FUN-NRC: Paraphrase-Augmented Phrase-Based SMT Systems for NTCIR-10 PatentMT



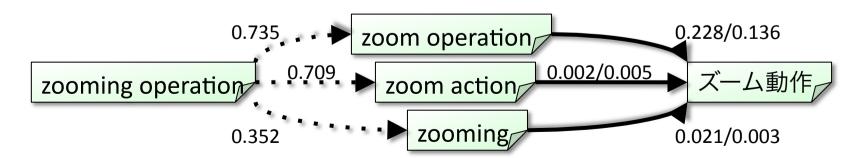
Future University Hakodate http://paraphrasing.org/~fujita/

Marine Carpuat



Summary of our systems

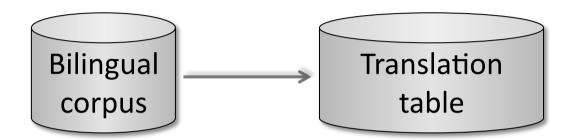
- Phrase-based SMT + paraphrases
 - State-of-the-art non-hierarchical system: PortageII @ NRC
 - Almost no language- or domain- specific knowledge
 - Phrase table augmentation
 - Paraphrases in both source & target languages (separately)
 - Comparison of paraphrase collections
 - Aggregation of multiple paths w/ feature engineering
 - Improved performance over a vanilla phrase-based SMT
 - at least BLEU, NIST, and RIBES



Motivation & proposed method

Modern SMT systems: Limitations

Principle



Limitations

- At source side
 - Unseen expressions will never be translated
 - They are either dropped or retained as is
- At target side
 - Only seen expressions can be generated as hypotheses
 - cf. Language models only ranks the given hypotheses

Expressions that convey the same meaning

Paraphrase: monolingual

Emma burst into tears and he tried to comfort her.

Emma cried, and he tried to console her.

Translation: cross-lingual

Désirez-vous obtenir des conseils pratiques sur le déménagement?

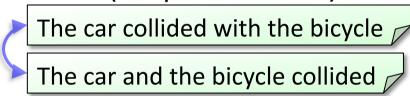
Are you looking for some helpful tips for moving?

Paraphrases

- Linguistic expressions in the same language that convey the same meaning
 - Word / word sequence



Clause (simple sentence)

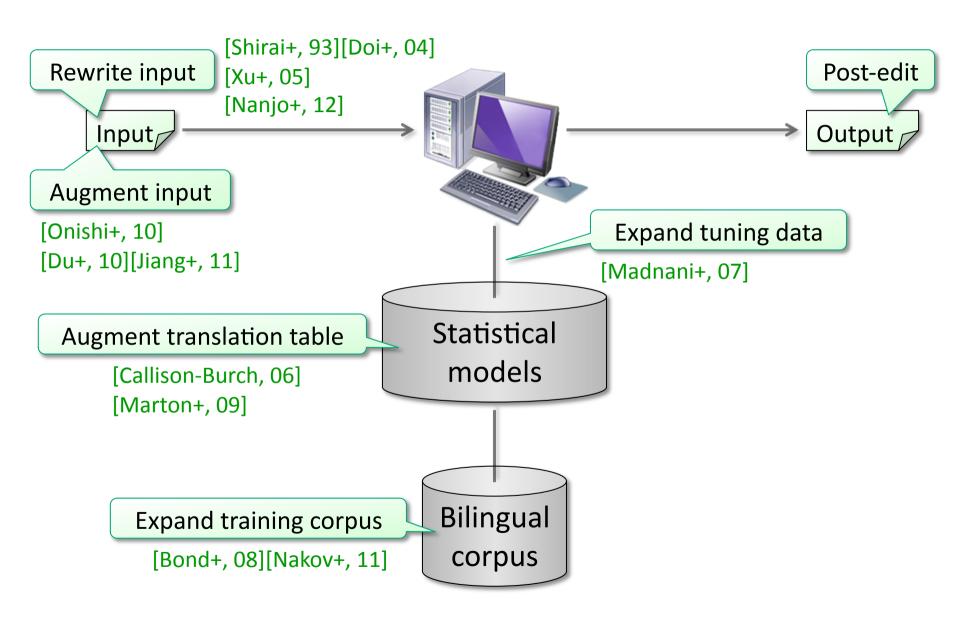


Beyond single clause

```
It was his best suit that John wore to the dance last night.

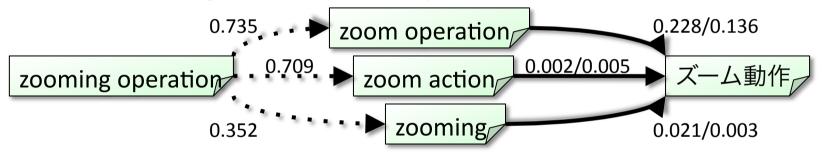
John wore his best suit to the dance last night.
```

Prior arts in integrating paraphrases to MT

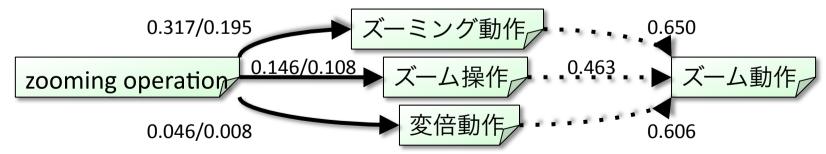


Augmentation of translation table

- Updates from [Callison-burch, 06][Marton+, 09]
 - Comparison of several paraphrase collections
 - Aggregation of multiple paths (both sides)
 - Source side (Saug): translate more phrases



Target side (Taug): generate more hypotheses



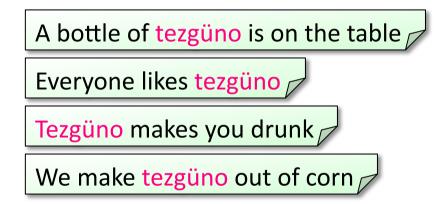
Feature engineering for decoding

Key issue: how to realize paraphrases?

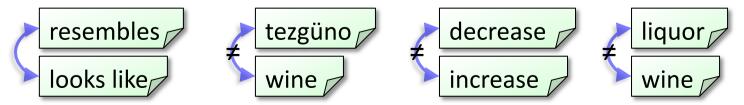
- Large-scale knowledge-base is indispensable
 - Handcrafting
 - Automatic paraphrase acquisition (PA)
- Pros. & cons. of prior arts
 - PA from Monolingual non-parallel corpora
 - Pro. Large → (potentially) high recall
 - Con. Only weak evidences → low precision
 - PA from Mono/Bi/Multi-lingual parallel corpora
 - Pro. Sentence-level equivalence → high precision
 - Con. Limited availability → low recall

PA from monolingual non-parallel corpora

- Distributional Hypothesis [Harris, 68]
 - Expressions that appear frequently in similar contexts have similar meanings
 - e.g., "Tezgüno" [Pantel+, 02]



- ◆ Similar to wine, cognac, whiskey → alcoholic beverage
- Con. Not necessarily equivalent: e.g., antonyms, hypernyms



PA from bilingual parallel corpora

- Translations as pivot [Bannard+, 05]
 - A more reliable evidence than context
 - Obtainable from bilingual parallel corpora
 - i.e., word alignment + phrase extraction

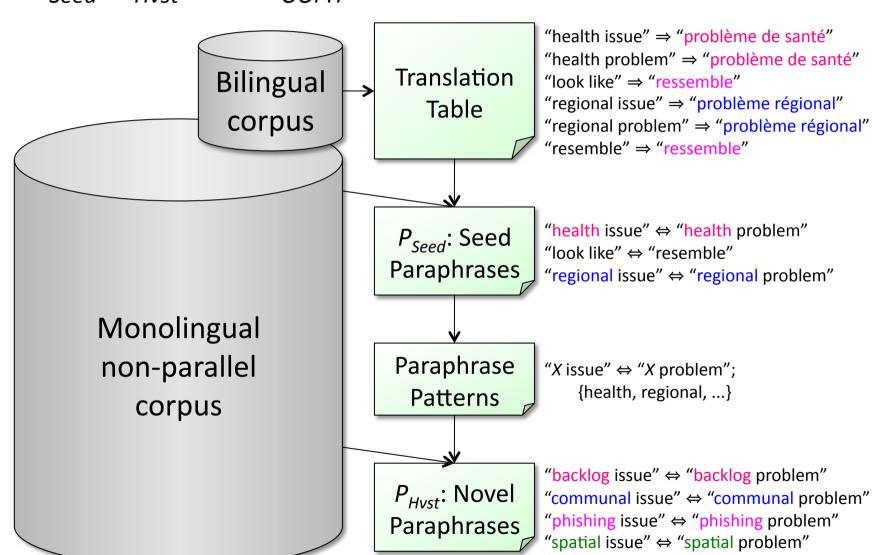
health issue | | | problème de santé | health problème de santé | health problème de santé | regional issue | problème régional regional problem | | problème régional | regional problem | regional proble

- Polysemy would generate non-paraphrases
- Con. Parallel corpora << monolingual non-parallel corpora

Paraphrase collections examined

[Fujita+, 12]

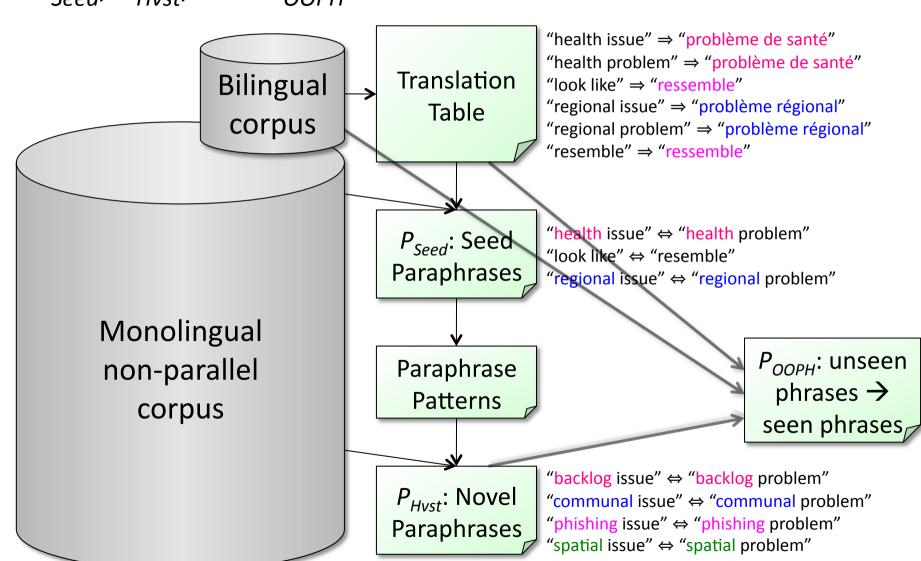
 P_{Seed} , P_{Hyst} , and P_{OOPH}



Paraphrase collections examined

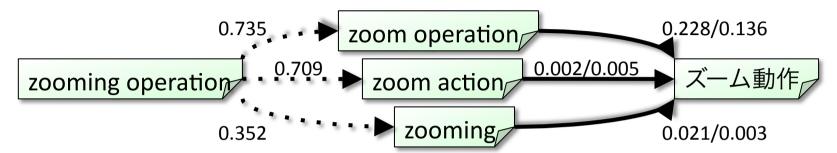
[Fujita+, 12]

 P_{Seed} , P_{Hvst} , and P_{OOPH}



Aggregation of multiple paths (1/2)

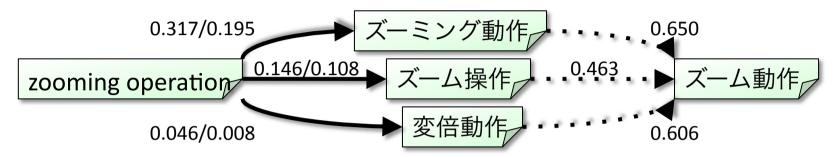
Source-side augmentation



- Translation scores
 - Forward $p(t|s') = \frac{\sum_{s \in S} \left(p(t|s) Para(s' \Rightarrow s) \right)}{\sum_{s \in S} Para(s' \Rightarrow s)}$
 - $\textbf{ Backward } \qquad p(s'|t) \quad = \quad \frac{\sum_{s \in S} \Big(p(s|t) Para(s \Rightarrow s') \Big)}{\sum_{s \in S} Para(s \Rightarrow s')}$

Aggregation of multiple paths (2/2)

Target-side augmentation



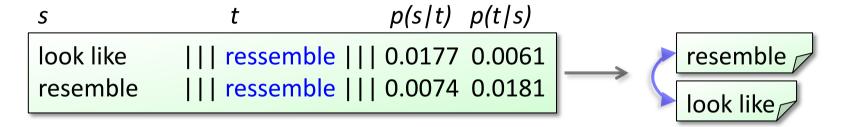
- Translation scores
 - Forward $p(t'|s) = \frac{\sum_{t \in T} \left(p(t|s) Para(t \Rightarrow t') \right)}{\sum_{t \in T} Para(t \Rightarrow t')}$
 - Backward $p(s|t') = \frac{\sum_{t \in T} \left(p(s|t) Para(t' \Rightarrow t) \right)}{\sum_{t \in T} Para(t' \Rightarrow t)}$

Paraphrase-related Features

Features in the translation model	Original	Source-side fabricated	Target-side fabricated	
(a1) Forward translation score	Cond.Prob.	[0,1]	[0,1]	
(a2) Backward translation score	Cond.Prob.	[0,1]	[0,1]	
(b1) Obtained from IBM2 alignment	True/False	False	False	
(b2) Obtained from HMM alignment	True/False	False	False False	
(b3) Obtained from IBM4 alignment	True/False	False	False	
(c1) Fabricated using Seed	False	True/False	True/False	
(c2) Fabricated using Hvst/OOPH	False	True/False	True/False	
(d1) Unseen in the phrase table	False	True/False	True/False	
(d2) Unseen in the bilingual data	False	True/False	True/False	
(e1) Paraphrase score (Saug/fwd)	1	[0,1]	1	
(e2) Paraphrase score (Saug/bwd)	1	[0,1]	1	
(e3) Paraphrase score (Taug/fwd)	1	1	[0,1]	
(e4) Paraphrase score (Taug/bwd)	1	1	[0,1]	

Score of each paraphrase pair (1/2)

- PivProb: Pivot-based paraphrase probability [Bannard+, 05]
 - For P_{Seed} only



Asymmetric score

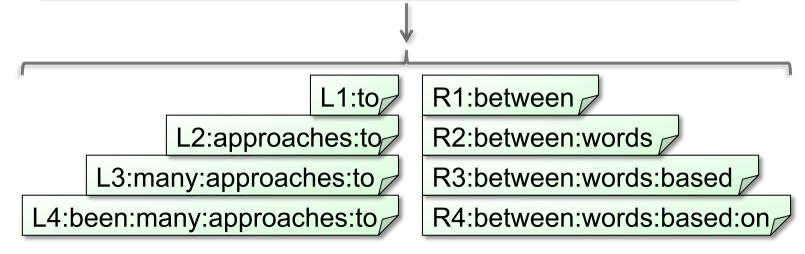
$$Para(s_1 \Rightarrow s_2) = p(s_2|s_1)$$

$$= \sum_{t \in tr(s_1) \cap tr(s_2)} p(s_2|t)p(t|s_1)$$

Score of each paraphrase pair (2/2)

- CosSim: cosine similarity of "contexts"
 - For all of P_{Seed} , P_{Hvst} , and P_{OOPH}
 - Contextual similarity in a monolingual corpus
 - Adjacent 1- to 4-grams of each token → feature vector
 - cf. cheap but noisy features, e.g., bag-of-words
 - cf. accurate but expensive features, e.g., dependency trees

There have been many approaches to compute the similarity between words based on their distribution in a corpus.



Dev & Test

Our base system

- Portagell 1.0 [National Research Council, 12]
 - A state-of-the-art phrase-based SMT system
 - Reasonably good results at NIST OpenMT 2012 [Foster, 12]
 - Advanced features (cf. Moses)
 - Kneser-Ney translation probability smoothing [Chen+, 11]
 - Hierarchical lexicalized reordering [Cherry+, 12]
 - Lattice-batch-MIRA optimization [Cherry & Foster, 12]
 - etc.
 - User-friendly features
 - Highly tuned libraries for using gigantic models [Germann+, 09]
 - High stability (cf. GIZA++)
 - Fits well to cluster computing environment

Training component models

- Provided data
 - Training bi-text
 - 3.2M sentence pairs
 - Monolingual text
 - Ja: 594M sentences (27.3B words)
 - En: 413M sentences (13.4B words)
 - Data for tuning
 - 2000 sentence pairs

- Component models
 - Language models
 - SRILM-5g
 - Translation models
 - IBM2
 - HMM
 - IBM4
 - Reordering models
 - Lexical model
 - Hierarchical lexical model
 - Paraphrase tables
- Parameter tuning

of learned phrasal equivalent pairs

extraction

filtering

expansion

of trans. pairs

Ja → En En → Ja IBM2 9.1M 9.4M HMM 230.6M 234.4M IBM4 80.6M 81.8M Union 260.4M 264.8M

of paraphrase pairs

	•		•	
	$th_{ ho}$	th_s	En	Ja
P _{Seed}	0	0	7.2M	5.1M
P _{Seed}	0.01	0.1	1.1M	0.8M
P _{Hvst}	0.01	0	272M	143M

dev&test data driven filtering

	$th_{ ho}$	th_s	En	Ja
P _{Seed}	0.01	0.1	0.7M	0.5M
P _{Seed}	0.01	0.1	3.8M	2.7M
P _{Hvst}	0.01	0.1	1.8M	1.5M

Avg. BLEU score over held-out data

On two 2006-2007 dev data (v7, v8)

	Para	Ja → En			En → Ja		
System	score	# of trans. pairs	BLEU		# of trans. pairs	BL	EU
Base system	-	18.0M	33.30		15.5M	37.64	
Saug-P _{Seed}	PivProb	27.3M	33.65	+0.35	24.6M	37.98	+0.34
Saug-P _{Seed}	Cosine	27.3M	33.27	-0.03	24.6M	37.73	+0.09
Saug-P _{Hvst}	Cosine	23.6M	33.22	-0.08	22.0M	37.89	+0.25
Saug-P _{OOPH}	Cosine	18.1M	33.72	+0.42	15.6M	38.16	+0.52
Saug- P_{Seed} + P_{Hvst}	Cosine	32.8M	32.91	-0.39	30.9M	37.76	+0.12
Taug-P _{Seed}	PivProb	22.9M	33.34	+0.04	19.6M	37.64	+0.00
Taug-P _{Seed}	Cosine	22.9M	33.56	+0.26	19.6M	38.19	+0.55
Taug-P _{Hvst}	Cosine	29.1M	33.43	+0.13	26.8M	37.98	+0.34
Taug-P _{OOPH}	Cosine	23.4M	33.21	-0.09	21.5M	38.08	+0.44
Taug- P_{Seed} + P_{Hvst}	Cosine	33.9M	32.99	-0.31	30.8M	37.53	-0.11

Official results

Human evaluation (Saug- P_{OOPH})

	Ja →	En	En → Ja		
	Score Ranking		Score	Ranking	
Adequacy	2.89/5.00	10th/18	2.67/5.00	10th/14	
Acceptability	0.43/1.00	8th/9	0.38/1.00	8th/9	

Automatic evaluation

	Ja → En			En → Ja		
System	BLEU	NIST	RIBES	BLEU	NIST	RIBES
Saug-P _{OOPH}	31.56	8.2507	0.6955	34.22	8.2345	0.7096
Taug-P _{Seed}	31.65	8.2198	0.6929	34.05	8.2116	0.7089
*Const-Saug- P_{Hvst}	30.58	8.1114	0.6911	32.89	8.0977	0.7048
*Const mixLM	30.65	8.1400	0.6906	22.59	7.1185	0.6651

^{*}Systems built using only bilingual data.

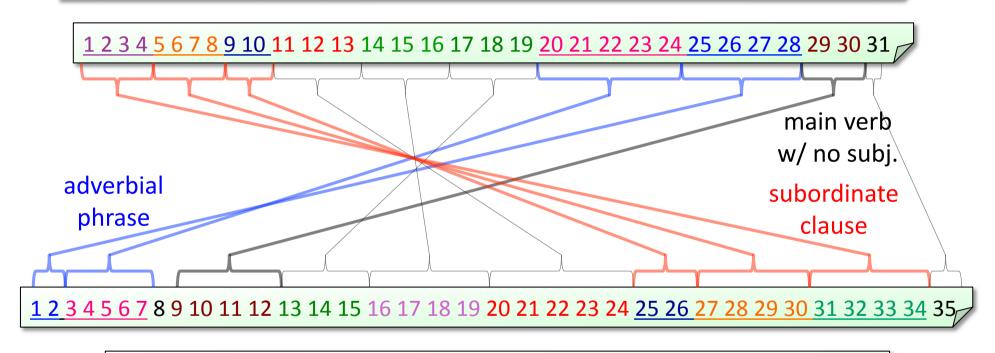
33.03 8.1101 0.7051

Implications

- Relatively high BLEU and NIST scores
 - Useful n-grams (~ phrases) were generated and selected
- Low RIBES score and human evaluation score
 - Reordering ability was poor
 - Features of superior systems
 - Structure-aware SMT
 - RBMT adapted to the patent domain

We've used 7 for the distortion limit ...

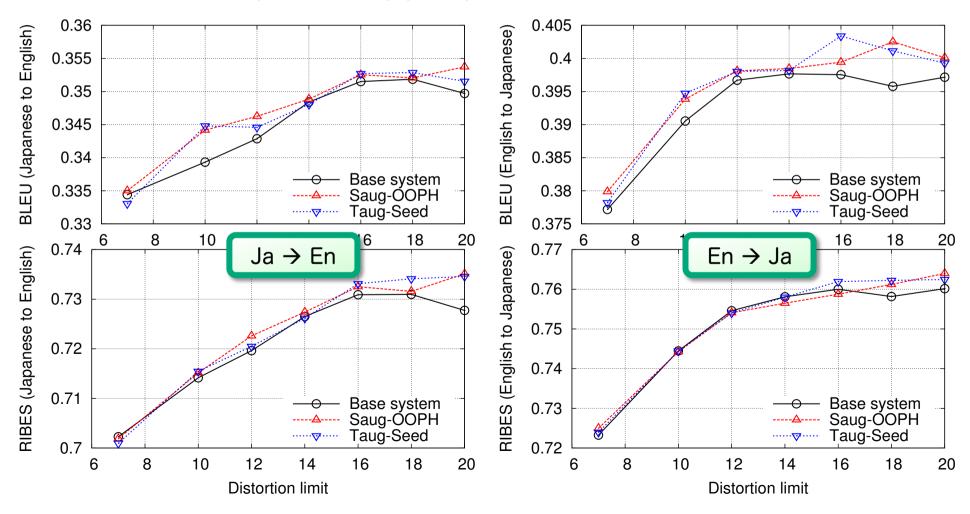
本/実施/形態/の/トレンチ/型/キャパシタ/120/を/含む/半導体/装置/の/製造/工程/の/一例/を/図/2/から/図/8/を/参照/し/て/説明/する/。/



Referring to FIGS. 2 to 8, description will be given to an example of a manufacturing process of the semiconductor storage device which comprises the trench capacitor 120 according to the embodiment.

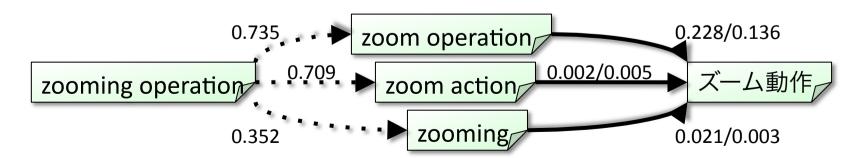
Relaxation of distortion limit

- Held-out data same as development
 - Obtained significantly higher score
 - Positive impact led by paraphrases was retained



Conclusion

- Phrase-based SMT + paraphrases
 - State-of-the-art non-hierarchical system: PortageII @ NRC
 - Almost no language- or domain- specific knowledge
 - Phrase table augmentation
 - Paraphrases in both source & target languages (separately)
 - Comparison of paraphrase collections
 - Aggregation of multiple paths w/ feature engineering
 - Improved performance over a vanilla phrase-based SMT
 - at least BLEU, NIST, and RIBES



Greatest thanks go to

- Supporters of the research program
 - NRC: National Research Council Canada
 - esp. All members in the Portage team
 - FUN: Future University Hakodate
 - JSPS: Japan Society for the Promotion of Science
- PatentMT task organizers