja	Ja-Zh	Zh-Ja
ation	36.22	38.03(-)	32.92(-)	39.68(-)
odel	35.12(-)	37.40(-)	31.96(-)	38.15(-)
n	36.29	38.48	33.36	39.85

	JPC			
ł	Ja-En	En-Ja	Ja-Zh	Zh-Ja
enation	35.81(-)	38.62(-)	32.76(-)	39.96(-)
Model	33.90(-)	38.19(-)	31.78(-)	38.74(-)
ation	36.25	39.58	33.53	40.76
enation	36.03(-)	39.48(-)		40.14(-)
Model	34.35(-)	39.04(-)		38.90(-)
ation	36.40	40.32		40.77

	ASPEC			
	Ja-En	En-Ja	Ja-Zh	Zh-Ja
enation	22.20(-)	33.94(-)	28.95(-)	37.62(-)
Model	22.79	34.80	29.47 (+)	38.96(-)
tion	22.80	34.91	29.28	39.18
enation	22.10(-)	34.55(-)		38.15(-)
Model	22.87(+)	35.42		39.74(-)
tion	22.74	35.36		39.87