

TRANSLATIONESE

BETWEEN HUMAN AND MACHINE TRANSLATION

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ORIGINAL OR TRANSLATION?

EXAMPLE (O OR T?)

We want to see countries that can produce the best product for the best price in that particular business . I have to agree with the member that free trade agreements by definition do not mean that we have to be less vigilant all of a sudden .

EXAMPLE (T OR O?)

I would like as my final point to say that we support free trade , but we must learn from past mistakes . Let us hope that negotiations for free trade agreements with the four Central American countries introduce a number of other dimensions absent from these first generation agreements .

UNDERLYING ASSUMPTIONS

- Research in Translation Studies can inform Natural Language Processing, and in particular improve the quality of machine translation
- Computational methodologies can shed light on pertinent questions in Translation Studies

OUTLINE

- 1 INTRODUCTION
- 2 IDENTIFICATION OF TRANSLATIONESE
- 3 TRANSLATION STUDIES HYPOTHESES
- 4 SUPERVISED CLASSIFICATION
- 5 UNSUPERVISED CLASSIFICATION
- 6 APPLICATIONS FOR MACHINE TRANSLATION
- 7 THE POWER OF INTERFERENCE
- 8 CONCLUSION

TRANSLATIONESE

THE LANGUAGE OF TRANSLATED TEXTS

- Translated texts differ from original ones
- The differences do not indicate poor translation but rather a statistical phenomenon, **translationese** (Gellerstam, 1986)
- Toury (1980, 1995) defines two **laws of translation**:

THE LAW OF INTERFERENCE Fingerprints of the source text that are left in the translation product

THE LAW OF GROWING STANDARDIZATION Effort to standardize the translation product according to existing norms in the target language and culture

TRANSLATIONESE

THE LANGUAGE OF TRANSLATED TEXTS

TRANSLATION UNIVERSALS (Baker, 1993)

“features which typically occur in translated text rather than original utterances and which are not the result of interference from specific linguistic systems”

SIMPLIFICATION (Blum-Kulka and Levenston, 1978, 1983)

EXPLICITATION (Blum-Kulka, 1986)

NORMALIZATION (Chesterman, 2004)

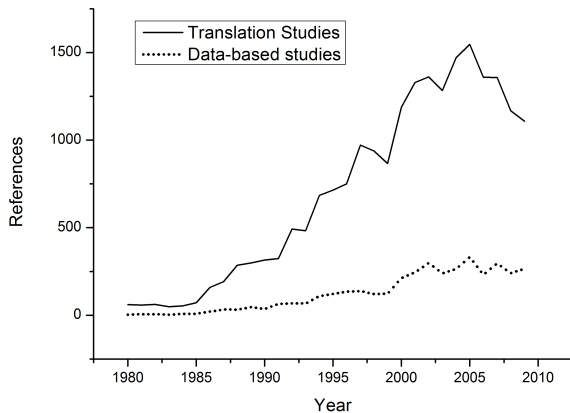
TRANSLATIONESE

WHY DOES IT MATTER?

- Language models for statistical machine translation
(Lembersky et al., 2011, 2012b)
- Translation models for statistical machine translation
(Kurokawa et al., 2009; Lembersky et al., 2012a, 2013)
- Cleaning parallel corpora crawled from the Web
(Eetemadi and Toutanova, 2014; Aharoni et al., 2014)
- Understanding the properties of human translation (Ilisei et al., 2010; Ilisei and Inkpen, 2011; Ilisei, 2013; Volansky et al., 2015; Avner et al., 2016)

CORPUS-BASED TRANSLATION STUDIES

EXAMPLE (SUN AND SHREVE (2013))



COMPUTATIONAL INVESTIGATION OF TRANSLATIONESE

- Translated texts exhibit lower lexical variety (type-to-token ratio) than originals (Al-Shabab, 1996)
- Their mean sentence length and lexical density (ratio of content to non-content words) are lower (Laviosa, 1998)
- Corpus-based evidence for the simplification hypothesis (Laviosa, 2002)

COMPUTATIONAL INVESTIGATION OF TRANSLATIONESE

EXAMPLE (PUNCTUATION MARKS ACROSS O AND T)

Mark	Frequency		Ratio	LL	Weight
	O	T			
,	37.83	49.79	0.76	T	T1
(0.42	0.72	0.58	T	T2
'	1.94	2.53	0.77	T	T3
)	0.40	0.72	0.56	T	T4
/	0.30	0.30	1.00	—	—
[0.01	0.02	0.45	T	—
]	0.01	0.02	0.44	T	—
"	0.33	0.22	1.46	O	O7
!	0.22	0.17	1.25	O	O6
.	38.20	34.60	1.10	O	O5
:	1.20	1.17	1.03	—	O4
;	0.84	0.83	1.01	—	O3
?	1.57	1.11	1.41	O	O2
-	2.68	2.25	1.19	O	O1

OUTLINE

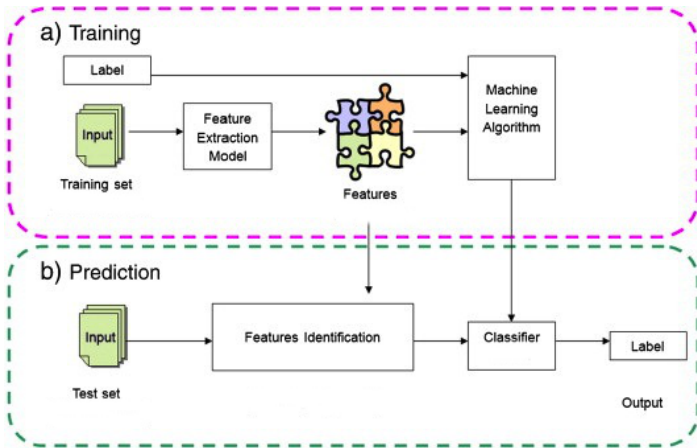
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METHODOLOGY

- Corpus-based approach
- Text classification with (supervised) machine-learning techniques
- Feature design
- Evaluation: ten-fold cross-validation
- **Un**supervised classification

TEXT CLASSIFICATION WITH MACHINE LEARNING

EXAMPLE (FROM HE ET AL. (2012))



TEXT CLASSIFICATION WITH MACHINE LEARNING

- **Supervised machine learning**: a **training** corpus lists **instances** of both classes
- Each instance in the two classes is **represented** by a set of numeric **features** that are extracted from the instances
- A generic machine-learning algorithm is trained to distinguish between **feature vectors** representative of one class and those representative of the other
- The trained classifier is tested on an 'unseen' text, the **test set**
- Classifiers assign **weights** to the features

TEXT CLASSIFICATION (AUTHORSHIP ATTRIBUTION)

APPLICATIONS

- Determine the gender/age of the author (Koppel et al., 2003)
- Tell Shakespeare from Marlowe (Juola, 2006)
- Identify suicide letters
- Spot plagiarism
- Filter out spam
- Identify the native language of non-native authors (Tetreault et al., 2013)

IDENTIFYING TRANSLATIONESE

USING TEXT CLASSIFICATION

- Baroni and Bernardini (2006)
- van Halteren (2008)
- Kurokawa et al. (2009)
- Ilisei et al. (2010); Ilisei and Inkpen (2011); Ilisei (2013)
- Koppel and Ordan (2011)
- Popescu (2011)
- Volansky et al. (2015); Avner et al. (2016)

EXPERIMENTAL SETUP

- Corpus: EUROPARL (Koehn, 2005)
- 4 million tokens in English (O)
- 400,000 tokens translated from each of the ten source languages (T): Danish, Dutch, Finnish, French, German, Greek, Italian, Portuguese, Spanish, and Swedish
- The corpus is tokenized and then partitioned into chunks of approximately 2000 tokens (ending on a sentence boundary)
- Part-of-speech tagging
- Classification with Weka (Hall et al., 2009), using SVM with a default linear kernel

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HYPOTHESES

SIMPLIFICATION Rendering complex linguistic features in the source text into simpler features in the target (Blum-Kulka and Levenston, 1983; Vanderauwerea, 1985; Baker, 1993)

EXPLICITATION The tendency to spell out in the target text utterances that are more implicit in the source (Blum-Kulka, 1986; Øverås, 1998; Baker, 1993)

NORMALIZATION Efforts to standardize texts (Toury, 1995), “a strong preference for **conventional grammaticality**” (Baker, 1993)

INTERFERENCE The fingerprints of the source language on the translation output (Toury, 1979)

MISCELLANEOUS

FEATURES SHOULD...

- ➊ Reflect frequent linguistic characteristics we would expect to be present in the two types of text
- ➋ Be content-independent, indicating formal and stylistic differences between the texts that are not derived from differences in contents, domain, genre, etc.
- ➌ Be easy to interpret, yielding insights regarding the differences between original and translated texts

SIMPLIFICATION

LEXICAL VARIETY Three different **type-token ratio** (TTR) measures, where V is the number of types and N is the number of tokens per chunk, V_1 is the number of types occurring only once in the chunk

$$V/N \quad \log(V)/\log(N) \quad 100 \times \log(N)/(1 - v_1/v)$$

MEAN WORD LENGTH In characters

SYLLABLE RATIO the number of vowel-sequences that are delimited by consonants or space in a word

MEAN SENTENCE LENGTH In words

LEXICAL DENSITY The frequency of tokens that are **not** nouns, adjectives, adverbs or verbs

MEAN WORD RANK The average **rank** of words in a frequency-ordered list of 6000 English most frequent words

MOST FREQUENT WORDS The frequencies of the N most frequent words, $N = 5, 10, 50$

EXPLICITATION

EXAMPLE (EXPLICITATION)

T**O**

israelische Ministerpräsident Benjamin Netanjahu Merkel

EXPLICIT NAMING The ratio of personal pronouns to proper nouns; this models the tendency to spell out pronouns

SINGLE NAMING The frequency of proper nouns consisting of a single token, not having an additional proper noun as a neighbor

MEAN MULTIPLE NAMING The average length (in tokens) of proper nouns

COHESIVE MARKERS The frequencies of several **cohesive markers** (*because, but, hence, in fact, therefore, ...*)

NORMALIZATION

REPETITIONS The frequency of content words (words tagged as nouns, verbs, adjectives or adverbs) that occur more than once in a chunk

EXAMPLE (REPETITIONS, BEN-ARI (1998))

O *Manchmal denke ich: Haben Sie vielleicht ein kaltes Herz? ... Haben Sie wirklich ein kaltes Herz?*

T *Je pense quelquefois: aurait-elle un cœur insensible? ... Avez-vous vraiment un cœur de glace?*

CONTRACTIONS Ratio of contracted forms to their counterpart full form

AVERAGE PMI The average PMI (Church and Hanks, 1990) of all bigrams in the chunk

THRESHOLD PMI Number of bigrams in the chunk whose PMI is above 0

INTERFERENCE

- Fingerprints of the source text, “source language shining through” (Teich, 2003)
- Not necessarily a mark of bad translation! Rather, a different distribution of elements in T and O
- Positive vs. negative interference

EXAMPLE (INTERFERENCE)

POSITIVE *doch* is under-represented in translation to German

NEGATIVE *One is* is over-represented in translations from German to English (triggered by *Man ist*)

INTERFERENCE

POS *n*-GRAMS Unigrams, bigrams and trigrams of POS tags, modeling variations in syntactic structure

CHARACTER *n*-GRAMS Unigrams, bigrams and trigrams of characters, modeling shallow morphology

PREFIXES AND SUFFIXES The number of words in a chunk that begin or end with each member of a list of prefixes/suffixes, respectively

CONTEXTUAL FUNCTION WORDS The frequencies in the chunk of triplets $\langle w_1, w_2, w_3 \rangle$, where at least two of the elements are function words, and at most one is a POS tag

POSITIONAL TOKEN FREQUENCY The frequency of tokens appearing in the first, second, antepenultimate, penultimate and last positions in a sentence

MISCELLANEOUS

FUNCTION WORDS The list of Koppel and Ordan (2011)

PRONOUNS Frequency of the occurrences of pronouns in the chunk

PUNCTUATION ? ! : ; - () [] ' ' " " / , .

- 1 The normalized frequency of each punctuation mark in the chunk
- 2 A non-normalized notion of frequency: n / tokens
- 3 $\%_p$, where p is the total number of punctuations in the chunk

RATIO OF PASSIVE FORMS TO ALL VERBS

SANITY CHECK Token unigrams and bigrams

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RESULTS: SANITY CHECK

Category	Feature	Accuracy (%)
Sanity	Token unigrams	100
	Token bigrams	100

RESULTS: SIMPLIFICATION

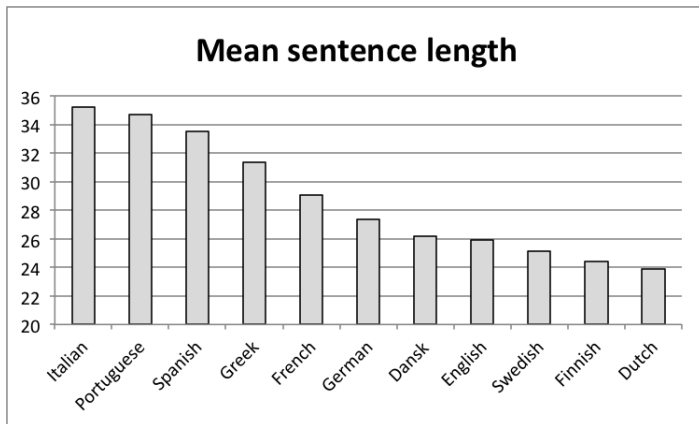
Category	Feature	Accuracy (%)
Simplification	TTR (1)	72
	TTR (2)	72
	TTR (3)	76
	Mean word rank (1)	69
	Mean word rank (2)	77
	<i>N</i> most frequent words	64
	Mean word length	66
	Syllable ratio	61
	Lexical density	53
	Mean sentence length	65

ANALYSIS: SIMPLIFICATION

- Lexical density fails altogether to predict the status of a text, being nearly on chance level (53% accuracy)
- The first two TTR measures perform relatively well (72%), and the indirect measures of lexical variety (mean word length, 66% and syllable ratio, 61%) are above chance level
- Mean word rank (77%) is closely related to the feature studied by [Laviosa \(1998\)](#) (n top words) with two differences: our list of frequent items is much larger, and we generate the frequency list not from the corpora under study but rather from an external much larger reference corpus
- In contrast, the design that follows [Laviosa \(1998\)](#) more strictly (n most frequent words) has a lower predictive power (64%)
- While mean sentence length is much above chance level (65%), the results are contrary to common assumptions in Translation Studies

SIMPLIFICATION

EXAMPLE (MEAN SENTENCE LENGTH PER 'LANGUAGE')



RESULTS: EXPLICITATION

Category	Feature	Accuracy (%)
Explicitation	Cohesive Markers	81
	Explicit naming	58
	Single naming	56
	Mean multiple naming	54

ANALYSIS: EXPLICITATION

- Explicit naming, single naming and mean multiple naming do not exceed 58% accuracy
- On the other hand, the classifier that uses 40 cohesive markers (Blum-Kulka, 1986; Koppel and Ordan, 2011) achieves 81% accuracy
- Such cohesive markers are far more frequent in T than in O
- For example, *moreover* is used 17.5 times more frequently in T than in O; *thus* 4 times more frequently; and *besides* 3.8 times

RESULTS: NORMALIZATION

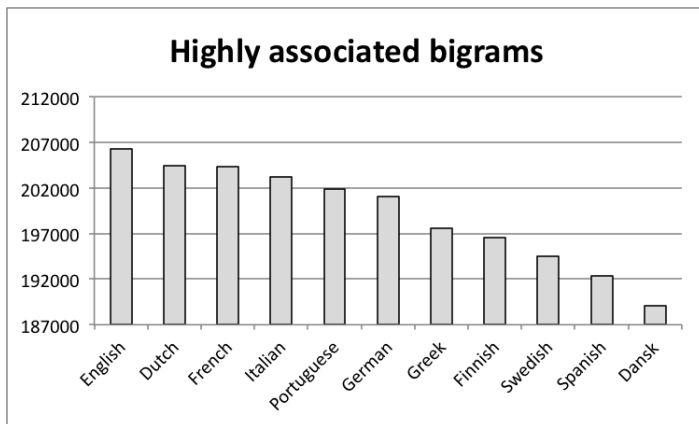
Category	Feature	Accuracy (%)
Normalization	Repetitions	55
	Contractions	50
	Average PMI	52
	Threshold PMI	66

ANALYSIS: NORMALIZATION

- None of these features perform very well
- Repetitions and contractions are rare in EUROPARL; the corpus may not be suited for studying these phenomena
- Threshold PMI, designed to pick on highly associated words and therefore attesting to many fixed expressions, performs considerably better, at 66% accuracy, but contrary to the hypothesis (Kenny, 2001)
- English has far more highly associated bigrams than translations: O has *stand idly*, *stand firm*, *stand trial*, etc.; conversely, T includes poorly associated bigrams such as *stand unamended*

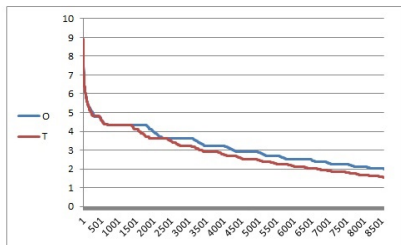
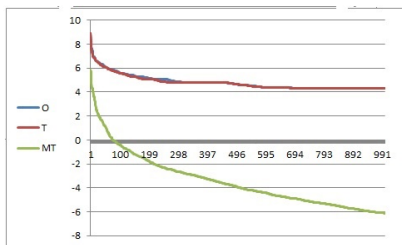
NORMALIZATION

EXAMPLE (NUMBER OF BIGRAMS WHOSE PMI IS ABOVE THRESHOLD ACCORDING TO 'LANGUAGE')



NORMALIZATION

EXAMPLE (TRANSLATED LANGUAGE IS LESS PREDICTABLE)



RESULTS: INTERFERENCE

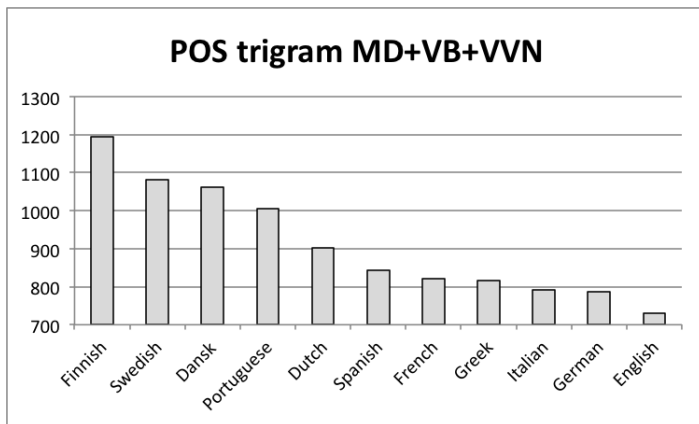
Category	Feature	Accuracy (%)
Interference	POS unigrams	90
	POS bigrams	97
	POS trigrams	98
	Character unigrams	85
	Character bigrams	98
	Character trigrams	100
	Prefixes and suffixes	80
	Contextual function words	100
	Positional token frequency	97

ANALYSIS: INTERFERENCE

- The interference-based classifiers are the best performing ones
- Interference is the most robust phenomenon typifying translations
- The character n -gram findings are consistent with Popescu (2011): they catch on both affixes and function words
- For example, typical trigrams in O are *-ion* and *all* whereas typical to T are *-ble* and *the*
- Part-of-speech trigrams is an extremely cheap and efficient classifier
- For example, $MD+VB+VBN$, e.g., *must be taken*, *should be given*, *can be used*

INTERFERENCE

EXAMPLE (THE AVERAGE NUMBER OF THE POS TRIGRAM
MODAL + VERB BASE FORM + PARTICIPLE IN O AND TEN TS)



ANALYSIS: INTERFERENCE

- Positional token frequency yields 97% accuracy
- The second most prominent feature typifying O is sentences opening with the word 'But'; there are 2.25 times more cases of such sentences in O
- A long prescriptive tradition in English forbids writers to open a sentence with 'But', and translators are conservative in their lexical choices (Kenny, 2001)
- This is in fact **standardization** rather than interference

ANALYSIS: INTERFERENCE

- Some interference features are coarse and may reflect corpus-dependent characteristics
- For example, some of the top character n -gram features in O include sequences that are 'illegal' in English and obviously stem from foreign names: *Haarder* and *Maat* or *Gazpron*
- To offset this problem we use only the top 300 features in several of the classifiers, with a minor effect on the results

RESULTS: REDUCED PARAMETER SPACE

(300 MOST FREQUENT FEATURES)

Category	Feature	Accuracy
Interference	POS bigrams	96
	POS trigrams	96
	Character bigrams	95
	Character trigrams	96
	Positional token frequency	93

RESULTS: MISCELLANEOUS

Category	Feature	Accuracy (%)
Miscellaneous	Function words	96
	Punctuation (1)	81
	Punctuation (2)	85
	Punctuation (3)	80
	Pronouns	77
	Ratio of passive forms to all verbs	65

ANALYSIS: MISCELLANEOUS

- The function words classifier replicates **Koppel and Ordan (2011)**; despite the good performance (96% accuracy) it is not very meaningful theoretically
- Subject pronouns, like *I*, *he* and *she* are prominent indicators of O, whereas virtually all reflexive pronouns (such as *itself*, *himself*, *yourself*) typify T
- T has about 1.15 times more passive verbs, but it is highly dependent on the source language
- Punctuation marks are good predictors
- The mark '.' (actually indicating sentence length) is a strong feature of O; ',' is a strong marker of T
- In fact, these two features alone yield 79% accuracy
- Parentheses are very typical to T, indicating explicitation
- Translations from German use many more exclamation marks, 2.76 times more than original English!!!

ANALYSIS: PUNCTUATION

EXAMPLE (PUNCTUATION MARKS ACROSS O AND T)

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SUPERVISED CLASSIFICATION

- Inherently dependent on data annotated with the translation direction
- May not be generalized to unseen (related or unrelated) domains: modality (written vs. spoken), register, genre, date, etc.

DATASETS

- Europarl, the proceedings of the European Parliament, between the years 2001-2006
- the Canadian Hansard, transcripts of the Canadian Parliament, spanning years 2001-2009
- literary classics written (or translated) mainly in the 19th century
- transcripts of TED and TEDx talks

SUPERVISED CLASSIFICATION

feature / corpus	EUR	HAN	LIT	TED
FW	96.3	98.1	97.3	97.7
char-trigrams	98.8	97.1	99.5	100.0
POS-trigrams	98.5	97.2	98.7	92.0
contextual FW	95.2	96.8	94.1	86.3
cohesive markers	83.6	86.9	78.6	81.8

PAIRWISE CROSS-DOMAIN CLASSIFICATION

USING FUNCTION WORDS

train / test	EUR	HAN	LIT	X-validation
EUR		60.8	56.2	96.3
HAN	59.7		58.7	98.1
LIT	64.3	61.5		97.3

LEAVE-ONE-OUT CROSS-DOMAIN CLASSIFICATION

USING FUNCTION WORDS

train / test	EUR	HAN	LIT	X-validation
EUR + HAN			63.8	94.0
EUR + LIT		64.1		92.9
HAN + LIT	59.8			96.0

CLUSTERING

ASSUMING GOLD LABELS

feature / corpus	EUR	HAN	LIT	TED
FW	88.6	88.9	78.8	87.5
char-trigrams	72.1	63.8	70.3	78.6
POS-trigrams	96.9	76.0	70.7	76.1
contextual FW	92.9	93.2	68.2	67.0
cohesive markers	63.1	81.2	67.1	63.0

CLUSTER LABELING

- Labeling determines which of the clusters is O and which is T
- Clustering can divide observations into classes but cannot label those classes
- Let O_m (O-markers) denote a set of function words that tend to be associated with O; T_m (T-markers) is a set of words typical of T
- Create unigram language models of O and T:

$$\begin{aligned} p(w \mid O_m) &= \frac{tf(w) + \varepsilon}{|O_m| + \varepsilon \times |V|} \\ p(w \mid T_m) &= \frac{tf(w) + \varepsilon}{|T_m| + \varepsilon \times |V|} \end{aligned}$$

- The similarity between a class X (either O or T) and a cluster C_i is determined using the Jensen-Shannon divergence (JSD) (Lin, 1991)

$$D_{JS}(X, C_i) = \sqrt[2]{JSD(P_X || P_{C_i})}$$

CLUSTER LABELING

- The assignment of the label X to the cluster C_1 is then supported by both C_1 's proximity to the class X and C_2 's proximity to the other class:

$$label(C_1) = \begin{cases} \text{"O"} & \text{if } D_{JS}(O, C_1) \times D_{JS}(T, C_2) < \\ & D_{JS}(O, C_2) \times D_{JS}(T, C_1) \\ \text{"T"} & \text{otherwise} \end{cases}$$

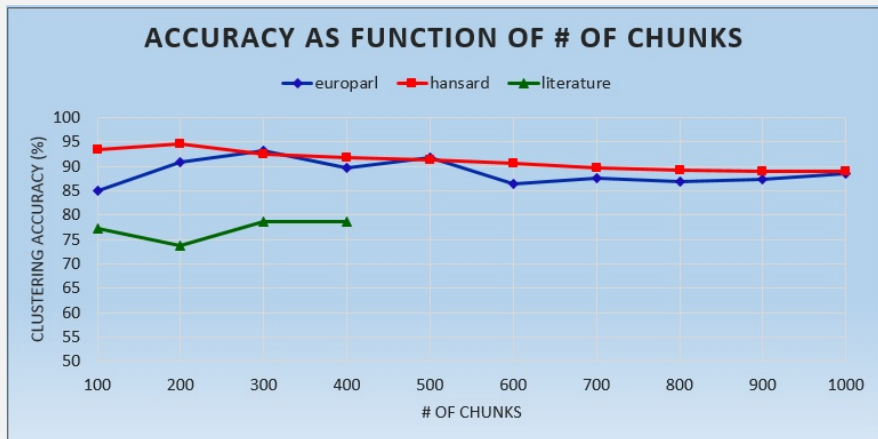
C_2 is then assigned the complementary label

- We select O- and T-markers from a random sample of Europarl and Hansard texts, using 600 chunks from each corpus
- Labeling precision is 100% in all clustering experiments
- This facilitates majority voting of several feature sets

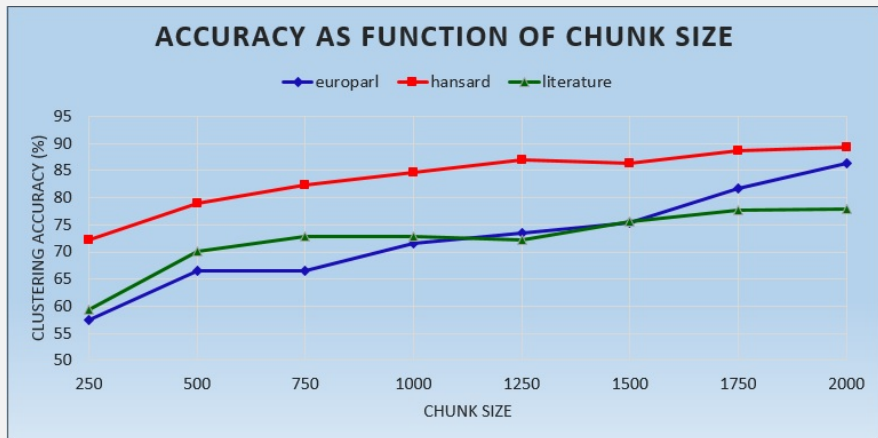
CLUSTERING CONSENSUS

method / corpus	EUR	HAN	LIT	TED
FW	88.6	88.9	78.8	87.5
FW				
char-trigrams	91.1	86.2	78.2	90.9
POS-trigrams				
FW				
POS-trigrams	95.8	89.8	72.3	86.3
contextual FW				
FW				
char-trigrams				
POS-trigrams	94.1	91.0	79.2	88.6
contextual FW				
cohesive markers				

SENSITIVITY ANALYSIS



SENSITIVITY ANALYSIS



MIXED-DOMAIN CLASSIFICATION

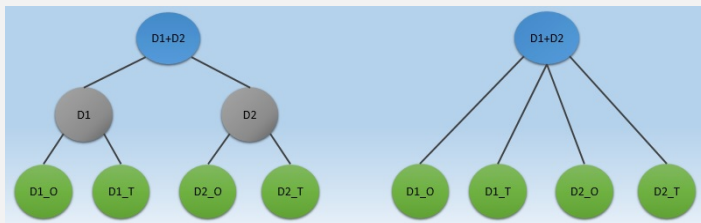
- The in-domain discriminative features of translated texts cannot be easily generalized to other, even related, domains
- Hypothesis: domain-specific features overshadow the features of translationese
- We mix 800 chunks each from Europarl and Hansard, yielding 1,600 chunks, half of them O and half T
- Running the clustering algorithm on this dataset yields perfect separation by domain (and chance-level identification of translationese)
- Adding the literature corpus and clustering to three clusters yields the same results

MIXED-DOMAIN CLASSIFICATION

method / corpus	EUR HAN	EUR LIT	HAN LIT	EUR HAN LIT
KMeans				
accuracy by domain	93.7	99.5	99.8	92.2
XMeans				
generated # of clusters	2	2	3	3
accuracy by domain	93.6	99.5	–	92.2

CLUSTERING IN A MIXED-DOMAIN SETUP

- Given a set of text chunks that come from multiple domains, such that some chunks are O and some are T, the task is to classify the texts to O vs. T, **independently of their domain**
- A **two-phase** approach
- A **flat** approach



CLUSTERING IN A MIXED-DOMAIN SETUP

method / corpus	EUR	EUR	HAN	EUR
	HAN	LIT	LIT	HAN LIT
Flat	92.5	60.7	77.5	66.8
Two-phase	91.3	79.4	85.3	67.5

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APPLICATIONS FOR MACHINE TRANSLATION

- Fundamentals of statistical machine translation (SMT)
- Language models
- Translation models

FUNDAMENTALS OF SMT

- Motivation

When I look at an article in Russian, I say, "This is really written in English, but it has been coded in some strange symbols. I shall now proceed to decode."

Warren Weaver, 1955

- The **noisy channel model**
- The best translation \hat{T} of a source sentence S is the target sentence T that maximizes some function combining the **faithfulness** of (T, S) and the **fluency** of T

FUNDAMENTALS OF SMT

- Standard notation: Translating a **foreign** sentence $F = f_1, \dots, f_m$ into an **English** sentence $E = e_1, \dots, e_l$
- The best translation:

$$\begin{aligned}
 \hat{E} &= \arg \max_E P(E | F) \\
 &= \arg \max_E \frac{P(F|E) \times P(E)}{P(F)} \\
 &= \arg \max_E P(F | E) \times P(E)
 \end{aligned}$$

- The noisy channel thus requires two components: a **translation model** and a **language model**

$$\hat{E} = \arg \max_{E \in \text{English}} \underbrace{P(F | E)}_{\text{Translation model}} \times \underbrace{P(E)}_{\text{Language model}}$$

FUNDAMENTALS OF SMT

- A **language model** to estimate $P(E)$ (estimated from a monolingual E corpus)
- A **translation model** to estimate $P(F | E)$ (estimated from a bilingual parallel corpus)
- A **decoder** that given F can produce the most probable E
- Evaluation: BLEU scores (Papineni et al., 2002)

LANGUAGE MODELS

RESEARCH QUESTIONS

- Test the fitness of language models compiled from translated texts vs. the fitness of LMs compiled from original texts
- Test the fitness of language models compiled from texts translated from other languages
- Test if language models compiled from translated texts are better for MT than LMs compiled from original texts

LANGUAGE MODELS

METHODOLOGY

- The fitness of a language model to a reference corpus is evaluated using **perplexity**

$$PP(LM, w_1 w_2 \dots w_N) = \sqrt[N]{\prod_{i=1}^N \frac{1}{P_{LM}(w_i | w_1 \dots w_{i-1})}}$$

- Train SMT systems (Koehn et al., 2007) using different LMs and evaluate their quality on a reference set
- Quality is measured in terms of BLEU scores (Papineni et al., 2002)

PERPLEXITY RESULTS

German to English translations				
Orig. Lang.	1-gram	2-gram	3-gram	4-gram
Mix	451.50	93.00	69.36	66.47
O-EN	<i>468.09</i>	<i>103.74</i>	<i>79.57</i>	<i>76.79</i>
T-DE	443.14	88.48	64.99	62.07
T-FR	460.98	99.90	76.23	73.38
T-IT	465.89	102.31	78.50	75.67
T-NL	457.02	97.34	73.54	70.56

PERPLEXITY RESULTS

French to English translations

Orig. Lang.	1-gram	2-gram	3-gram	4-gram
Mix	472.05	99.04	75.60	72.68
O-EN	<i>500.56</i>	<i>115.48</i>	<i>91.14</i>	<i>88.31</i>
T-DE	486.78	108.50	84.39	81.41
T-FR	463.58	94.59	71.24	68.37
T-IT	476.05	102.69	79.23	76.36
T-NL	490.09	110.67	86.61	83.55

PERPLEXITY RESULTS

Italian to English translations

Orig. Lang.	1-gram	2-gram	3-gram	4-gram
Mix	395.99	88.46	67.35	64.40
O-EN	<i>415.47</i>	<i>99.92</i>	<i>79.27</i>	<i>76.34</i>
T-DE	404.64	95.22	73.73	70.85
T-FR	395.99	89.44	68.38	65.54
T-IT	384.55	81.90	60.85	57.91
T-NL	411.58	98.78	76.98	73.94

PERPLEXITY RESULTS

Dutch to English translations

Orig. Lang.	1-gram	2-gram	3-gram	4-gram
Mix	434.89	90.73	69.05	66.08
O-EN	<i>448.11</i>	100.17	<i>78.23</i>	<i>75.46</i>
T-DE	437.68	93.67	71.54	68.57
T-FR	445.00	97.32	75.59	72.55
T-IT	448.11	<i>100.19</i>	78.06	75.19
T-NL	423.13	83.99	62.17	59.09

LANGUAGE MODELS

ABSTRACTION

- No punctuation
- No named entities
- No nouns
- No words: only parts of speech

ABSTRACTION RESULTS

Orig. Lang.	No Punctuation	
	Perplexity	Improvement (%)
MIX	105.91	19.73
O-EN	<i>131.94</i>	
T-DE	122.50	7.16
T-FR	99.52	24.58
T-IT	112.71	14.58
T-NL	126.44	4.17

ABSTRACTION RESULTS

Named Entity Abstraction			
Orig.	Lang.	Perplexity	Improvement (%)
MIX		93.88	18.51
O-EN		<i>115.20</i>	
T-DE		107.48	6.70
T-FR		88.96	22.77
T-IT		99.17	13.91
T-NL		110.72	3.89

ABSTRACTION RESULTS

Orig. Lang.	Noun Abstraction	
	Perplexity	Improvement (%)
MIX	36.02	11.34
O-EN	40.62	
T-DE	38.67	4.81
T-FR	34.75	14.46
T-IT	36.85	9.30
T-NL	39.44	2.91

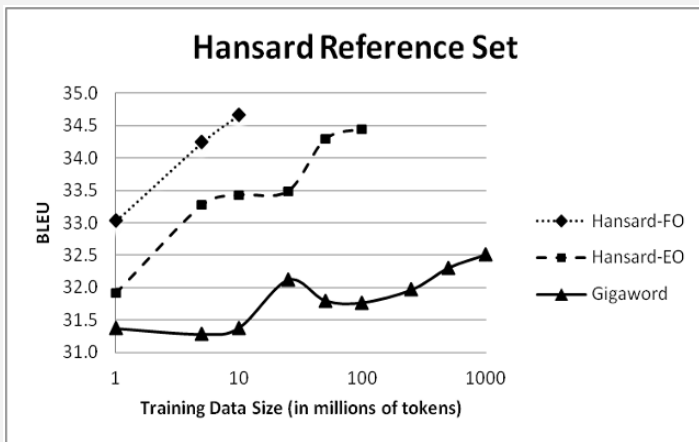
ABSTRACTION RESULTS

Part-of-speech Abstraction			
Orig.	Lang.	Perplexity	Improvement (%)
MIX		7.99	2.66
O-EN		8.20	
T-DE		8.08	1.47
T-FR		7.89	3.77
T-IT		8.00	2.47
T-NL		8.11	1.11

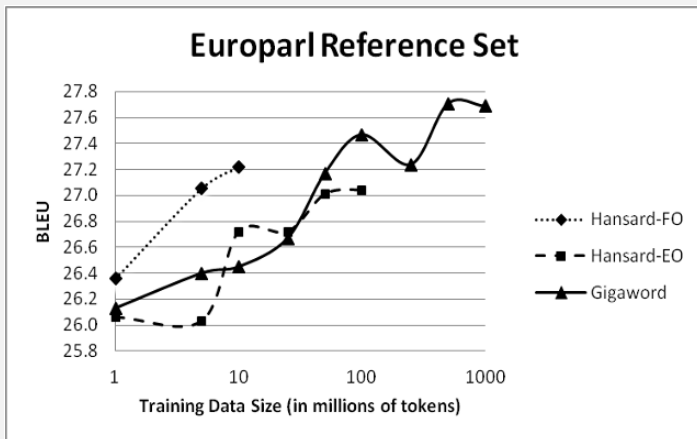
MACHINE TRANSLATION RESULTS

DE to EN		FR to EN		IT to EN		NL to EN	
LM	BLEU	LM	BLEU	LM	BLEU	LM	BLEU
MIX	21.43	MIX	28.67	MIX	25.41	MIX	24.20
O-EN	<i>21.10</i>	O-EN	<i>27.98</i>	O-EN	24.69	O-EN	<i>23.40</i>
T-DE	21.90	T-DE	28.01	T-DE	<i>24.62</i>	T-DE	24.26
T-FR	21.16	T-FR	29.14	T-FR	25.37	T-FR	23.56
T-IT	21.29	T-IT	28.75	T-IT	25.96	T-IT	23.87
T-NL	21.20	T-NL	28.11	T-NL	24.77	T-NL	24.52

DOES SIZE MATTER?



DOES SIZE MATTER?



TRANSLATION EXAMPLES

COHESIVE MARKERS

SOURCE *Enfin, ce qui est grave dans le rapport de M. Olivier, c'est qu'il propose une constitution tripotage.*

O *Finally, which is serious in the report of Mr Olivier, is that it proposes a constitution tripotage.*

T *Finally, and this is serious in the report by Mr olivier, it is **because** it proposes a constitution tripotage.*

SOURCE *C'est quand même quelque chose de précieux qui a été souligné par tous les membres du conseil européen.*

O *Even when it is something of valuable which has been pointed out by all the members of the European Council.*

T *It is **nevertheless** something of a valuable which has been pointed out by all the members of the European Council.*

TRANSLATION EXAMPLES

VERBS

SOURCE *Une telle Europe serait un gage de paix et marquerait le refus de tout nationalisme ethnique.*

O *Such a Europe would be a show of peace and would the rejection of any ethnic nationalism.*

T *Such a Europe would be a show of peace and would **mark** the refusal of all ethnic nationalism.*

SOURCE *Votre rapport, madame Sudre, met l'accent, à juste titre, sur la nécessité d'agir dans la durée.*

O *Your report, Mrs Sudre, its emphasis, quite rightly, on the need to act in the long term.*

T *Your report, Mrs Sudre, **places** the emphasis, quite rightly, on the need to act in the long term.*

TRANSLATION EXAMPLES

INTERFERENCE

SOURCE *On ne dit rien non plus sur la responsabilité des fabricants, notamment en grande-bretagne, qui ont été les premiers responsables.*

O *We **do not say nothing more** on the responsibility of the manufacturers, particularly in Britain, which were the first responsible.*

T *We **do not say anything either** on the responsibility of the manufacturers, particularly in great Britain, who were the first responsible.*

TRANSLATION MODELS

RESEARCH QUESTIONS

- Are parallel corpora (manually) translated in the same direction of the MT task better than ones directed in the other direction?
- If corpora consisting of texts (manually) translated in both directions are available, how to build a translation model adapted to the unique properties of the translated text?

TRANSLATION MODELS

DIRECTION MATTERS!

Task	$S \rightarrow T$	$T \rightarrow S$
FR-EN	33.64	30.88
EN-FR	32.11	30.35
DE-EN	26.53	23.67
EN-DE	16.96	16.17
IT-EN	28.70	26.84
EN-IT	23.81	21.28

TRANSLATION MODELS

DIRECTION MATTERS!

Task: French-to-English		
Corpus subset	$S \rightarrow T$	$T \rightarrow S$
250K	34.35	31.33
500K	35.21	32.38
750K	36.12	32.90
1M	35.73	33.07
1.25M	36.24	33.23
1.5M	36.43	33.73

TRANSLATION MODELS

DIRECTION MATTERS!

Task: English-to-French

Corpus subset	$S \rightarrow T$	$T \rightarrow S$
250K	27.74	26.58
500K	29.15	27.19
750K	29.43	27.63
1M	29.94	27.88
1.25M	30.63	27.84
1.5M	29.89	27.83

TRANSLATION MODELS

DOMAIN ADAPTATION

GOAL: Given any bi-text consisting of both $S \rightarrow T$ and $T \rightarrow S$ subsets, improve translation quality by taking advantage of information pertaining to the direction of translation

TECHNIQUES:

- Union: simple concatenation of corpora
- Two phrase-tables: train a phrase table for each subset and pass both to MOSES
- Phrase table interpolation: using perplexity minimization (Sennrich, 2012)
- Add a feature in the phrase table indicating the direction of translation

TRANSLATION MODELS

ADAPTATION RESULTS

Task: French-to-English

System	MIX	MIX-EO	MIX-FO
$S \rightarrow T$	35.21	35.21	35.73
UNION	35.27	35.36	35.94
PPLMIN-1	35.46	35.59	36.26
PPLMIN-2	35.75	35.65	36.20
CrEnt	35.54	35.45	36.75
PplRatio	35.59	35.78	36.22

TRANSLATION MODELS

ADAPTATION RESULTS

Task: English-to-French

System	MIX	MIX-FO	MIX-EO
$S \rightarrow T$	29.15	29.15	29.94
UNION	29.27	29.44	30.01
PPLMIN-1	29.64	29.94	29.65
PPLMIN-2	29.50	30.45	30.12
CrEnt	29.47	29.45	30.44
PplRatio	29.65	29.62	30.34

OUTLINE

- 1 INTRODUCTION
- 2 IDENTIFICATION OF TRANSLATIONESE
- 3 TRANSLATION STUDIES HYPOTHESES
- 4 SUPERVISED CLASSIFICATION
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- 7 THE POWER OF INTERFERENCE**
- 8 CONCLUSION

THE POWER OF INTERFERENCE

- Translations to English from L_1 differ from translations to English from L_2
- Translations from two languages are more similar to each other when the two source languages are closer
- The native language of ESL speakers can be accurately identified by looking at their English texts

CROSS-CLASSIFICATION

- A classifier is trained to distinguish between O and T translated from L_1 ; it is then used to distinguish O from T translated from L_2 (Koppel and Ordan, 2011)

EXAMPLE (TRAIN ON L_1 , TEST ON L_2)

	IT	FR	ES	DE	FI
IT	99	93	91	75	63
FR	90	98	90	83	70
ES	85	90	98	82	69
DE	73	74	74	98	70
FI	58	70	64	81	99

CLUSTERING OF TRANSLATIONS FROM SEVERAL LANGUAGES

- First, translations to English from 14 European languages were used for cross-classification using POS trigrams as features
- The accuracy of classification was 76% (compare to a baseline of $100/14=7\%$)
- Then, an unsupervised hierarchical clustering algorithm grouped together English (and French) texts translated from 16 European languages
- Texts were represented using feature vectors, similarly to the supervised experiments

CROSS-CLASSIFICATION

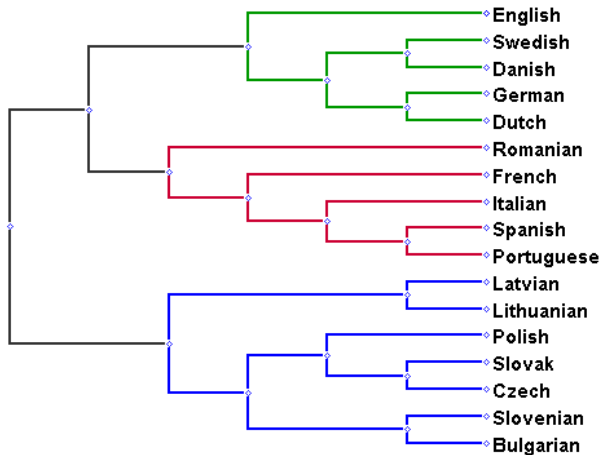
EXAMPLE (CONFUSION MATRIX OF 14-WAY CLASSIFICATION OF ENGLISH (LEFT) AND FRENCH (RIGHT) TRANSLATIONESE)

EN	NL	DE	DA	SV	PT	ES	FR	IT	RO	LT	PL	SK	CS
84	4	2	2	4	0	0	1	1	0	0	0	1	1
6	66	13	2	8	0	1	3	0	0	0	0	1	0
2	16	71	2	2	0	3	4	0	0	0	0	0	0
2	5	4	74	12	0	2	1	0	0	0	0	0	0
4	4	1	13	73	0	0	4	1	0	0	0	0	0
0	0	0	0	0	75	3	7	7	1	2	0	3	2
1	0	2	2	1	3	74	11	5	0	0	0	0	1
2	6	4	0	1	4	15	57	10	0	0	1	0	0
3	0	4	0	0	13	4	12	63	0	0	0	0	1
0	0	0	0	0	0	0	0	0	96	3	1	0	0
0	0	0	0	0	1	0	0	0	2	93	0	3	1
0	4	1	0	1	1	0	1	0	0	2	80	6	4
2	0	0	1	0	1	0	0	0	0	1	5	78	10
1	3	1	1	1	2	0	2	0	0	0	3	13	73

EN	NL	DE	DA	SV	PT	ES	FR	IT	RO	LT	PL	SK	CS
40	11	3	7	7	1	6	2	2	0	0	9	6	6
10	43	25	4	10	0	1	4	2	0	0	0	1	0
8	32	41	1	5	0	6	3	1	0	0	1	2	0
13	7	6	56	12	0	0	3	0	0	0	3	0	0
7	13	9	5	46	2	3	1	2	0	0	6	2	4
3	0	1	0	2	56	1	0	3	4	9	6	9	6
4	4	4	0	3	3	54	7	15	0	0	2	3	1
3	7	2	1	4	2	9	62	6	0	0	1	2	1
4	0	4	0	8	9	18	11	41	0	0	3	1	1
0	0	0	0	0	4	0	0	0	75	17	1	3	0
1	0	0	0	0	12	0	0	0	22	54	2	4	5
9	2	0	0	11	5	0	0	1	2	2	42	14	12
4	1	0	1	1	10	0	1	3	2	8	14	38	17
5	3	2	1	5	6	0	0	1	2	6	17	15	37

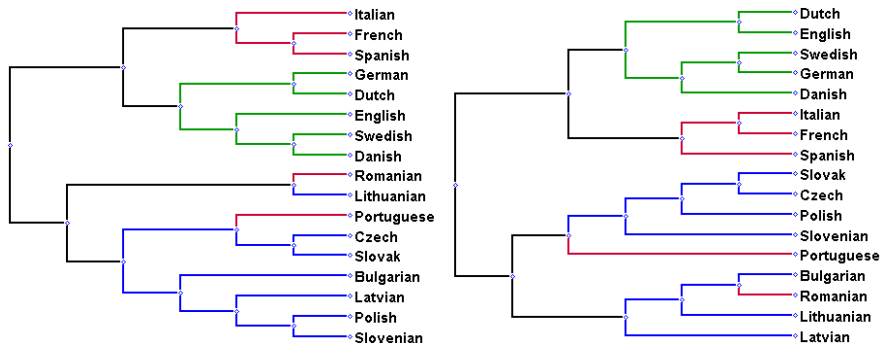
THE EUROPEAN TREE OF LANGUAGES

EXAMPLE (“GOLD” TREE)



THE EUROPEAN TREE OF LANGUAGES

EXAMPLE (TREES OBTAINED WITH POS-TRIGRAMS, ENGLISH (LEFT) AND FRENCH (RIGHT))



THE EUROPEAN TREE OF LANGUAGES

EXAMPLE (EVALUATION OF TYPOLOGY TREES AGAINST GOLD TREE)

Feature	<i>Dist</i>		<i>Dist_w</i>	
	EN T	FR T	EN T	FR T
POS-trigrams	1.02	1.16	1.07	1.34
positional tokens	1.10	1.15	1.30	1.37
function words	1.32	1.82	1.43	1.90
cohesive markers	1.95	1.95	2.15	2.03
feature combination	1.00	1.46	1.13	1.58
random tree	2.00		1.95	

NATIVE LANGUAGE IDENTIFICATION

- Given a set of essays composed by ESL students, identify the authors' native language (out of 11 languages)
- The dataset consists of TOEFL essays, contributed by the ETS
- Each text is annotated by the prompt, the proficiency level and the native language
- The task is to identify the native language
- Features
- Results (Tsvetkov et al., 2013)

NATIVE LANGUAGE IDENTIFICATION

	ARA	CHI	FRE	GER	HIN	ITA	JPN	KOR	SPA	TEL	TUR	P (%)	R (%)	F_1
ARA	80	0	2	1	3	4	1	0	4	2	3	80.8	80.0	80.4
CHI	3	80	0	1	1	0	6	7	1	0	1	88.9	80.0	84.2
FRE	2	2	81	5	1	2	1	0	3	0	3	86.2	81.0	83.5
GER	1	1	1	93	0	0	0	1	1	0	2	87.7	93.0	90.3
HIN	2	0	0	1	77	1	0	1	5	9	4	74.8	77.0	75.9
ITA	2	0	3	1	1	87	1	0	3	0	2	82.1	87.0	84.5
JPN	2	1	1	2	0	1	87	5	0	0	1	78.4	87.0	82.5
KOR	1	5	2	0	1	0	9	81	1	0	0	80.2	81.0	80.6
SPA	2	0	2	0	1	8	2	1	78	1	5	77.2	78.0	77.6
TEL	0	1	0	0	18	1	2	1	1	73	3	85.9	73.0	78.9
TUR	4	0	2	2	0	2	2	4	4	0	80	76.9	80.0	78.4

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CONCLUSION

- Machines can accurately identify translated texts
- Translation “universals” should be reconsidered. Not only are they dependent on genre and register, they also vary greatly across different pairs of languages
- The best performing features are those that attest to the ‘fingerprints’ of the source on the target
- Interference, a pair-specific phenomenon, dominates other manifestations of translationese
- Translationese features are overshadowed by more salient features of the text, including genre, register, domain, etc.

CONCLUSION

- Language models compiled from translated texts are better for SMT than ones compiled from original texts
- Translation models translated in the same direction as that of the SMT task are better than ones translated in the reverse direction
- Translation models can be adapted to translationese, thereby improving the quality of SMT

FUTURE DIRECTIONS

- The features of Hebrew translationese: morphological markers (Avner et al., 2016)
- The features of **machine** translationese
- Robust identification of machine translation output
- More generally, the similarities and differences among various interference phenomena:
 - Translation
 - Non-native speakers
 - Learners' productions

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MAIN PUBLICATIONS

- Ella Rabinovich and Shuly Wintner. **Unsupervised Identification of Translationese.** *Transactions of the Association for Computational Linguistics* 3:419-432, 2015
- Vered Volansky, Noam Ordan and Shuly Wintner. **On the features of translationese.** *Digital Scholarship in the Humanities* 30(1):98-118, April 2015
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