Document-level Statistical MT: from Connectives to Pronouns

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"Machine Translation meets Translators" Workshop at the University of Zurich, May 16, 2017 Since its start in the 1950s, and especially in the past 20 years, machine translation has made less and less use of linguistics



- State-of-the-art MT is slipping down the MT pyramid
- From rule-based, to examplebased, to statistical systems
 - Within rule-based: from interlingua (representing meaning), to transfer (syntactic), to direct
- Neural MT: opaque interlingua?

The success of statistical MT

- "Whenever I fire a linguist, our system performance improves"
 - said Frederik Jelinek around 1980, marking the statistical turn in automatic speech recognition, followed later by machine translation
- What is statistical MT?
 - translation as a noisy channel (Weaver 1947, then Brown et al. 1993)
 - 1. Learn <u>n-gram based</u> translation and language models.
 - 2. Decode the source sentence: find the target sentence that maximizes the probabilities given by the translation model and the language model.
- Until recently, had state of the art performance
 - phrase-based or hierarchical SMT, or direct rule-based MT
 - since 2015, neural networks for MT have reached higher performance



Formal definition of SMT

- Goal: given *s*, find *t* which maximizes P(*t*|*s*)
- Rewritten using Bayes's theorem as:





Formal definition of NMT

- Artificial neural networks: units/activation + connections/strengths
- How NMT works (Cho et al., EMNLP 2014)
 - represent words as individual units → learn to encode an abstract representation of a source sentence using stacked layers of units → decode representation into a foreign sentence
- Key additional contribution
 - "attention mechanism" (Bahdanau, Cho and Bengio, ICLR 2015)
- Enhancements to outperform SMT (Sennrich et al., WMT 2016)
 - character-based NMT for unknown words (byte-pair)
 - training on parallel data obtained from SMT output
 - very large computing power using GPUs (e.g., Google NMT)



Document-level machine translation

- Statistical or neural MT: efficient, good coverage, readable
- But systems always translate sentence by sentence
 - do not propagate information along a series of sentences
- Discourse information is helpful for coherent text translation
 - referring information, lexical chains: noun phrases, terms, pronouns
 - argumentative relations, as signaled by discourse connectives
 - verb tense, mode, aspect | style, register, politeness



Plan of this talk

- 1. Motivation and method
- 2. Document/discourse-level linguistic features for MT
 - a. Disambiguation of English discourse connectives for MT
 - b. Translation of English verb tenses into French
 - c. Towards coherent translation of referring expressions
 - i. coreference similarity as a criterion for MT from Spanish into English
 - ii. consistent translation of repeated nouns from Chinese and German into English
- 3. Conclusion and perspectives



Credits

- Large collaboration started in 2010 supported by the Swiss National Science Foundation through two consecutive Sinergia projects
 COMTIS: Improving the coherence of MT by modeling inter-sentential relations
 MODERN: Modeling discourse entities and relations for coherent MT
 Also with support from the SUMMA EU project
- Research groups and people
 - Idiap NLP group: Thomas Meyer, Ngoc Quang Luong, Najeh Hajlaoui,
 Xiao Pu, Lesly Miculicich Werlen, Jeevanthi Liyanapathirana, Catherine Gasnier
 - University of Geneva, Department of Linguistics: Jacques Moeschler, Sandrine Zufferey, Bruno Cartoni, Cristina Grisot, Sharid Loaiciga
 - University of Geneva, CLCL group: Paola Merlo, James Henderson, Andrea Gesmundo
 - University of Zurich, Institute of Computational Linguistics: Martin Volk, Mark Fishel,
 Laura Mascarell, Annette Rios Gonzales, Don Tuggener
 - Utrecht Institute of Linguistics: Ted Sanders, J. Evers-Vermeul, Martin Groen, Jet Hoek



FONDS NATIONAL SUISSE Schweizerischer Nationalfonds Fondo nazionale svizzero Swiss National Science Foundation

1. Motivation and method

- 2. Document-level linguistic features for SMT
 - a. English discourse connectives for MT
 - b. Translation of English verb tenses into French
 - c. Coherent translation of referring expressions
 - i. coreference similarity as a criterion for MT
 - ii. consistent translation of repeated nouns
- 3. Conclusion and perspectives

1. MOTIVATION AND METHOD

Examples: problems with discourse connectives

- Source: Why has no air quality test been done on this particular building since we were elected?
- SMT: Pourquoi aucun test de qualité de l'air a été réalisé dans ce bâtiment <u>car</u> nous avons été élus ?
- Human: Comment se fait-il qu'aucun test de qualité de l'air n'ait été réalisé dans ce bâtiment <u>depuis</u> notre élection?
- Source: What stands between them and a verdict is this doctrine that has been criticized <u>since</u> it was first issued.
- SMT: Ce qui se situe entre eux et un verdict est cette doctrine qui a été critiqué *parce qu'* il a d'abord été publié.
- Human: Seule cette doctrine critiquée <u>depuis</u> son introduction se trouve entre eux et un verdict.



Example: problems with verb tenses

- Source: Grandmother *drank* three cups of coffee a day.
- SMT: Grand-mère <u>*a bu*</u> trois tasses de café par jour.
- Human: Grand-maman <u>buvait</u> trois tasses de café par jour.
- Source: ... that we <u>support</u> a system that <u>is</u> clearer than the current one ...
- SMT: ... que nous <u>soutenir</u> un système qui <u>est</u> plus claire que le système actuel ...
- Human: ... que nous <u>soutenons</u> un système qui <u>soit</u> plus clair que le système actuel ...



Example: problem with NP coherence

- Source: Am 3. Juni schleppten Joe, Mac und ich die erste Traglast zum Lager II, während <u>die Träger</u> die unteren Lager mit Vorräten versorgten. [..] Am nächsten Morgen kamen <u>die Träger</u> unbegleitet vom Lager II zu uns herauf, als wir noch in den Schlafsäcken lagen.
- SMT: Le 3 Juin Joe, Mac, et j'ai traîné la première charge au camp II, tandis que <u>le support</u> fourni avec le roulement inferieur fournitures.
 [...] Le lendemain matin, <u>le transporteur</u> est arrive seul à partir de Camp II a nous, car nous étions encore dans leurs sacs de couchage.
- Human: Le 3, Joe, Mac et moi montâmes les premières charges au camp II, tandis que <u>les porteurs</u> faisaient la navette entre les camps inferieurs. [...] Nous étions encore dans nos sacs de couchage, le lendemain matin, lorsque <u>les porteurs</u> arrivèrent du camp II.



Examples: problems with pronouns

- Source: The table is made of wood. <u>*It*</u> is magnificent.
- SMT: La table est faite de bois. <u>*II*</u> est magnifique.
- Human: La table est en bois. <u>Elle</u> est magnifique.
- Source: The European commission must make good these omissions as soon as possible. <u>It</u> must also cooperate with the Member States ...
- SMT: La commission européenne doit réparer ces omissions dès que possible. <u>II</u> doit également coopérer avec les états membres ...
- Human: ... <u>Elle</u> ...



Sum	mary	v of				-	
our goals			1. Connective	2. Pronoun	3. Verb tense		
The matrix	has been reduced	four times,	since	it	was	too large.	
La	a été	quatre	depuis qu'	il	a été	trop grand.	×
matrice	réduite	éduite fois,	car	elle	était	trop grande.	\checkmark

Current machine translation systems: red

Using longer-range dependencies: green



<u>1. Linguistic analyses</u> Cohesion markers for MT Features for classification Cross-linguistic perspective

Method

2. Corpus data and annotation Define tagset and guidelines Locate problematic examples Execute annotation and deliver data

5. Evaluation

Define metrics of coherencePerformance of past systemsApply metrics

3. Automatic labeling of cohesion markers Build and test classifiers using surface features

<u>4. SMT of labeled texts</u> Phrase-based SMT for labeled texts Factored SMT models using labels

Method

1. Define and analyze the phenomena to target

- design theoretical models, keeping in mind objective and tractability
- propose features for automatic recognizers

2. Create data for training and evaluation

- define labeling instructions
- annotate data sets (which can also be used for corpus linguistics)
- validate linguistic models through empirical studies
- 3. Automatic disambiguation (= labeling = classification = recognition)
 - design and implement automatic classifiers
 - e.g. using machine learning over annotated data, based on surface features
- 4. Combine the automatically-assigned labels with MT
 - adapt MT systems (SMT or RBMT) or design new text-level translation models and decoding algorithms

5. Evaluation

• assess improvements for the targeted phenomena and overall quality



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Putting the method into application

• Phenomena discussed in this talk

a. Discourse connectives b. Verb tenses c. Nouns/pronouns

• Languages

English, French, German, Italian, Arabic, Chinese, Spanish

- Domains/corpora
 - parliamentary debates: Europarl (EU languages)
 - transcribed lectures: TED (ALL)
 - Alpine Club yearbooks: Text+Berg (FR, DE)
 - news: data from the Workshops on SMT (ALL)



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2.a. DISAMBIGUATION OF ENGLISH DISCOURSE CONNECTIVES

What are discourse connectives?

- Small words, big effects
 - signal discourse relations between sentences or clauses
 - additional, temporal, causal, conditional, etc.
- Theoretical descriptions
 - Rhetorical Structure Theory (Mann and Thompson)
 - Discourse Representation Theory (Asher et al.)
 - Cognitive approach to Coherence Relations (Sanders et al.)
 - annotation-oriented: Penn
 Discourse Treebank (PDTB)
 (Prasad, Webber, Joshi et al.)

- Connectives are challenging for translation because they may convey different relations, which are translated differently
 - while <u>contrastive</u> or <u>temporal</u>: French mais or pendant que
 - since <u>causal</u> or <u>temporal</u>:
 French *puisque* or *depuis que*
- Wrong translations of connectives lead to:
 - low coherence or readability
 - distorted relationships between sentences
 - correct relations are sometimes impossible to recover

Annotation of discourse connectives for translation (Cartoni, Meyer, Zufferey)

- Penn Discourse Tree Bank (PDTB): complex hierarchy of senses
 - difficult to annotate, not necessarily relevant to MT
- Annotation through translation spotting
 - annotators identify the human translation of each connective (in Europarl)
 - observed translations are clustered into a posteriori "senses" relevant to MT
 - fewer labels, cheaper to annotate (e.g. while has 21 PDTB labels vs. 5 here)

Connective			Training set			Testing set
	EP	PDTB	Distribution of labels (%)	EP	PDTB	Distribution of labels (%)
although	168	312	Ct: 68.9; Cs: 31.1	15	16	Ct: 48.4; Cs: 51.6
however	348	450	Ct: 47.8; Cs: 52.2	70	35	Ct: 47.6; Cs: 52.4
meanwhile	102	177	Ct: 77.3; T: 22.7	28	14	Ct: 76.2; T: 23.8
since	339	174	Ca: 38.7; T: 59.6; T/Ca: 1.7	82	10	Ca: 30.4; T: 67.4; T/Ca: 2.2
(even) though	276	306	Ct: 33.3; Cs: 66.7	69	14	Ct: 33.7; Cs: 66.3
while	236	744	Ct: 14; Cs: 23; T: 15; T/Ct: 46.6; T/Ca: 1.4	58	37	Ct: 22.8; Cs: 33.7; T: 9.8; T/Ct:
yet	326	99	Ct: 23.2; Cs: 29.8; Adv: 47	77	2	Ct: 30.4; Cs: 19; Adv: 50.6
Total	1795	2262	-	399	128	-



Features for the automatic disambiguation of connectives

Hong Kong-NNP trade figures illustrate-PRESENT the toy makers' reliance on factories across the border-NN. -JOINT- In-IN 1989's first seven months, -JOINT- domestic exports fell-VBD-PAST-1 29%, to HK\$3.87 billion-NN, -CONTRAST- while-IN re-exports-NN rose-VBD-PAST 56%, to HK\$11.28 billion-NN.

• syntactic features

- connective, punctuation, context words, context tree structures, auxiliary verbs
- WordNet antonymy features
 - similarity scores (word distance) and antonyms from the clauses
- TimeML features
- discourse relation features
 - discourse relations from a discourse parser
- polarity features
 - using a polarity lexicon, count positive and negative words, account for negation
- translational features
 - baseline translation (e.g. *tandis que*), sense from dictionary (*contrast*), position (25)
- Extracted from the current and the previous sentences



Automatic labeling of connectives (Th. Meyer)

- For each (new, unseen) discourse connective
 - given the features extracted from the text
 - determine its most probable label ("sense")
- Use of machine learning for classification
 - Maximum Entropy classifier
 - 1. trained on manually labeled data
 - experimented with PDTB and/or Europarl
 - 2. tested on unseen data



Automatic connective labeling: F1 scores

Data	Method	although	however	meanwhile	since	(even) though	while	yet
Training (c.v.)	All_Features	0.69 ± 0.04	0.85 ± 0.05	0.86 ± 0.01	0.93 ± 0.05	0.77 ± 0.04	0.76 ± 0.04	0.88 ± 0.07
Test: Europarl	Majority class	0.52	0.52	0.76	0.68	0.66	0.34	0.51
and PDTB	All_Features	0.58	0.73	0.71	0.90	0.69	0.45	0.78
(WSJ s. 23)	Best	0.61	0.60	0.74	0.87	0.71	0.43	0.72
	All_Synt+Dep	0.65	0.67	0.79	0.89	0.7	0.47	0.72
Test: Europarl	All_Features	0.60	0.69	0.79	0.90	0.67	0.45	0.78
	Best	0.80	0.56	0.82	0.85	0.72	0.43	0.74
	All_Synt+Dep	0.73	0.66	0.89	0.88	0.71	0.50	0.73
Test: PDTB	All_Features	0.56	0.83	0.57	0.90	0.79	0.46	1.0
(WSJ s. 23)	Best	0.44	0.69	0.57	1.0	0.64	0.43	0.0
	All_Synt+Dep	0.56	0.69	0.57	1.0	0.64	0.43	0.50

• Findings

- scores compare well to human agreement levels (80-90%)
- classifying each connective separately is better than jointly
- using all features is the best option



How do we use labeled connectives in SMT?

Four possible methods have been tested

- 1. Replace in the system's phrase table all unambiguous occurrences of the connective with the correct one
- 2. Train the system on (a) manually or on (b) automatically labeled data, with labels concatenated to words (e.g., *while_Temporal*)
- 3. Use a connective-specific SMT system only when the connective labeler is confident enough (otherwise use a baseline one)
- 4. Use Factored Models as implemented in the Moses system
 - word-level linguistic labels are separate translation features
 - a model of labels is learned when training, then used when decoding



How do we measure the improvement of connective translation? (Meyer, Hajlaoui)

- Measuring translation quality
 - subjective measures: fluency, fidelity \rightarrow too expensive for everyday use
 - objective, reference-based measures: **BLEU** (or **METEOR**, etc.)
 - comparison of a candidate text with one or more reference translations in terms of common n-grams (usually from 1 to 4)
 - connectives are not frequent \rightarrow small effects expected on BLEU scores
- Count how many connectives are correctly translated: ACT metric [Accuracy of Connective Translation]
 - given a source sentence with a discourse connective C
 - use automatic alignment to find out:
 - how C is translated in the reference and in the candidate translations
 - compare the translations: identical | "synonymous" | incompatible | absent



Improvement of SMT and connectives

- 1. Modified phrase table Tested on ~10,000 occurrences of 5 types: **34%** improved, **20%** degraded, **46%** unchanged
- 2. Concatenated labels

(a) trained on manually labeled data: 26% improved, 8% degraded, 66% unchanged
(b) trained on automatically labeled data: 18% improved, 14% degraded, 68% unchanged

3. Thresholding based on automatic labeler's confidence With two connectives only: improvement of **0.2-0.4** BLEU points

4. Factored models in Moses SMT

Languages	Test set	System	BLEU	Δ	p	ACT	Δ	p
EN/FR	nt2012	baseline	26.1			56.28		
		labeled connectives	25.8	-0.3	**	57.68	1.40	*
	nt2010	baseline	24.4			68.12		
		labeled connectives	24.3	-0.1	**	68.60	0.48	*
	nt2008+sy2009	baseline	28.9			61.36		
		labeled connectives	29.2	0.3	*	60.94	-0.42	*
EN/DE	nt2012	baseline	11.8			62.28		
		labeled connectives	11.8	0.0	n/s	65.08	2.80	**
	nt2010	baseline	15.0			62.42		
		labeled connectives	15.0	0.0	n/s	69.28	6.86	***
	nt2008+sy2009	baseline	13.0			71.06		
		labeled connectives	13.1	0.1	n/s	70.30	-0.76	n/s



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2.b. TRANSLATING VERB TENSES

Cross-lingual modeling of verb tenses (Grisot and Moeschler)

- Two well-known models
 - event time, reference time, speech time (Reichenbach)
 - four classes of aspect (Vendler)
- What are the relevant properties that would enable correct translation of English tenses into French ones?
 - focus on English simple past
- Theoretical hypothesis:
 simple past <u>narrative</u>
 → passé simple or passé composé
 simple past <u>non-narrative</u>
 → imparfait





Empirical studies of tense translation

- Approaches: narrativity-based vs. general tense correlation
- 1. Annotation of narrativity (C. Grisot)
 - English/French parallel corpus
 - 576 EN simple past verb phrases
 - inter-annotator agreement on 71% of instances: $\kappa = 0.44$
 - ➔ narrativity correctly predicts 80% of translated tenses
- 2. Annotation of translated tense for all English VPs (S. Loaiciga)
 - rules for precise alignment of VPs in Europarl
 - annotated ca. 320,000 VPs, with about 90% precision
 - → confirmed divergencies between EN and FR tenses



Observed EN/FR tense divergencies for 322,086 verb phrases (Loaiciga)

	English								
French	Past continuous	Past perfect continuous	Past perfect	Present continuous	Present perfect continuous	Present perfect	Present	Simple past	Total
Imparfait	462	7	365	146	18	463	1 510	8 060	11 031
	54%	27%	24%	1%	2%	1%	1%	21%	3%
Impératif				37	1	6	203	11	258
Imperum				0%	0%	0%	0%	0%	0%
Passé composé	139	2	214	282	325	26 5 2 1	1253	19 402	48 1 38
russe compose	16%	8%	14%	1%	33%	61%	1%	49%	15%
Passé récent			1	8	3	187	2	3	204
i usse recent			0%	0%	0%	0%	0%	0%	0%
Passé simple	4		6	16	2	54	42	374	498
r asse simple	1%		0%	0%	0%	0%	0%	1%	0%
Plus-que-parfait	27	8	782	2	4	217	22	1 1 2 8	2 1 9 0
Thus-que-partan	3%	31%	52%	0%	0%	1%	0%	3%	1%
Présent	216	9	102	18 077	617	14736	211 334	9779	254 870
Fiesent	25%	35%	7%	96%	63%	34%	97%	25%	79%
Subjonctif	15		28	258	6	1 0 5 3	2 969	568	4 897
Subjoitetti	2%		2%	1%	1%	2%	1%	1%	2%
Total	863	26	1 498	18 826	976	43 237	217 335	39 325	322 086
Total	100%	100%	100%	100%	100%	100%	100%	100%	100%



Features for automatic prediction of narrativity or (directly) translated tense

If the situation were-VBD-PAST-SV-1-0 to change-VBP-INFINITIVE-0-0-0, it would-MD-CONDITIONAL-CSV-0-0 clearly also change-VBP-INFINITIVE-0-0-0 as far as-synch we are-VBP-PRESENT-CSV-0-0 concerned-VBN-0-0-0.

- all verbs in the current and previous sentences
- word positions
- verb POS and trees
- auxiliaries and tenses
- TimeML features
- temporal connectives (from a hand-crafted list)
- synchrony/asynchrony of the connectives
- semantic roles
- imparfait indicator: yes/no
- subjonctif indicator: yes/no
- Extracted from the current and the previous sentences



Automatic annotation: results

- Using a maximum entropy classifier
- 1. Automatic annotation of narrativity (+/-)
 - training on 458 instances, testing on 118
- 2. Prediction of translated tense
 - training/testing on 196'000 instances
 with 10-fold cross-validation



Improvements of SMT using narrativity

- Scores from human evaluators
 - Is the narrativity label correct?
 - 2. Are verb tenses and lexical choices improved?

Criterion	Rating	N .	%	Δ
Labeling	correct	147	71.0	
	incorrect	60	29.0	
Verb	+	35	17.0	
tense	=	157	75.8	+9.7
	—	15	7.2	
Lexical	+	19	9.2	
choice	=	176	85.0	+3.4
	—	12	5.8	



Improvements of SMT using predicted tense labels

• Oracle = prefect prediction

•	BLEU scores		Baseline	Oracle	Predicted	# Sent.
		Imparfait	24.10	25.32	24.57	122
	per target	Passé composé	29.80	30.82	30.08	359
	tense	Impératif	19.08	19.72	18.70	4
	lense	Passé simple	13.34	16.15	14.09	6
		Plus-que-parfait	21.27	23.44	23.22	17
		Présent	27.55	27.97	27.59	2,618
		Subjonctif	26.81	27.72	26.07	78
		Passé recent	24.54	30.50	30.08	3

• Manual evaluation of a sample

		TAM				
French tense	System	Incorrect	Corr	rect		
			\neq ref	= ref		
	Baseline	82	15	41		
Imparfait	Predicted	42	23	73		
	Oracle	13	4	121		



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2.c. REFERENTIAL COHERENCE IN MT

Can we improve MT of nouns using document/discourse-level information?

- Translate nouns so as coreference relations from the source text are preserved in the translated text

 challenge: compute coreference automatically
- Translate repeated nouns consistently,
 i.e. using the same translation
 - challenge: learn when to enforce consistency


Previous work on consistency and coreference

- How do human and MT consistency compare? Is consistency correct?
 - it is often the case that there is "one translation per discourse" (Carpuat 2009)
 - "the trouble with MT consistency" (Carpuat and Simard, 2012)
 - systems are often (and wrongly) more consistent than humans, due to lack of coverage
 - inconsistencies (i.e. errors) are often due to semantic/syntactic mistakes
 - human translators are often more consistent with nouns than verbs (Guillou 2013)
 - encourage consistent translation by "caching" (Tiedemann, 2010; Gong et al., 2011)
- How can coreference help MT?
 - anaphora resolution is somewhat helpful for pronoun translation, but surface features do better (Hardmeier et al. 2015; Guillou et al. 2016; Loaiciga et al. *in preparation*)
- Coreference is a good reason to enforce noun consistency, but surface features can also help to decide when/how to correct inconsistencies



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2.c.i. USING A COREFERENCE SCORE TO RE-RANK MT HYPOTHESES

Using coreference similarity for MT

- Principle
 - preserve the information conveyed in translation: here, information about the entities (i.e. grouping of mentions)
 - → better translations should have coreference links that are more similar to those of the source text
- Maximize a global coreference similarity score by re-ranking hypotheses from the Moses SMT decoder
 - Spanish-to-English translation using gold coreference links on the source side, from AnCora-ES (Recasens and Martí 2010), as test data

Miculicich Werlen L. & and Popescu-Belis A. (2017) - Using Coreference Links to Improve Spanish-to-English Machine Translation. *Proceedings of the EACL Workshop on Coreference Resolution Beyond OntoNotes (CORBON)*, Valencia, p. 30-40, 4 April 2017.



Motivating example

Source	Human Translation	Baseline SMT
La película narra la historia de [un joven parisiense] _{c1} que marcha a Rumanía en busca de [una cantante zíngara] _{c2} , ya que [su] _{c1} fallecido padre escuchaba siempre [sus] _{c2} canciones.	The film tells the story of [a young Parisian] _{c1} who goes to Romania in search of [a gypsy singer] _{c2} , as [his] _{c1} deceased father use to listen to [her] _{c2} songs.	The film tells the story of [a young Parisian] _{c1} who goes to Romania in search of [a gypsy singer] _{c2} , as [his] _{c2} deceased father always listened to [his] _{c1} songs.
Pudiera considerarse un viaje fallido, porque [Ø] _{c1} no encuentra [su] _{c1} objetivo, pero el azar [le] _{c1} conduce a una pequeña comunidad	It could be considered a failed journey, because [he] _{c1} does not find [his] _{c1} objective, but the fate leads [him] _{c1} to a small community	It could be considered [a failed trip] _{c3} because [it] _{c3} does not find [its] _{c3} objective, but the chance leads \emptyset to a small community



Challenge: compute a reliable "coreference score" for a translation

- For any candidate translation, measure the similarity between its coreference links and those of the source text
- 1. Apply a coreference resolver to the source text and the translation
 - NB: this is the major source of errors in estimating the CSS
 - NB: in this work, we use ground truth links on the source side (fixed), and only run automatic coreference resolution (Stanford Core NLP Tools) on translations
- 2. Project mentions from the candidate translation back to the source (i.e. referring expressions: nouns, pronouns)
- 3. Apply existing metrics for evaluating coreference links on the source text
 - MUC: number of links to be inserted or deleted
 - B3: precision and recall at cluster-level for each mention
 - CEAF: precision and recall at cluster-level for each entity
 - → CSS (coreference similarity score): average of MUC, B3 and CEAF



Empirical verification: CSS increases with better translations (on 3k words from AnCora-ES)

		BLEU	MUC	B ³	CEAF	
	Human translation	-	37	32	41	
Hypothesized Translation Quality	Commercial NMT	49.7	28	26	36	
	Baseline PBSMT	43.4	23	24	33	

Automatic Coreference Quality

F1 scores (%)



Using the CSS for document-level MT

- Phrase-based ES-EN statistical MT: Moses
 - trained on WMT 2013 (14M sentences)
 - tuned on News Commentary 2011 (5.5k s.)
 - tested on News Test 2013 (3k s., BLEU = 30.8)
- For each sentence of a translated text
 - get from Moses the 1000-best hypotheses
 - select those that differ in the translations of mentions
- Beam search to maximize the CSS
 - starting from the first sentence, search among the hypotheses for those that improve the text-level CSS



Evaluation

(10 test documents, with our translations)

Metric	PBSMT	NMT	PBSMT + Re-ranking
BLEU	46.5 <u>+</u> 4.3	46.9 <u>±</u> 3.7	41.7 <u>±</u> 3.9
Accuracy of pronoun translation	0.35±0.07	0.37±0.07	0.40±0.1
Accuracy of noun translation	0.78 <u>+</u> 0.08	0.78 <u>±</u> 0.07	0.74±0.01

- The number of pronouns identical to the reference translation increases
 - especially for a second approach, based on post-editing mentions
 - see (Miculicich & APB, 2017)





Findings

- The principle of "maximizing coreference similarity with the source" fails to increase the accuracy of noun translation
 - possible causes
 - imperfect (ca. 60-70%) automatic coreference resolution (\rightarrow no simple solution)
 - imperfect use of the criterion in SMT (\rightarrow could try Docent)
 - optimal translation is not among 1000-best hypotheses (20% of the cases)
 - requires coreference resolution for every translation hypothesis
- Our 2nd method has promising results for pronoun translation: post-editing the mentions & maximizing coreference features

→ Narrow our focus to repeated nouns

partial overlap with coreference, but more tractable



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2.c.ii. ENFORCING TRANSLATION CONSISTENCY OF REPEATED NOUNS

First attempt: consistent translation of noun compounds (DE, ZH \rightarrow EN)

• Motivating example

Src: das Bundesamt für Landestopographie [...] dieses Amt war in der Lage,
 Ref: Seul cet office était en mesure,
 SMT: Que ce poste était dans la situation,

- Assumptions: given a compound (XY) and a subsequent occ. of the head noun (Y)
 - assume that the latter is a mention of the former (co-reference)
 - assume the translation of Y in XY is more accurate than of Y alone
- Method: replace the translation of the second occurrence with the first one
- Challenges
 - avoid non-compound XY, and non-coreferent XY/Y pairs
 - correctly identify the translations of XY and Y

Mascarell L., Fishel M., Korchagina N., and Volk M. (2014) - Enforcing consistent translation of German compound coreferences. In Proceedings of the 12th Konvens Conference, Hildesheim, Germany.

Pu X., Mascarell L., Popescu-Belis A., Fishel M., Luong N.Q., & Volk M. (2015) - Leveraging Compounds to Improve Noun Phrase Translation from Chinese and German. ACL-IJCNLP 2015 Student Research Workshop, Beijing, p.8-15.



Example of a Chinese compound

1. CHINESE SOURCE SENTENCE	她以为自买了双两英寸的高跟鞋, 但实际上那是一双三英寸高的鞋。
2. SEGMENTATION, POS TAGGING, IDENTIFICATION OF COMPOUNDS AND THEIR CO-REFERENCE	她#PN 以为#VV 自#AD 买#VV 了#AS 双#CD 两#CD 英 寸#NN 的#DEG 高跟鞋#NN , #PU 但#AD 实际上#AD 那 #PN 是#VC 一#CD 双#M 三#CD 英寸#NN 高#VA 的 #DEC 鞋#NN 。#PU
3. BASELINE TRANSLATION INTO ENGLISH (STATISTICAL MT)	She thought since bought a pair of two inches high heel , but in fact it was a pair of three inches high shoes .
4. AUTOMATIC POST-EDITING OF THE BASELINE TRANSLATION USING COMPOUNDS	She thought since bought a pair of two inches high heel , but in fact it was a pair of three inches high heel .
5. COMPARISON WITH A HUMAN REFERENCE TRANSLATION	She thought she'd gotten a two-inch heel but she'd actually bought a three-inch heel . ✓



Improvement of SMT using compounds

- Test data for SMT: ZH/EN and DE/FR
 - training sets: about 200k sentences | tuning: about 2k sentences
 - testing: 800/500 sentences with ca. 250 XY/Y pairs
- BLEU scores
 - ZH/EN: 11.18 → 11.27 | DE/FR: 27.65 → 27.48
- Comparison of the *Y* translations (in % of total)
 - our 2 systems are closer to the reference than the baseline

			CAC	HING	POST-EDITING		
			= ref	≠ref	= ref	\neq ref	
ZH/EN	BASELINE	= ref	59.3	4.1	42.3	4.5	
		≠ref	13.8	22.8	20.3	32.9	
DE/FR	BASELINE	= ref	70.1	10.3	73.9	5.0	
DE/FK		≠ref	4.3	15.2	3.5	17.5	



Second attempt: consistent translation of repeated nouns

- Automatically enforcing consistent noun translations
 - learn whether two occurrences of the same noun must be translated identically or not, based on several features, but *not coreference*
- Method
 - 1. Detect two close occurrences of the same noun in the source
 - 2. Find their baseline translations by a PBSMT using word alignment
 - 3. If they differ, decide whether/how to edit: $1^{st} \rightarrow 2^{nd}$, or vice-versa
 - 4. Based on this decision, post-edit and/or re-rank the PBSMT output

Pu X., Mascarell L. & Popescu-Belis A. (2017) - Consistent Translation of Repeated Nouns using Syntactic and Semantic Cues. *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics (EACL)*, Valencia, 5-7 April 2017.



Example

- Source: nach einfuehrung dieser politik [...] die politik auf dem gebiet der informationstechnik [...]
- *Reference:* once the **policy** is implemented [...] the information technology **policy** [...]
- *MT:* after introduction of **policy** [...] the **politics** in the area of information technology[...]



Example

- Source: 赞扬 联合国 人权 事务 高级 专员 办事处 高度 优先 从事 有关 国家 机构 的 工作, [...], 鼓励 高级 专员 确保 作出 适当 安排 和 提供 预算 资源
- *Reference:* commends the high priority given by the office of the united nations high **commissioner** for human rights to work on national institutions, [...], encourages the high **commissioner** to ensure that appropriate arrangements are made and budgetary resources provided.
- *MT:* praise the human rights high **commissioner** was the high priority to offices in the country, [...], to encourage senior **specialists** to make sure that make appropriate and provided budget resources.



Data and classifiers

- Training data = with the correct consistency decisions
 - source text + baseline MT output + reference translation
 - detect pairs of repeated source nouns, inconsistently translated by baseline
 - use word-aligned reference translation to set the correct decision
 - if the two reference translations differ, then label as 'none' [else...]
 - if the reference translation is equal to one of the baseline translations, then paste this word over the other one $('1 \rightarrow 2' \text{ or } '2 \rightarrow 1')$ [else...]
 - label as 'none'
- Testing data = same as above (to test the classifier) or parallel (to test end-to-end MT)
- Extracted pairs (UN Corpora)
 - ZH/EN: 3,301 train, 647 test | DE/EN: 11,289 train, 695 test
- Classifiers
 - experimented with decisions trees, random forests, Naïve Bayes, SVM
 - syntactic and semantic features



Syntactic features

Features	Values
Source noun (Chinese)	专员
Distance in sentences between the two source occurrences	0
Translation of the first occurrence (labeled NN)	commissioner
Translation of the second occurrence (labeled NN)	specialists
Number of sibling nodes of the 1st occurrence	4
Number of sibling nodes of the 2nd occurrence	2
Sign of the difference between the above (+1, 0, -1)	1
Number of words of the 1st occurrence and its siblings	2
Number of words of the 2nd occurrence and its siblings	1
Sign of the difference between the above $(+1, 0, -1)$	1
Number of nodes in the first NP ancestor of 1st occ.	15
Number of nodes in the first NP ancestor of 2nd occ.	7
Sign of the difference between the above $(+1, 0, -1)$	1
Number of words in the first NP ancestor of the 1st occ.	6
Number of words in the first NP ancestor of the 2nd occ.	2
Sign of the difference between the above (+1, 0, -1)	1
Distance between the first NP ancestor and the 1st occ.	3
Distance between the first NP ancestor and the 2nd occ.	3
Sign of the difference between the above (+1, 0, -1)	0
Class (1, 2, 0)	1





Semantic features

- For each of the two occurrences (1st and 2nd)
- Features of the *local context* (in source and target)
 - values of 3 surrounding words to the left and right, within the same sentence
- Features of the *discourse context* (in target only)
 - cosine similarity between the vector representation (word2vec) of the translated word and the vector of its context
 - context = average of 20 words before and 20 after the word
 - *interpretation*: if inconsistency is due to the sense ambiguity of the source noun, use semantic similarity to decide which of the two translations best matches its context



Data

UN data to train/test the classifiers											
	Training		Testing								
Sent.	Words	Nouns	Sent.	Nouns							
150K	4.5M	11,289	7,771	225K	695						
185K	3,4M	3,301	3,000	121K	647						

	WIT ³ data for building SMT												
	Tra	ining	Tur	ning	LM								
	Sent.	Words	Sent.	Words	Sent.	Words							
DE-EH	193K	3.6M	2,052	40K	217K	4,4M							
ZH-EN	185K	3,4M	2,457	54K	4,8M	800M							



Noun pair classification, for ZH/EN and DE/EN, with 10-fold cross-validation

Prediction of correct translation for repeated nouns in Chinese											
	Syntactic	features	Semantic	c features	All features						
	Acc. (%)	К	Acc. (%)	К	Acc. (%)	К					
SVM	72.1	0.48	60.2	0.00	60.2	0.00					
J48	74.5	0.54	60.2	0.00	73.9	0.51					
RF	75.3	0.54	68.4	0.29	70.7	0.35					
MaxEnt	76.7	0.65	69.5	0.32	83.3	0.75					

Prediction of correct translation for repeated nouns in German											
	Syntactic	features	Semantic	e features	All features						
	Acc. (%)	К	Acc. (%)	К	Acc. (%)	К					
SVM	77.9 0.67		38.1	0.00	38.1	0.00					
J48	77.0 0.66		64.8	0.45	79.7	0.69					
RF	82.0	0.73	73.5	0.60	84.5	0.77					
MaxEnt	80.8	0.71	76.8	0.65	83.4	0.75					



Integration with MT

1. Post-editing

edit the baseline translation depending on the classifier's decision

2. Re-ranking

- obtain the 10,000-best translation hypotheses from the SMT system
- search among them for highest ranking one in which the repeated word is translated as predicted by the classifier
- if none is found, keep the best hypothesis
- 3. Re-ranking + Post-editing
 - same as (2), but if none is found, post-edit the baseline translation



Classification and MT results (BLEU scores) for ZH/EN and DE/EN

		Syntactic features					Semantic features					All features				
	Acc.	K	BLEU		Acc.	κ		BLEU		Acc.	K		BLEU			
	Acc. h	h	PE	RR	RR+PE	Acc.	r.	PE	RR	RR+PE	Acc.	n n	PE	RR	RR+PE	
Baseline	-	-	11.07	11.07	11.07	-	-	11.07	11.07	11.07	-	-	11.07	11.07	11.07	
J48	66.3	0.42	11.17	11.20	11.30	33.1	0.00	11.07	11.07	11.07	33.1	0.00	11.07	11.07	11.07	
SVM	71.9	0.53	11.23	11.27	11.33	33.1	0.00	11.07	11.07	11.07	62.1	0.43	11.18	11.26	11.26	
RF	71.7	0.53	11.22	11.24	11.27	55.2	0.33	11.04	11.07	11.12	54.9	0.32	11.16	11.20	11.24	
MaxEnt	73.7	0.60	11.27	11.33	11.35	56.1	0.34	10.87	11.11	11.18	72.5	0.56	11.21	11.33	11.36	
Oracle	100	1.00	11.40	11.52	11.64	100	1.00	11.40	11.52	11.64	100	1.00	11.40	11.52	11.64	

Table 4: Prediction of the correct translation (accuracy (%) and *kappa*) and translation quality (BLEU) for repeated nouns on the *Chinese test set*. Maximum Entropy was the best method found on the dev set.

		Syntactic features					Semantic features					All features				
	Acc.	K	BLEU		Acc.	κ		BLEU		Acc.	κ		BLEU			
	Acc. κ	ĥ	PE	RR	RR+PE	Acc.	n.	PE	RR	RR+PE	Acc.	n n	PE	RR	RR+PE	
Baseline	-	-	17.10	17.10	17.10	-	-	17.10	17.10	17.10	-	-	17.10	17.10	17.10	
SVM	71.4	0.57	17.59	17.65	17.72	32.8	0.00	17.10	17.10	17.10	32.8	0.00	17.10	17.10	17.10	
J48	70.5	0.56	17.59	17.61	17.70	48.2	0.23	17.13	17.27	17.33	69.4	0.54	17.56	17.60	17.66	
RF	70.2	0.55	17.55	17.62	17.68	54.4	0.32	17.21	17.34	17.37	67.6	0.52	17.53	17.57	17.63	
MaxEnt	78.3	0.67	17.63	17.66	17.75	63.5	0.49	17.39	17.47	17,49	68.7	0.53	17.58	17.59	17.67	
Oracle	100	1.00	17.78	17.83	17.99	100	1.00	17.78	17.83	17.99	100	1.00	17.78	17.83	17.99	

Table 5: Prediction of the correct translation (accuracy (%) and *kappa*) and translation quality (BLEU) for repeated nouns on the *German test set*. Maximum Entropy was the best method found on the dev set.



Pronoun MT: coreference (anaphora) or not?

- Active research topic, shared tasks since 2015

 focusing on divergencies such as *it* → *il* | *elle* | *ce* | ...
- Studies by Idiap's NLP group (Luong et al., 2016-7)
 - 1. Pronoun-aware language model
 - post-edit translated pronouns based on neighboring nouns
 - 2. Anaphora-aware decoder with uncertainty modeling
 - learn probabilities for pronoun translation based on probability distributions of the antecedents
- Many other studies
 - surface features outperform anaphora resolution
 - no need for antecedent, just a guess of translation



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3. CONCLUSION AND PERSPECTIVES

Conclusion

- Long-range dependencies can be modeled thanks to linguistic theories, and their automatic annotation, although imperfect, can benefit SMT
- Genuine collaboration between: theoretical linguistics and pragmatics, corpus linguistics, natural language processing, and machine translation
- Some outputs
 - publications: available from COMTIS and MODERN websites
 - resources: annotations of discourse connectives and verb phrases
 - software: automatic connective labeler, ACT and APT metrics



Perspectives

- Correct and consistent [pro]noun translation remains an open problem
 - improved anaphora/coreference resolution is beneficial to MT
 - but using only coreference-related *features* seems the best approach
 - dilemma: invest research in the classifiers or in the MT?
- Future work
 - word sense disambiguation and MT (especially for nouns)
 - larger use of context in neural MT (for nouns and pronouns)
 - how do we integrate these complex, heterogeneous knowledge sources into efficient and robust SMT or NMT systems?
- Sinergia MODERN and COMTIS: established discourse-level MT
 - worked on connectives and verb tenses, before pronouns/nouns
 - workshops every two years: DiscoMT 2013, 2015, 2017
 - shared tasks on pronoun prediction in translations: 2015, 2016, 2017



SNSF Press release on April 3, 2017 and subsequent press articles

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Ubersetzungsprogramme wie «Google Translate» verwenden Statistik, um die wahrscheinlichste Übersetzung von Wortgruppen in Sätzen zu liefern. Hinter menschlichen Übersetzerinnen lie-gen die Maschinen jedoch noch meilen-weit zurück. Einer der Gründe: Die Algorithmen schauen nicht über die Grenzen eines Satzes hinaus. Dadurch haben sie etwa Mühe mit Pronomen, wie «sie» oder «diese», da das, woraut sie sich beziehen, in einem anderen atz steht. Forschende um Andrei Popescu-Belis

4 8755 mml

vom Forschungsinstitut Idiap in Martigny VS wollen das im Rahmen eines vom Schweizerischen Nationalfonds SNF unterstützten Projekts ändern, indem sie den Algorithmus auch angrenzende Sätze analysieren lassen. Damit soll die Pehlerrate deutlich gesenkt werden. (104)

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la" ou "celle-ci", qui se s	diercheurs se sont notamment pe abstituent à d'autres éléments de nombre important d'erreurs com	texte. Souvent, ces dem	iers se trouvent h	

Indrei Popesco-Belis donne un exemple simple, mais qui trompe aisément les systèmes les plus sophis ante a acheté une excellente voiture. Elle n'est pas très joile." En anglais, Google Translate la traduit en "My aunt loogist an excellent car. But ske is not very pretty."

Coutil a traduit "elle" par "she". Comme ce pronom est réservé aux personnes de genre féminin, le lecteur anglophone lins que c'est "me tante" qui "n'est pas très jolie".

Le piège de la statistique

Le système est induit en erreur, car il soit que le qualificatif "pas très joile" s'applique plus souvent à des personne qu'à des cojets. Si on le substitue par "nouliée" ou "en panne", plus fréquemment appliqués aux objets, le pronom aux plus de chaense d'itre concetement muduit par 1".

Pour obtenir un résultat pertinent, le traducteur automatique aurait dù considérer les informations contenues dans a première prinas. C'est dans les grandes lignes ce que fait le système mis au point par les chercheurs de l'Allage e colaboration avec les départements de lingüésique des inversités de Genére et Othend NB, aimi que en collaboration avec les départements de linguistique des universit l'institut de linguistique computationnelle de l'Université de Zurich.

Les chercheurs utilisent essentiellement des outils d'apprentissage automatique (ou *machine learnin essai, ils introduisent ou retirent des centaines de paramètires, que les algorithmes ajustent, jusqu'à o chine learning"). A chaque



Maschinelles Übersetzen über die Satzgrenze hinaus

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ir Carolini iercher d'Andrei Popescu-Belis, cheerbeur senior à l'Institut de reeherche idiap, à Martigay. A la tête d'un consortium suisse uet l'efferenzableises a chivaleggai de morredliss bentrolegara prece umélioren les outils de traduction automatique. El a présenté -

failages 7 -Chierare a seu assochtic et scieccarens tross déjà la seu reade d'emploi survéaliste parcé entre les maine d'un traducteur

REPA



Google soll besser übersetzen

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Aachine translation: going beyond sentence by sentence



eventing sentence by sentence, translation algorithms cenil much of the context and make mistakes. A peaker supporter y the SMSF has descenced new algorithmic techniques designed to dis a batter jub of tableg the ender text into account,

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Franz'sisch und Englisch, sowie Englisch und Spanisch. Programme ele Googie Translate irren sich beim Übersetzen von Prosonnen bei diesen Sprachpaaren in rund der Hälfte der Fälle.

Maschinelles Lemen

Das von Popsson-Belle. Trans gemeinnam mit Kollegen von den Universitäten Genf, Zärich und Utrecht entwickelte Teolomist d Rehternat auf 20 Ponent, wie der 3NP aberlit. Der Yrick Die Wessenschafter beradents den Uterstranzugeigerführtem entliche machtintlicen Lersen bei, auch augemande Sitze na berücknis

THANK YOU FOR YOUR ATTENTION! ANY QUESTIONS?

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