# Computational Approaches to Translation Studies

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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

# 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 Standardization: Adjust the translation product according to existing norms in the target language and culture

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## 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)

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## 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)

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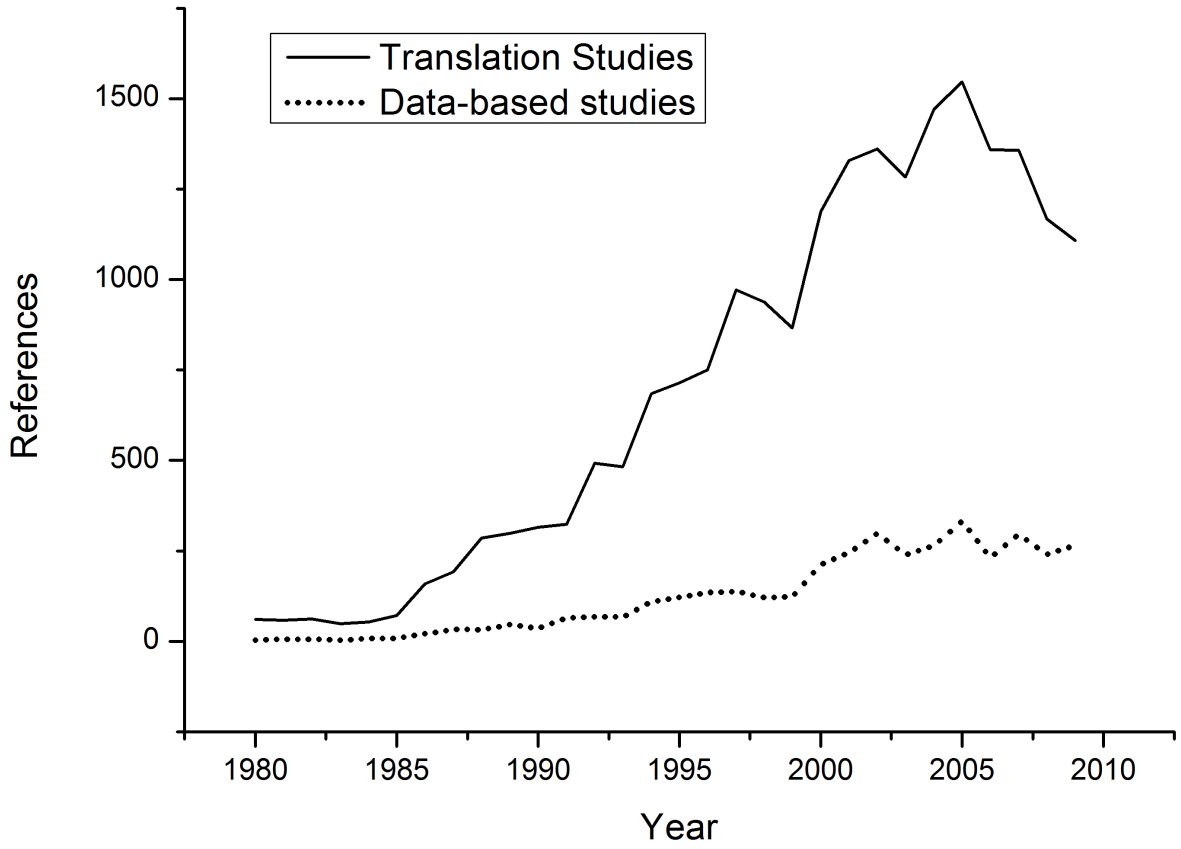
# Corpus-based Translation Studies

## 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)

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# Computational Investigation of Translationese

## Example (Punctuation marks across O and T)

| Mark | Frequency O | Frequency T | Ratio | LL | Weight |
|---|---|---|---|---|---|
| , | 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

# Methodology

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

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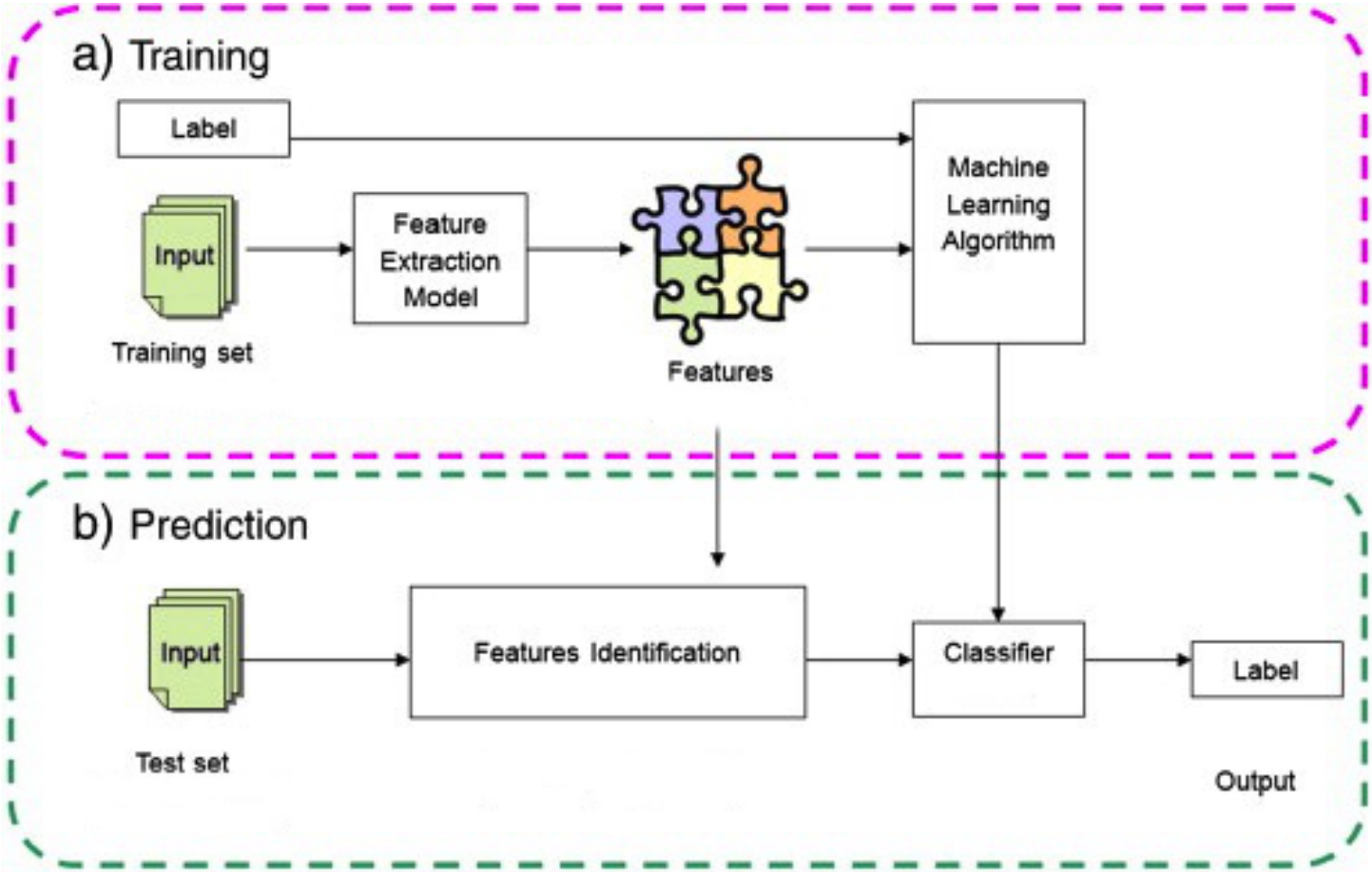
# Text Classification with Machine Learning

## 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
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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)

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# Features Should...

1. Reflect frequent linguistic characteristics we would expect to be present in the two types of text
2. Be content-independent, indicating formal and stylistic differences between the texts that are not derived from differences in contents, domain, genre, etc.
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# 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

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

**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, $N = 5, 10, 50$

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| *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*, ...)

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**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?*

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**Contractions** Ratio of contracted forms to their counterpart full form

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**Contractions** Ratio of contracted forms to their counterpart full form

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**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 functions 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

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**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: $\frac{p}{|\text{chunk}|}$, 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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# Outline

# Results: Sanity Check

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

# Results: Simplification

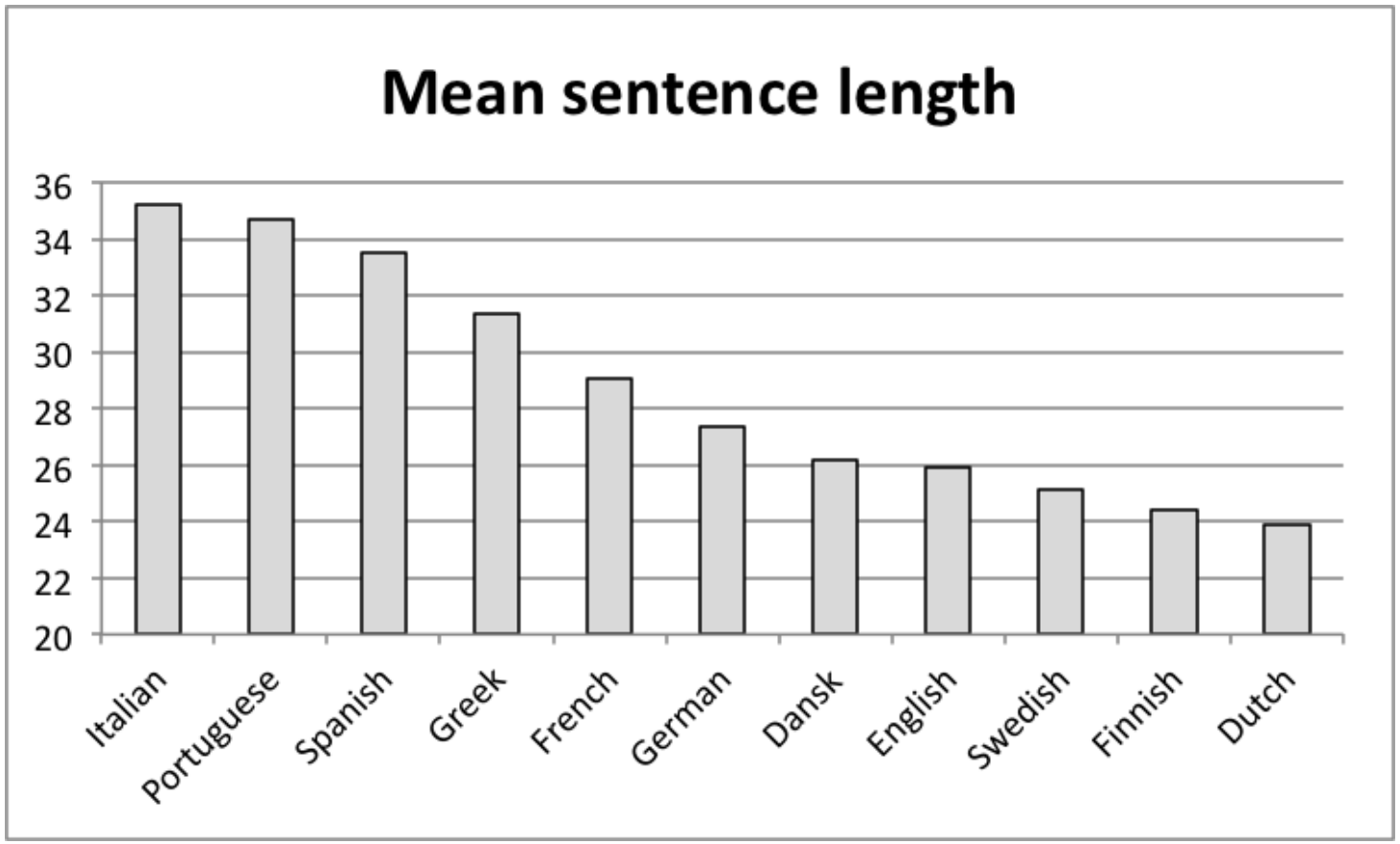
| Category | Feature | Accuracy (%) |
|---|---|---|
| Simplification | TTR (1) | 72 |
| | TTR (2) | 72 |
| | TTR (3) | 76 |
| | Mean word rank (1) | 69 |
| | Mean word rank (2) | 77 |
| | $N$ most frequent words | 64 |
| | Mean word length | 66 |
| | Syllable ratio | 61 |
| | Lexical density | 53 |
| | 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

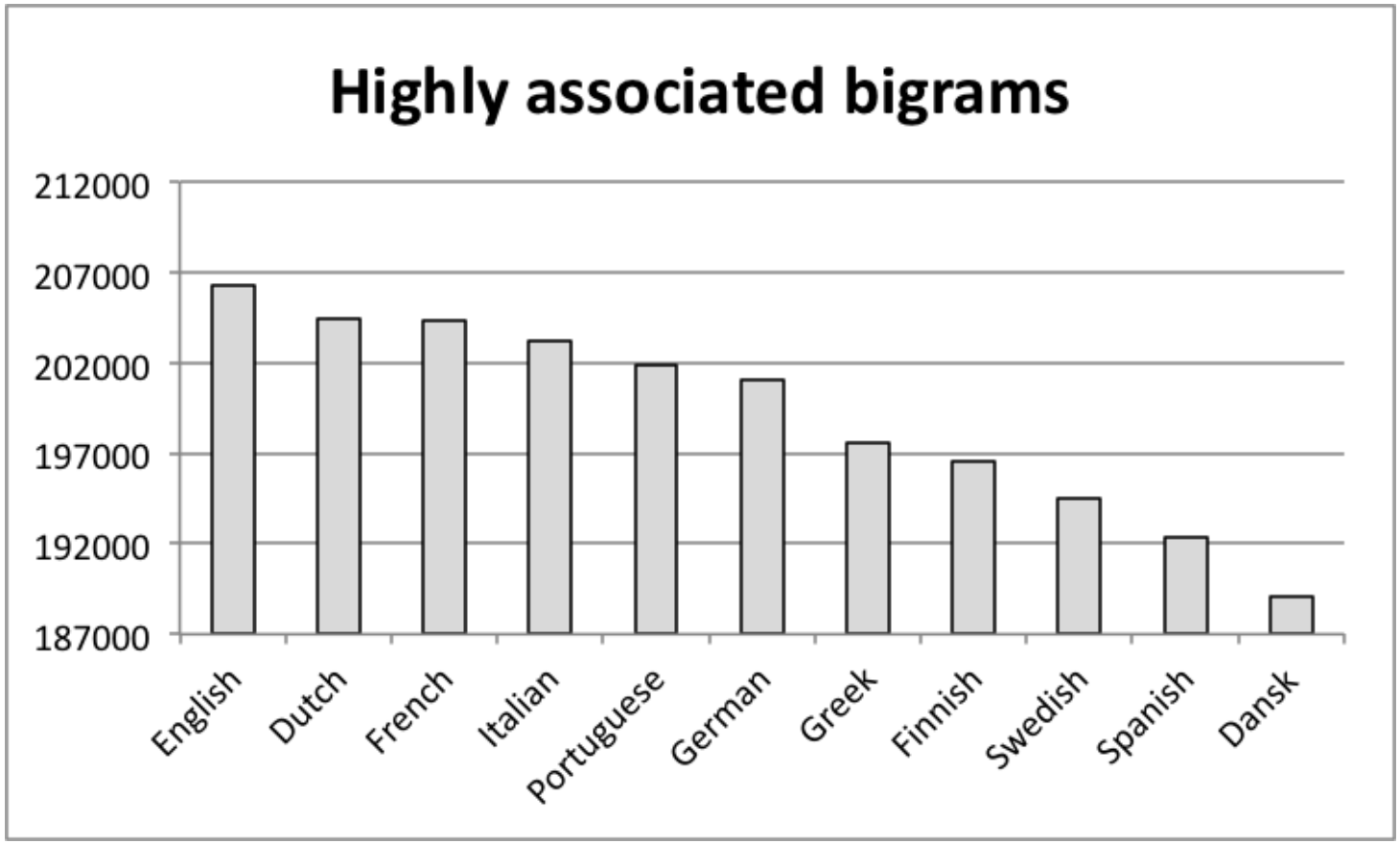
| Category | Feature | Accuracy (%) |
|---|---|---|
| Normalization | Repetitions | 55 |
| | Contractions | 50 |
| | Average PMI | 52 |
| | Threshold PMI | 66 |

# 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*

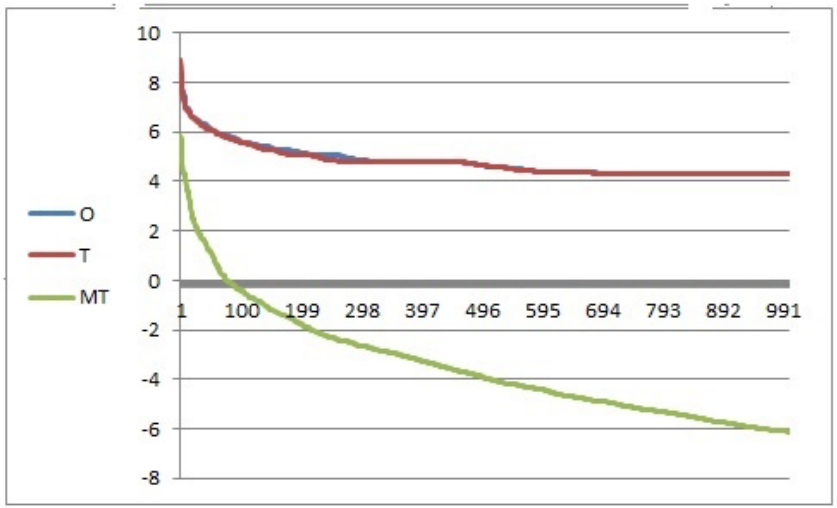
# Normalization

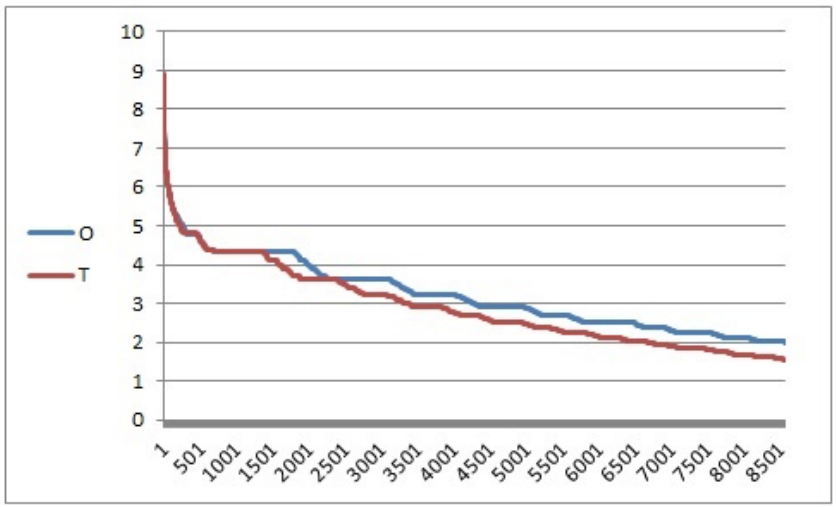
## Example (Number of bigrams whose PMI is above threshold according to 'language')



# Normalization

## Example (Translated language is less predictable)



# Results: Interference

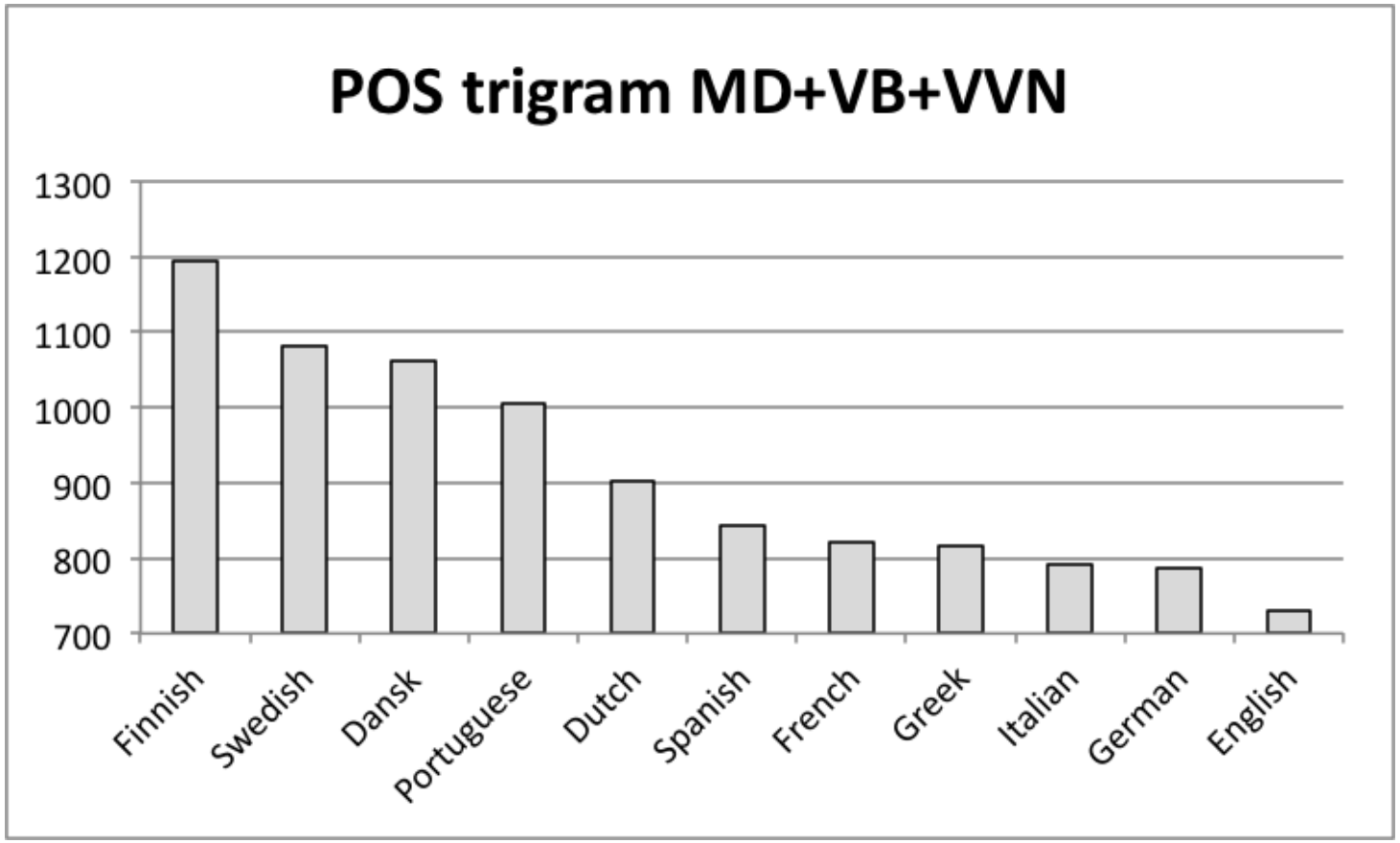
| Category | Feature | Accuracy (%) |
|---|---|---|
| Interference | POS unigrams | 90 |
| | POS bigrams | 97 |
| | POS trigrams | 98 |
| | Character unigrams | 85 |
| | Character bigrams | 98 |
| | Character trigrams | 100 |
| | Prefixes and suffixes | 80 |
| | Contextual function words | 100 |
| | 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: *H**aa**rder* and *M**aa**t* or *Ga**zp**ron*
- 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)

| Mark | Frequency O | Frequency T | Ratio | LL | Weight |
|---|---|---|---|---|---|
| , | 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

# 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.

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# 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
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# 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:

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

- 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)

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

- 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

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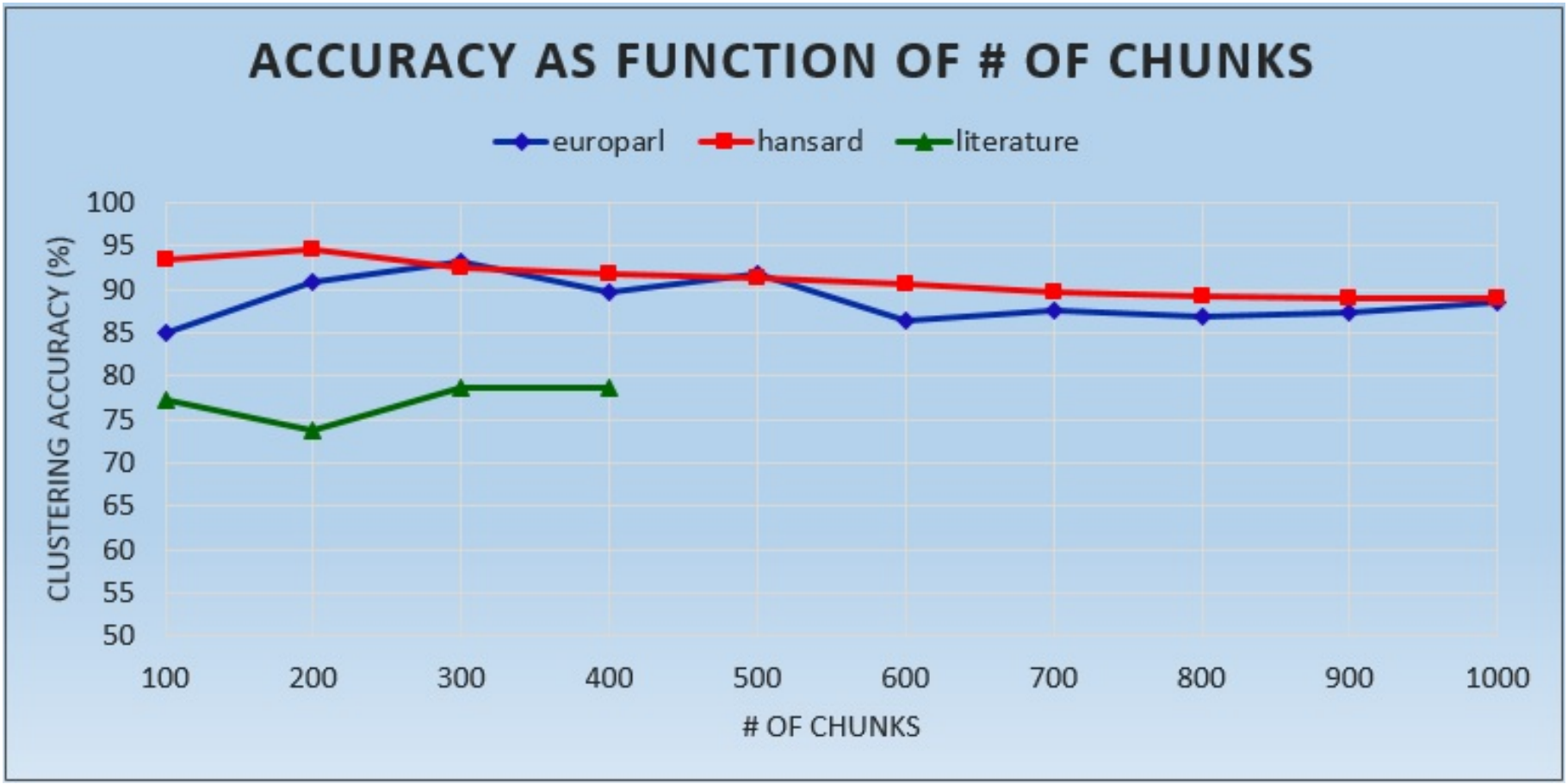
# Clustering Consensus

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

# Sensitivity Analysis



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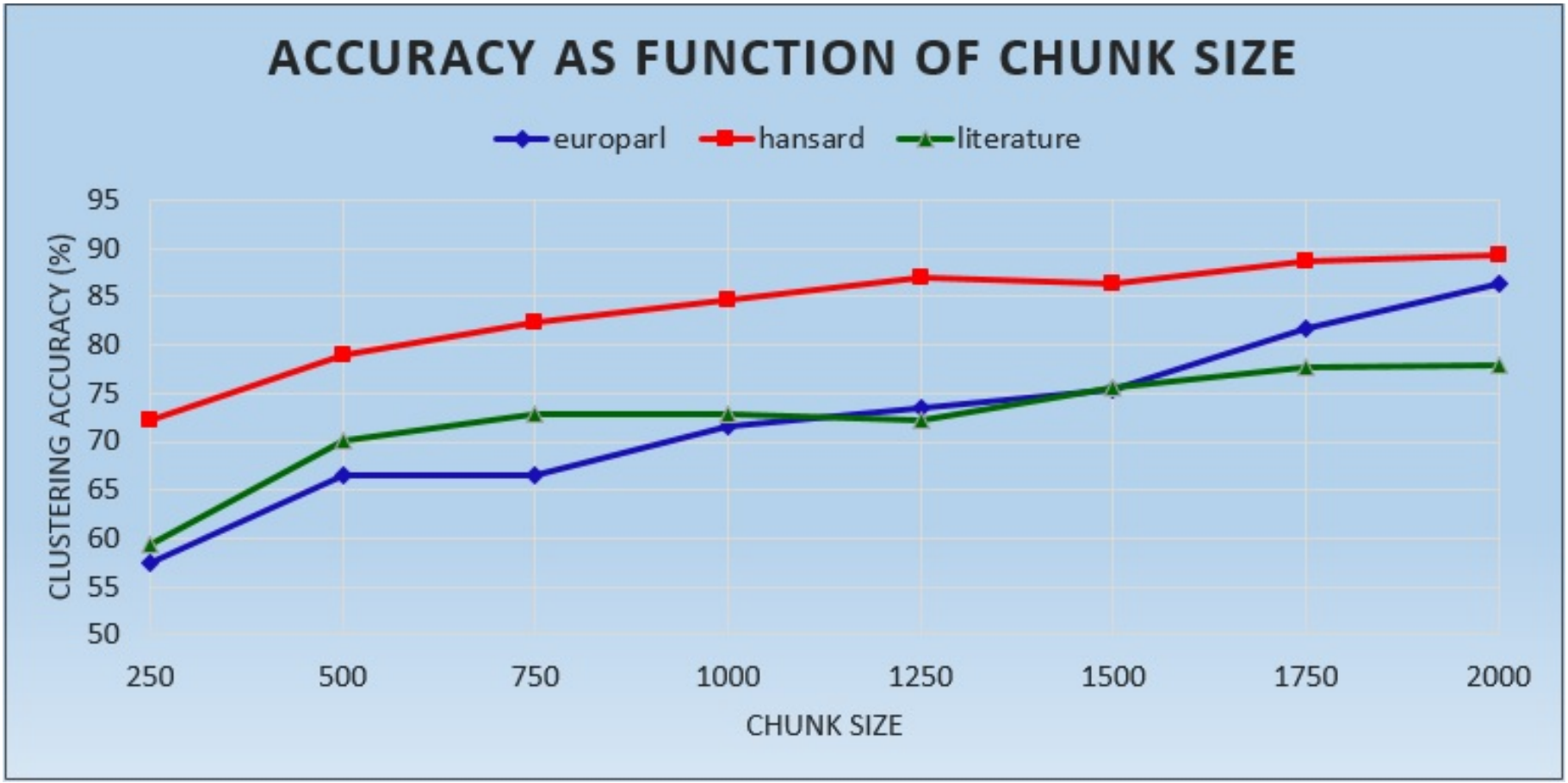

# Mixed-domain Classification

- 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 Europral 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

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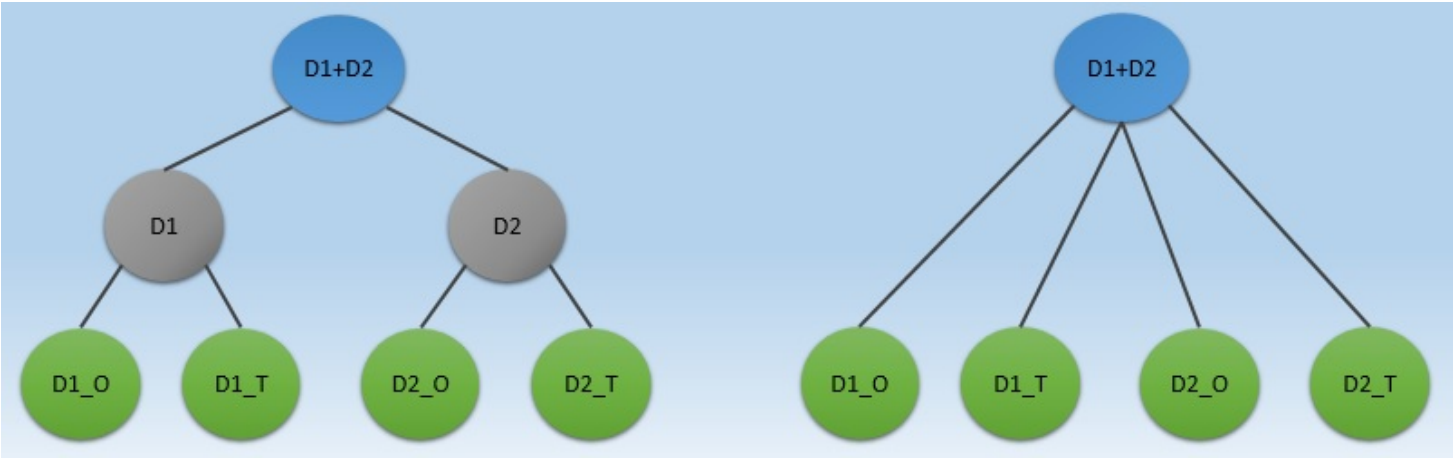
# Mixed-domain Classification

| 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 HAN | EUR LIT | HAN LIT | EUR HAN LIT |
|---|---|---|---|---|
| Flat | **92.5** | 60.7 | 77.5 | 66.8 |
| Two-phase | 91.3 | **79.4** | **85.3** | **67.5** |

# Outline

# Applications for Machine Translation

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

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# 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 $T$

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# Fundamentals of SMT

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

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

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

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- A **language model** to estimate $P(E)$ (estimated from a monolingual $E$ corpus)
- A **translation model** to estimate $P(F \mid E)$ (estimated from a bilingual parallel corpus)
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# 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
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# Language Models

## Methodology

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

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

- Train SMT systems (Koehn et al., 2007) using different LMs and evaluate their quality on a reference set
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# 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 | *468.09* | *103.74* | *79.57* | *76.79* |
| 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 | *500.56* | *115.48* | *91.14* | *88.31* |
| 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 | *415.47* | *99.92* | *79.27* | *76.34* |
| 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 | *448.11* | 100.17 | *78.23* | *75.46* |
| T-DE | 437.68 | 93.67 | 71.54 | 68.57 |
| T-FR | 445.00 | 97.32 | 75.59 | 72.55 |
| T-IT | 448.11 | *100.19* | 78.06 | 75.19 |
| T-NL | **423.13** | **83.99** | **62.17** | **59.09** |

# Language Models

## Abstraction

- No punctuation
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# Abstraction Results

| No Punctuation | | |
|---|---|---|
| **Orig. Lang.** | **Perplexity** | **Improvement (%)** |
| MIX | 105.91 | 19.73 |
| O-EN | *131.94* | |
| 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 | *115.20* | |
| 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

| Noun Abstraction | | |
|---|---|---|
| **Orig. Lang.** | **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

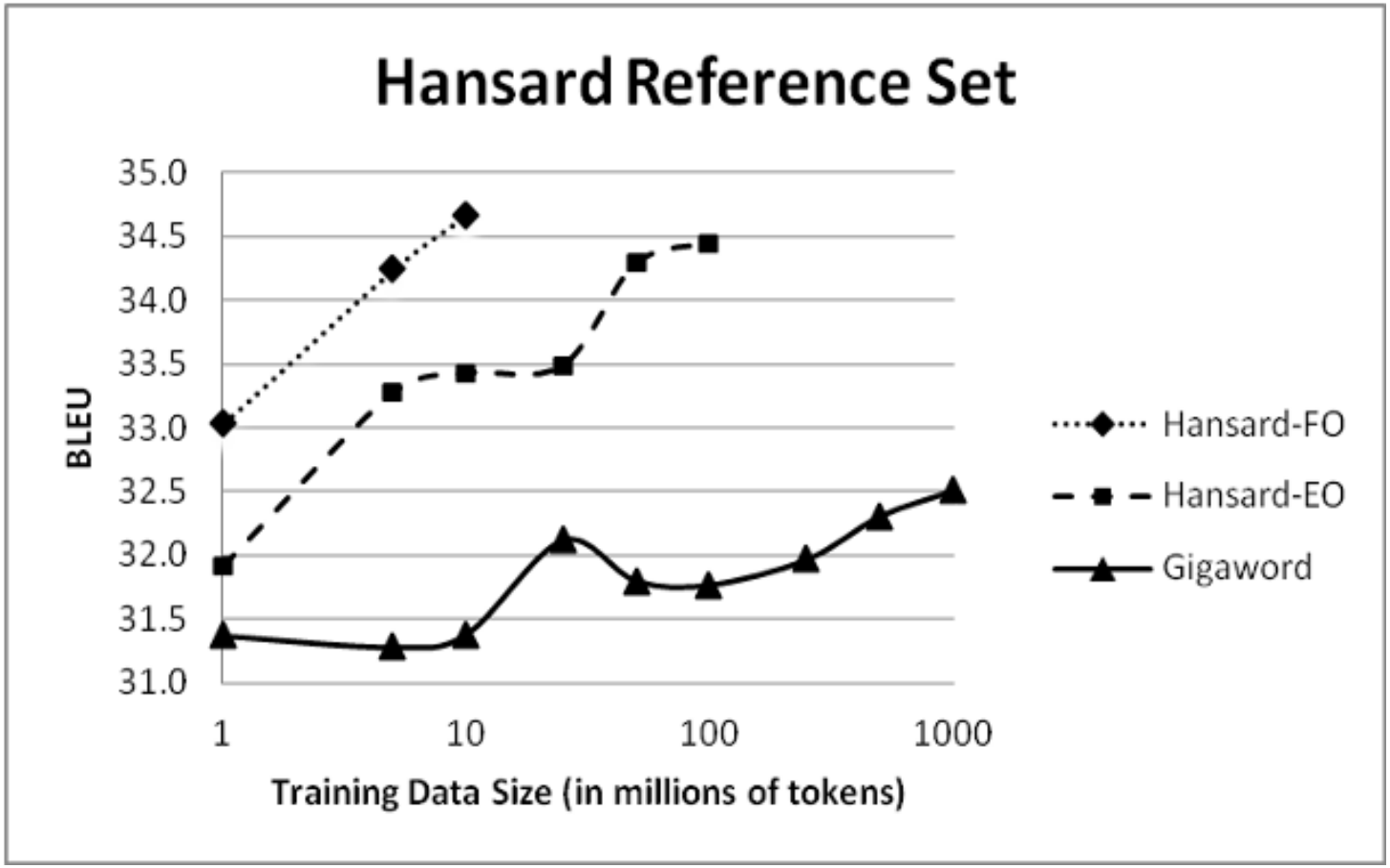
| DE to EN | |
|---|---|
| **LM** | **BLEU** |
| MIX | 21.43 |
| O-EN | *21.10* |
| T-DE | **21.90** |
| T-FR | 21.16 |
| T-IT | 21.29 |
| T-NL | 21.20 |

| FR to EN | |
|---|---|
| **LM** | **BLEU** |
| MIX | 28.67 |
| O-EN | *27.98* |
| T-DE | 28.01 |
| T-FR | **29.14** |
| T-IT | 28.75 |
| T-NL | 28.11 |

| IT to EN | |
|---|---|
| **LM** | **BLEU** |
| MIX | 25.41 |
| O-EN | 24.69 |
| T-DE | *24.62* |
| T-FR | 25.37 |
| T-IT | **25.96** |
| T-NL | 24.77 |

| NL to EN | |
|---|---|
| **LM** | **BLEU** |
| MIX | 24.20 |
| O-EN | *23.40* |
| T-DE | 24.26 |
| T-FR | 23.56 |
| T-IT | 23.87 |
| T-NL | **24.52** |

# Does Size Matter?



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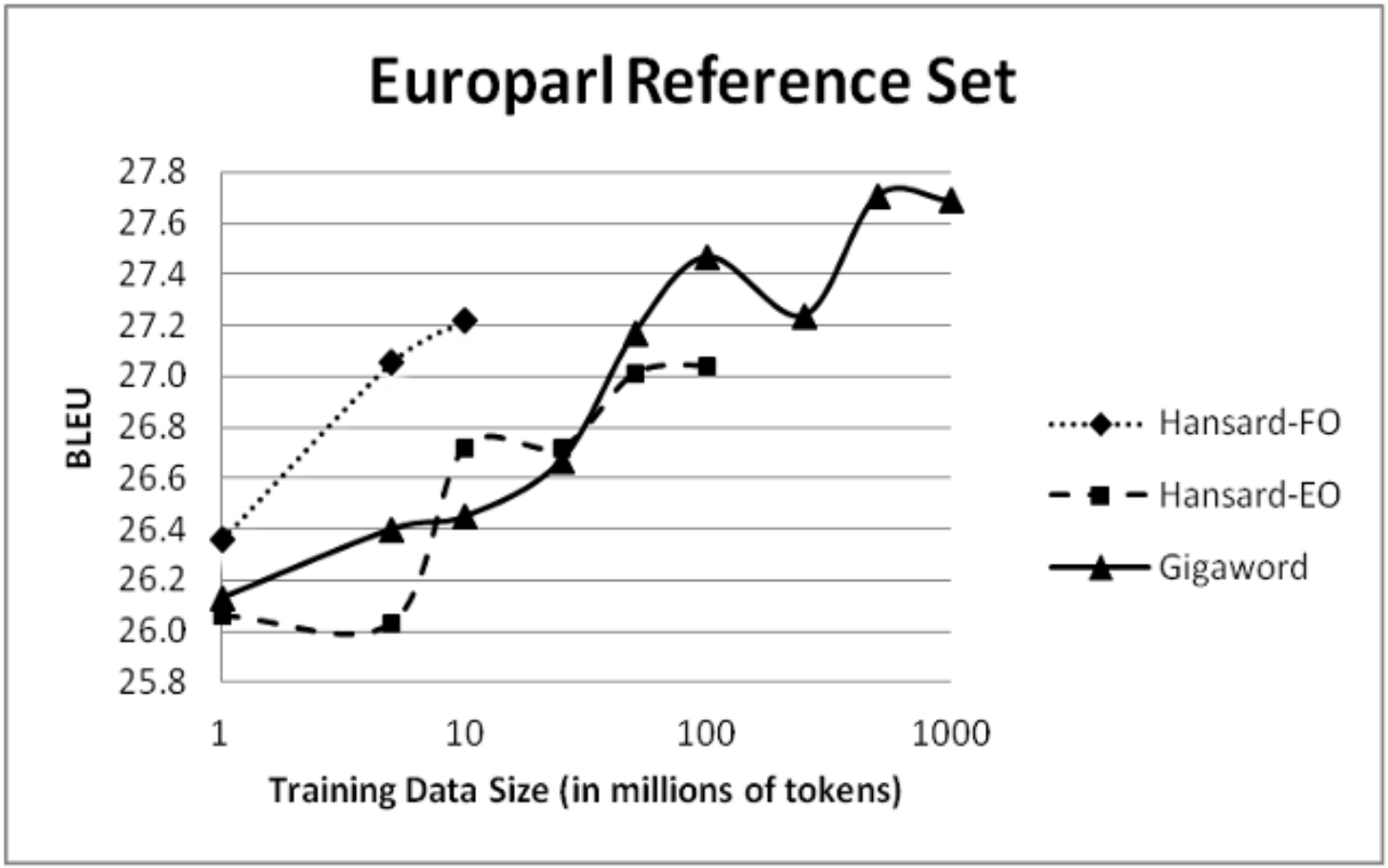

# Translation Examples

## 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?

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# 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
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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

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# 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

# 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

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# 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 L1, test on L2)

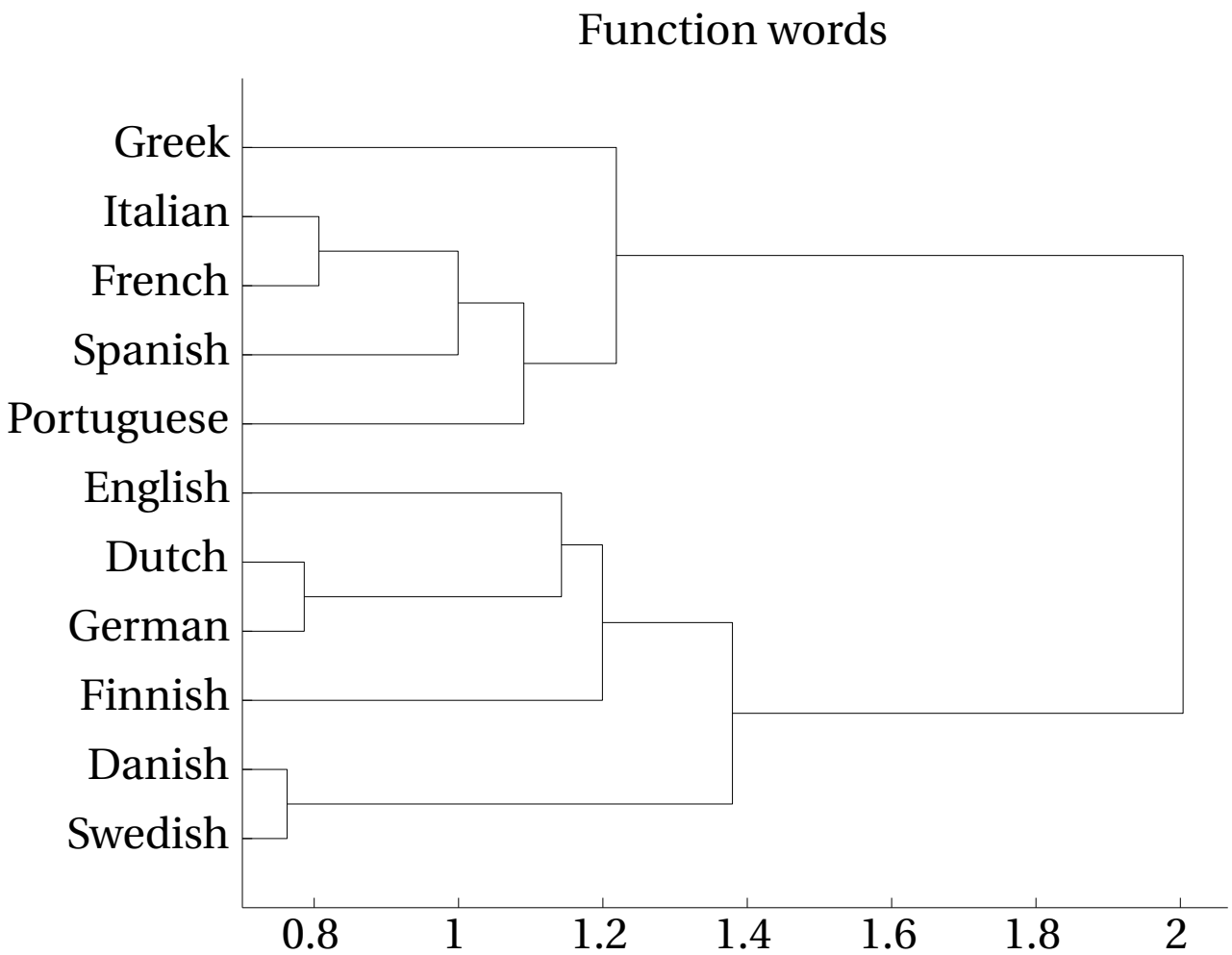
| | IT | FR | ES | DE | FI |
|---|---|---|---|---|---|
| IT | 99 | 93 | 91 | 75 | 63 |
| FR | 90 | 98 | 90 | 83 | 70 |
| ES | 85 | 90 | 98 | 82 | 69 |
| DE | 73 | 74 | 74 | 98 | 70 |
| FI | 58 | 70 | 64 | 81 | 99 |

# Clustering of Translations from Related Languages

- An unsupervised hierarchical clustering algorithm groups together English texts translated from ten European languages
- Texts are represented using feature vectors, similarly to the supervised experiments

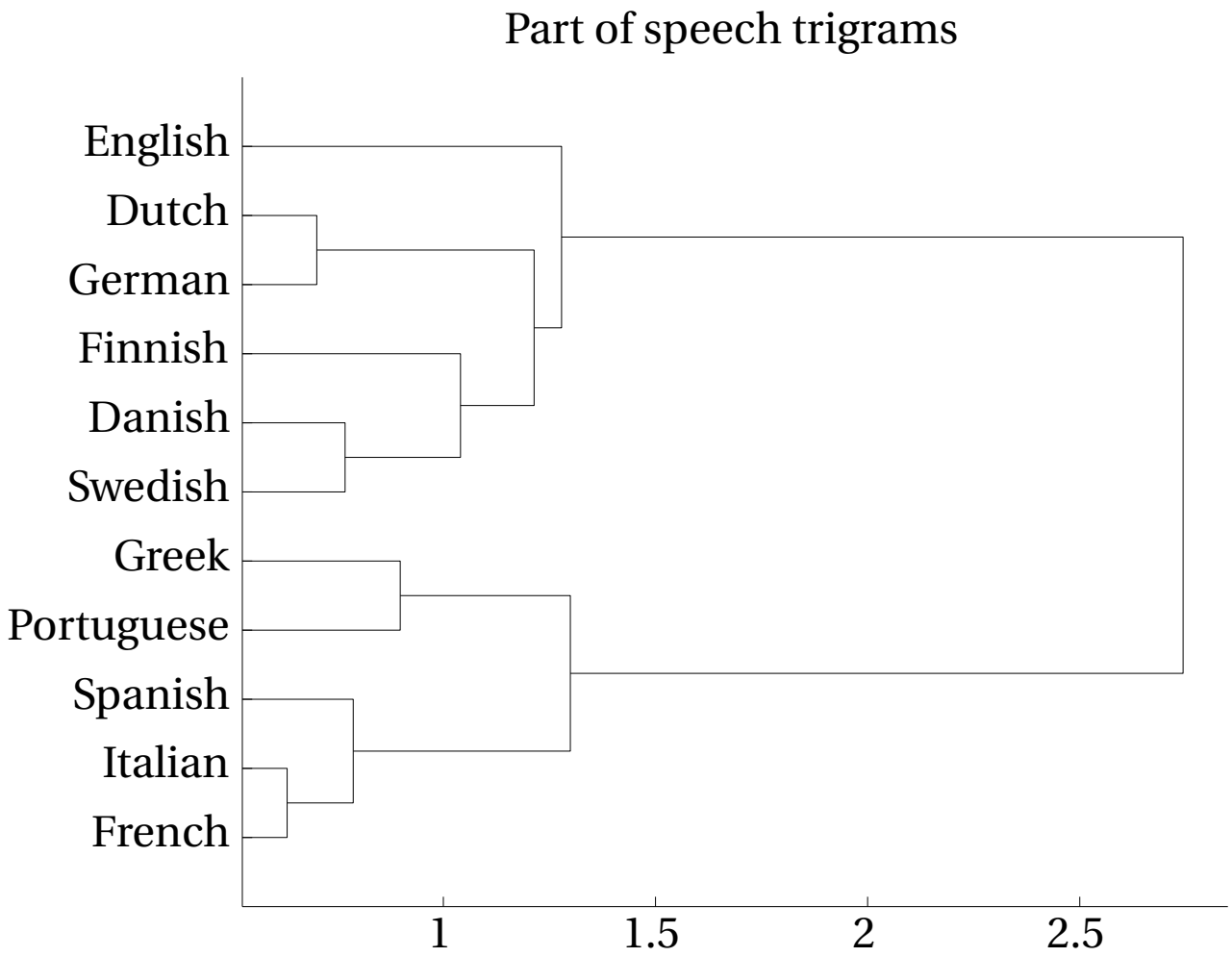
# Clustering of Translations

## Example (Clustering based on function words)



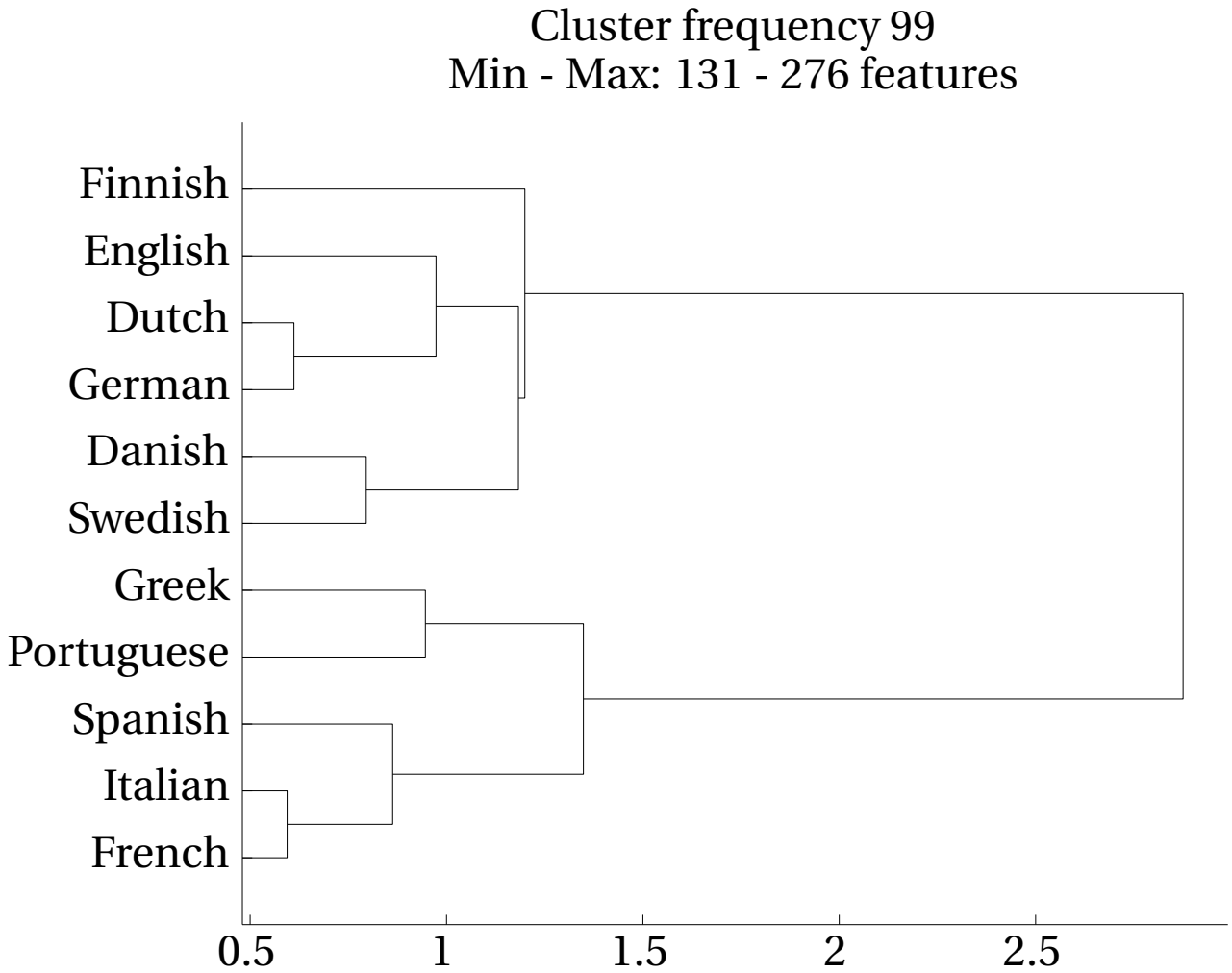
# Clustering of Translations

## Example (Clustering based on POS trigrams)



# Clustering of Translations

## Example (Frequent letter trigrams)



# 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 |

# Outline

# 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.

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- Language models compiled from translated texts are better for SMT than ones compiled from original texts
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- The features of Hebrew translationese: morphological markers (Avner et al., 2016)
- The features of **machine** translationese
- Robust identification of machine translation output
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- 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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