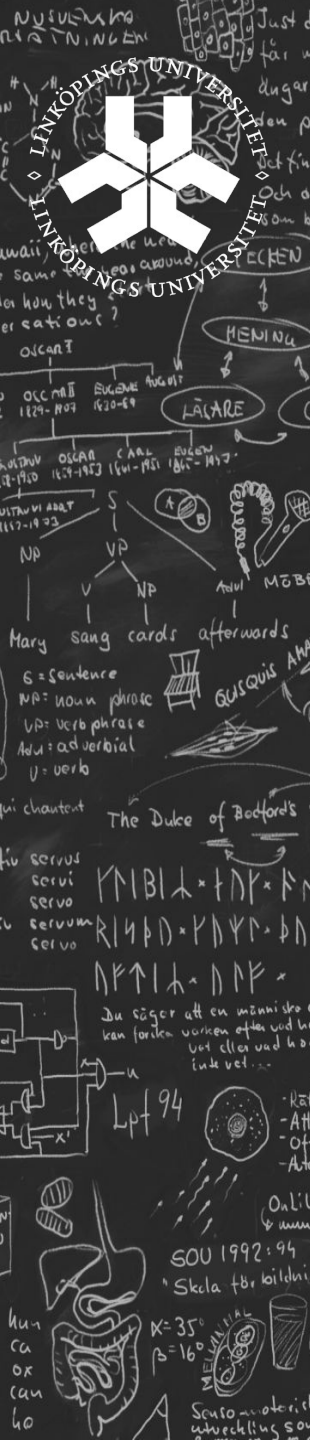

NLP for the translation class

Lars Ahrenberg and Ljuba Tarvi

2nd workshop on NLP for Computer-Assisted Language Learning

Oslo, May 22, 2013

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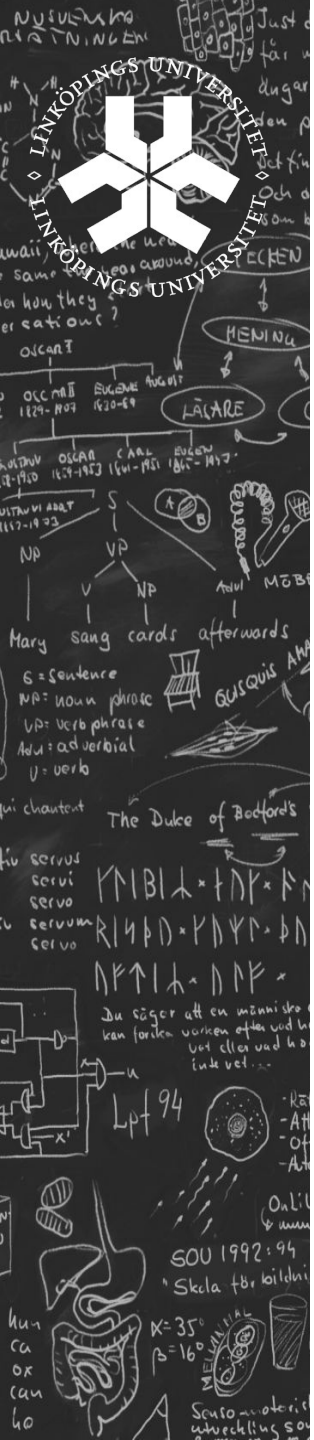

Overview

- Background
- Our proposal
- The Token-Equivalence Method (TEM)
- Alignment experiments
- Conclusions

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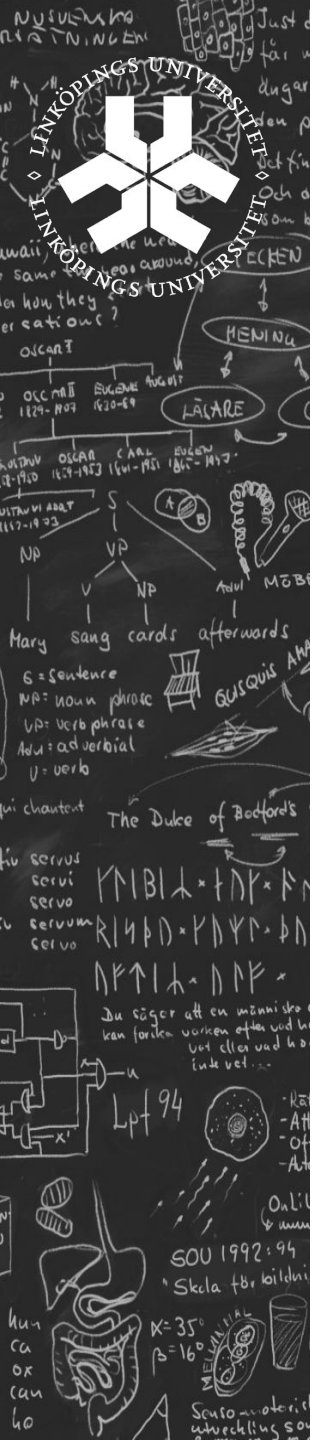
Process of a translation exercise



	Before class		In class	After class
Teacher Tasks:	Define exercise (text + brief) Preprocessing Distribution	Reading for assessment and grading, Preparation	Classroom presentation and discussion	Final grading
Student tasks:	Translation, Delivery			Revision

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Examples of computational aids for the translation exercise

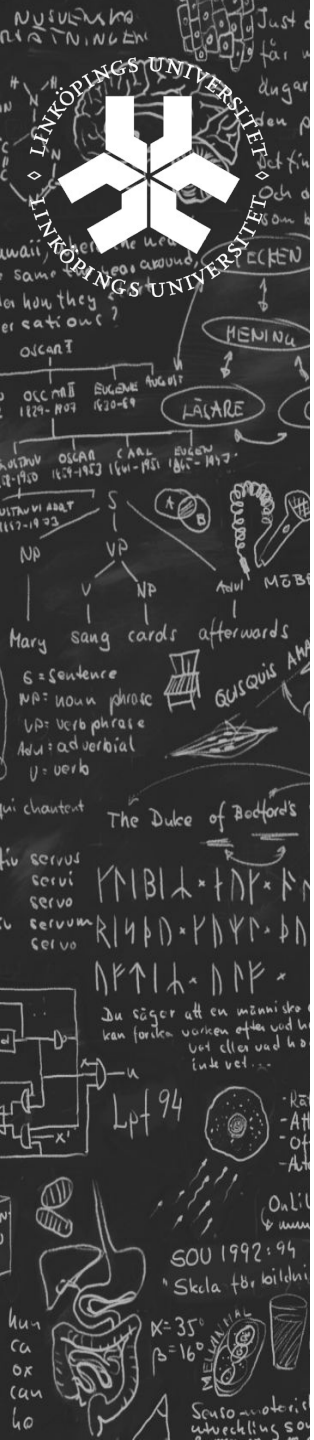
- E-learning environments
  - Fictumová, 2004, 2007
- Corpora
  - Lopez-Rodriguez and Tercedor-Sanchez, 2008;
  - Pastor and Alcina, 2009
- CAT tools
- Assessment of translations as literal or liberal
  - Shei and Pain, 2002

Our idea

- Computer-aided support for the Token-Equivalence Method (TEM; Tarvi, 2004)
- A new application area for alignment technology

  Supporting
  - teacher's assessment and grading
  - discussion in class

Process of a translation exercise



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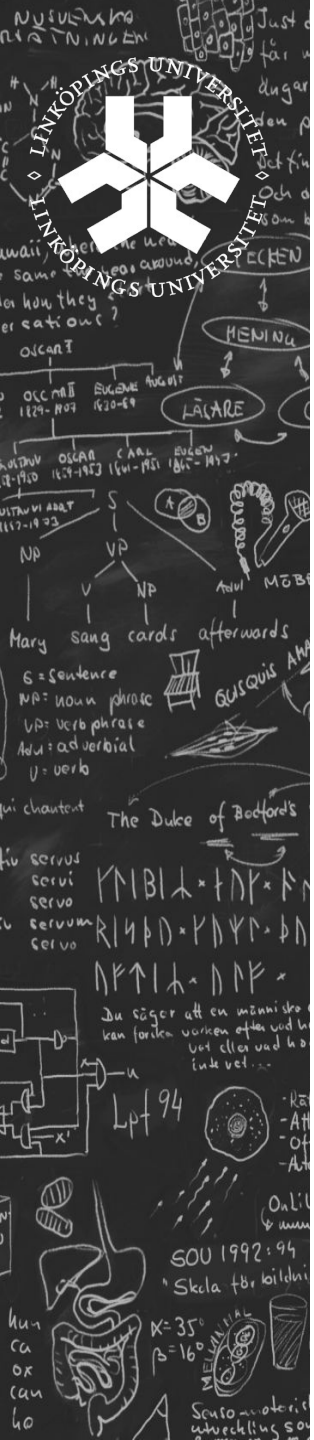
Token alignment as a basis for instruction in class

- Segment views
  - display of different translations of the same source segment
- Token views
  - display of different translations of the same token(s)
- Type views
  - e.g. frequency tables of translations of words and phrases
- Global views
  - metrics and grades computed for the full text or parts thereof



The Token-Equivalence Method (TEM)

- Token correspondences, based on
  - content words
  - denotational meaning
- Frames
  - metrics that quantify relations between source and translation
  - combined to rank translations

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An example (RU - EN)

Pushkin, Eugene Onegin, stanza LIX: 1-2

- *Proshla lyubov, yavilas' muza, i projasnilsya tyomnyi um.*

Translation (by Nabokov)

- *Love passed, the Muse appeared, and the dark mind cleared up.*

Indexing tokens

- *1:Proshla 2:lyubov, 3:yavilas' 4:muza, 5:i 6:projasnilsya 7:tyomnyi 8:um.*

  [passed] [love] [appeared] [muse] [and] [cleared up] [dark] [mind]

- *1:Love 2:passed, 3:the 4:Muse 5:appeared, 6:and 7:the 8:dark 9:mind 10:cleared 11:up.*

”Standard” alignment representation

- 1-2 2-1 3-5 4-4 5-6 6-10 6-11 7-8 8-9 0-3 0-7

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multiword correspondence

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null links

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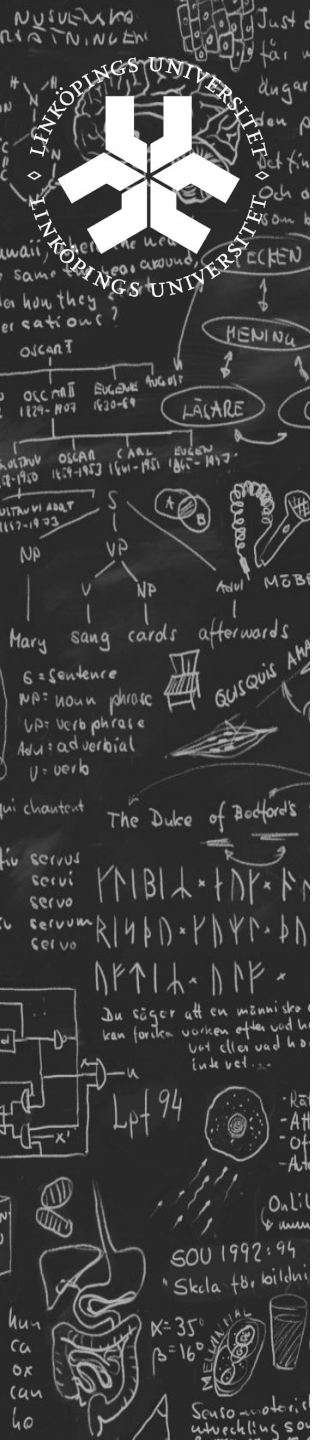
Differences TEM and standard SMT alignment

Aspect	TEM	SMT
Approach	manual	automatic
Punctuation	ignored	tokenized
Token types	two types	one type
Multiword units	single tokens	several tokens



Some definitions

- t_S: a source token
- t_T: a target token
- null(t): a token without correspondent
- nonnull(t): a token with at least one correspondent
- cont(t): a content token
- gram(t): a grammar token

TEM frames

- Basic content frame
  - ”the percentage of source content tokens that have received a translation”
  - BCF = 100 * | { t_s | cont(t_s)∧nonnull(t_s) } | / |{t_s}|
- Optional content frame
  - OCF = | { t_T | cont(t_T)∧null(t_T) } |

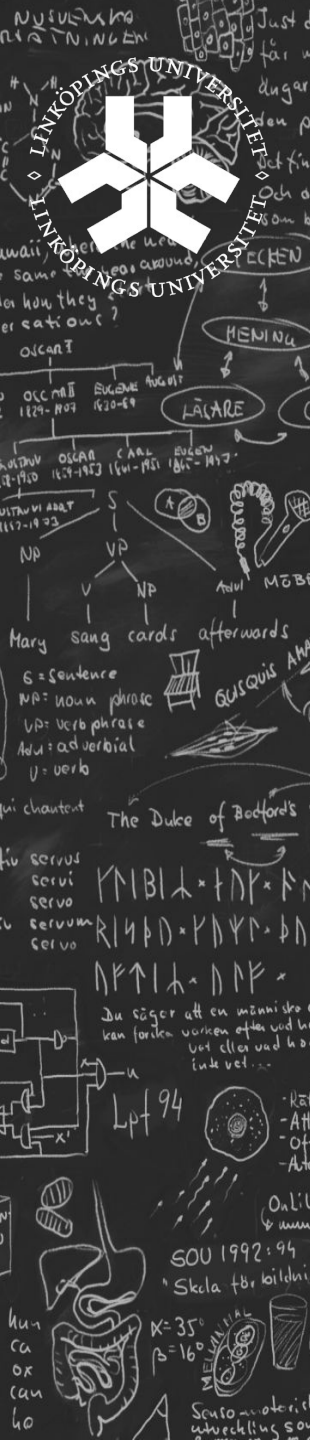
TEM frames (cont.)

- Basic formal frame
  - ”the number of grammar tokens in the translation”
  - BFF = $| \{ t_T \mid gram(t_T) \wedge null(t_T) \} |$
- Optional formal frame 1
  - ”the percentage of source tokens that are translated by a token of the same part-of-speech”
- Optional formal frame 2
  - ”the percentage of pairs of source tokens whose order and dependency relation is kept under translation”

The translation quotient (TQ)

- The TQ is defined as the average of all frames that are expressed as percentages:
- TQ = (BCF + OFF1 + OFF2) / 3

- All frames may be used to compute a rank for each translation



Word alignment for the translation class

- Source texts are short
- Translations, on the other hand, may be many
- Source texts are known beforehand
- Content tokens and grammar tokens should be treated differently

→ Statistical and rule-based methods may be combined

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Alignment experiments

- Russian-English data
  - 8 translations of 17 stanzas from Eugene Onegin
- English-Swedish data
  - 5 translations of two small extracts of English prose text used as exercisez in a course.
  - ***J.D. Salinger. Catcher in the rye, New York, 1951 Roddy Doyle: The Van, 1991.***
- Systems used
  - Giza++ (both corpora)
  - A ”pressure-aligner” (only EN-SE), using
    - a dictionary
    - part-of-speech patterns
    - alignment topology

Alignment results, RU-EN, Giza++ (model 4)

	Precision	Recall	F-measure
1 trl, all links	0,308	0,298	0,303
8 trls, no null links	0,434	0.467	0.450
8 trls, all links	0,482	0.480	0.481

Note: the gold standard used has some 40% added tokens, while Giza++ gives 20%.

Alignment results for EN-SE, Giza++ (model 4)

	Precision	Recall	F-value
1 trl, no null links	0.751	0.652	0.698
1 trl, all links	0.681	0.681	0.681
5 trls, no null links	0.816	0.698	0.752
5 trls, all links	0.752	0.738	0.745

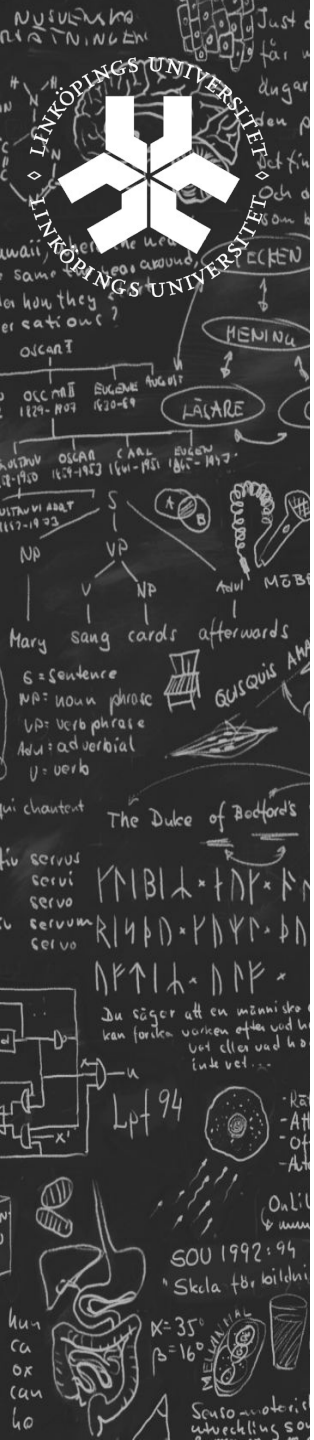
Alignment results for EN-SE, rule-based aligner

	Precision	Recall	F-value
PA1, no null links	0.815	0.492	0.614
PA1, all links	0.502	0.554	0.527
PA2, no null links	0.885	0.608	0.721
PA2, all links	0.606	0.664	0.633

PA1 has a small lexicon, while PA2 has a lexicon adapted for the corpus.

Alignment results for EN-SE, combinations of Giza++ and rule-based aligner

	Precision	Recall	F-value
Union, no null	0.775	0.777	**0.776**
Union, all	0.739	**0.789**	0.763
Intersection, no null	**0.980**	0.530	0.688
Intersection, all	0.875	0.543	0.670
Grown, no null	0.849	0.665	0.746
Grown, all	0.794	0.660	0.721



Observations on alignment performance

- As expected, adding more translations improves the results of the statistical aligner
- Since the source text is known, and small, creating a dictionary for the source adapted for the task is not so much work and improves the results of the pressure aligner substantially
- A combination of statistical and dictionary-based alignment can give very high precision
- All possibilities have not been explored yet...

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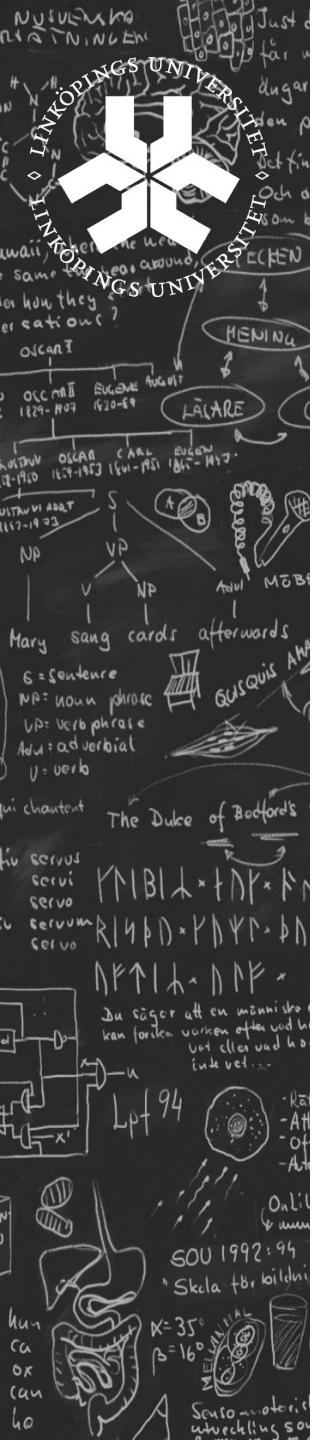
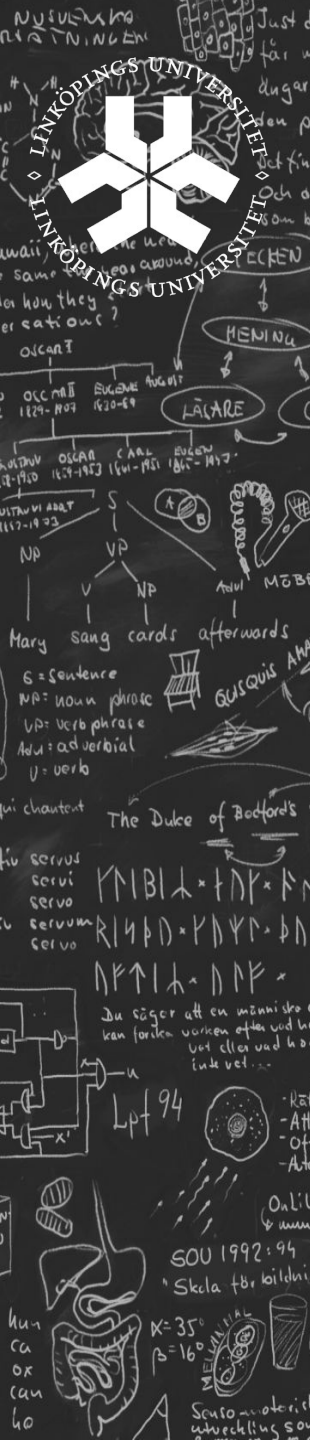


Conclusions

- There is much work ahead
  - implementation
  - trying it out
- Even with further improvements in the automatic tools, there will still be much to do for the teacher in reviewing and correcting token alignments
  - Need for good interactive tools!



Thank You

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