INF5820/INF9820

LANGUAGE TECHNOLOGICAL APPLICATIONS

1

Jan Tore Lønning, Lecture 9, 19 Oct. 2016 jtl@ifi.uio.no

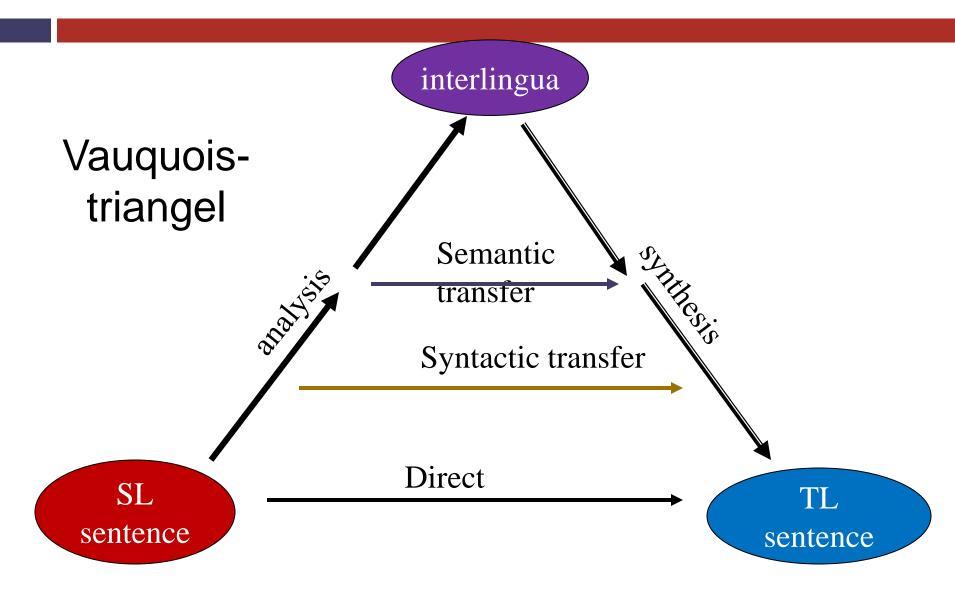
Today

Hybrid translation: □ Linguistic rule-based + probability ranking Linguistic information in STATMT Morphology Word/order - syntax □ State of the art: alternatives Tree-based translation Neural networks

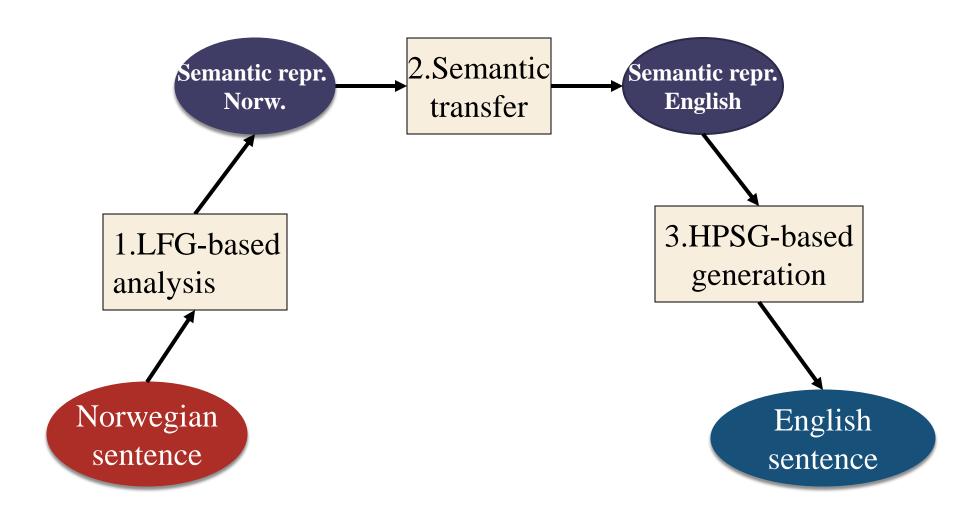
The LOGON project

- \Box MT: Norwegian \rightarrow English
- Tourist texts hiking descriptions
- □ High quality limited recall
- 2003-2007
- Strategy
 - Mainly rule-based:
 - Semantic transfer
 - Probability ranking

Alternative strategies



Back bone: Semantic transfer



Minimal Recursion Semantics

		icrosoft Internet Explorer pr	ovided by Univers	sitete t i	Oslo			l l da .		
Contraction of the second seco						- + ×	readability typog	raphy space	₽ -	
🚔 🍄 🔡 🛪 🎉 LOG 🎉 LOG 🎉 Dani 😥 Ord 🥻 LOG 🥻 KUN 🌈 Apé 🕨 Uni 🥻 L 🗙 👘 🏠 🛪 📾 🔹 🔂 🖓 🖶									• 💮 T <u>o</u> ols 🔹 »	
Reset Hytta har ofte tatt imot turister fra England. Analyze Translate										
results: ⊙ all ⊖ first output: □ tree 🗷 mrs show 5 🔽 results										
[4 of 4 analyses; processing time: 0.52 seconds]										
compare selection transfer generate avm scope										_
	TOP INDEX	h23 e24								
		1	def_q_rel<0:5>ta*imo			not_v_rel<15:19> bare_div_q_rel<20:45>				
		prpstn_m_rel<0:45> LBL h23	LBL h19	_hytte	_n_rel<0:5>	LBL	 h25	LBL	h15	
		ARG0 e24	ARG0 x17	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	h21	ARG	0 e24	ARG0	x10	
#		MARG h22	RSTR h18	ARG0) x17	ARG		RSTR	h14	
0	RELS	5	BODY h20			ARG	2 x10	BODY	h16	1
	REED	ι	proper_q_rel<38:45> _fra_p_rel<34:37>		nemed mission (F)		1-10.11	1		
		_turist_n_rel<25:33>	LBL	h6	LBL	h9	named_rel<38:45 LBL h12		h25	
		LBL h9	ARG0		ARG0	e11	ARG0 xt		e4	
		ARG0 x10	RSTR		ARG1	x10		ARG1	e24	
			BODY	h/	ARG2	x8				
HCONS { h14 =q h9 , h5 =q h12 , h18 =q h21 , h22 =q h25 }										
•										
] Internet		🕄 100% 🔻 //

Analysis of Norwegian

□ Grammar: NorGram,

- A multipurpose computational grammar based on LFG
 - Developed at UiB since 1998
- LOGON
 - extended grammatical coverage
 - equipped it with an MRS semantics module
- Currently developed further in the INESS-prosject
 - <u>http://clarino.uib.no/iness/xle-web</u>

Processing

- The XLE system from PARC
- Morphological processing developed at UiB on top of earlier projects (tagging, UiB & UiO & NTNU)
- Compositional analysis of compounds

Generation

Grammar

- The English Resource Grammar (ERG)
- A multipurpose computational grammar based on HPSG
- Continuously developed since 1994 (CSLI Stanford)
- Refined, domain-adapted, and extended by LOGON
- Open source, used in other ongoing projects
- □ Processing
 - Adapted technology from DELPH-IN consortium
 - LOGON: forty times faster generation algorithms

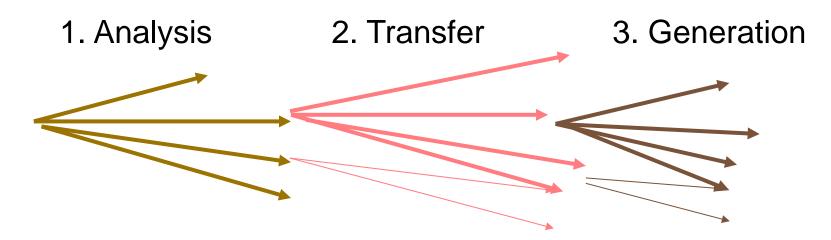
Transfer

Grammar

- Hand-coded transfer rules (7000 rules)
- Semi-automatic acquisition of transfer correspondences
 - for open class words
 - from a dictionary (Kunnskapsforlagets store No-En)
 - (ca 10 000)
- Processing
 - Typed unification-based formalism for rewriting of MRSs
 - Design and implementation from scratch
 - Non-deterministic rewriting of MRS-fragments

Today

□ Hybrid translation: Linguistic rule-based + probability ranking Linguistic information in STATMT Morphology Word/order - syntax □ State of the art: alternatives Tree-based translation Neural networks



□ Challenge: Each step generates many different hypotheses

□ Approach:

- Stochastic models score the alternative outcomes of each component: Parsing, Transfer, Generation
- The per-component scores are calculated together and the final outcomes are ranked.
- Component models are trained on corpora and treebanks.

- \square |< |Toppen er luftig, og har en utrolig utsikt!| (83) --- 2 x 24 x 12 = 12
- \square |> |the top is airy and has an incredible view | [85.9] <0.70> (1:0:0).
- \square |> |the summit is airy and has an incredible view | [87.4] <1.00> (1:4:0).
- \square |> |the top is breezy and has an incredible view | [87.7] <0.46> (1:6:0).
- \square |> |the top is airy and has an unbelievable view | [88.9] <0.70> (1:1:0).
- \square |> |the peak is airy and has an incredible view | [89.1] <0.96> (1:2:0).
- \square |> |the summit is breezy and has an incredible view | [89.1] <0.66> (1:10:0).
- \square |> | the summit is airy and has an unbelievable view | [90.3] <1.00> (1:5:0).
- \square |> |the top is breezy and has an unbelievable view | [90.7] <0.46> (1:7:0).
- \square |> |the peak is breezy and has an incredible view | [90.8] <0.66> (1:8:0).
- \square |> |the peak is airy and has an unbelievable view | [92.0] <0.96> (1:3:0).
- \square |> | the summit is breezy and has an unbelievable view | [92.1] <0.66> (1:11:0).
- \square |> |the peak is breezy and has an unbelievable view | [93.8] <0.66> (1:9:0).
- □ |= 64:19 of 83 {77.1+22.9}; 58:9 of 64:19 {90.6 47.4}; 55:9 of 58:9 {94.8 100.0} @ 64 of 83 {77.1} <0.51 0.67>.

Parse ranking

- □ First build a parse bank
 - Demo on http://erg.delph-in.net/logon
- Then use this for building a discriminator to select/rank between candidates
- □ Choices:
 - Features
 - Learning algorithm

Generation ranker

Roughly 30 realizations per MRS

□ First attempt:

N-gram language model

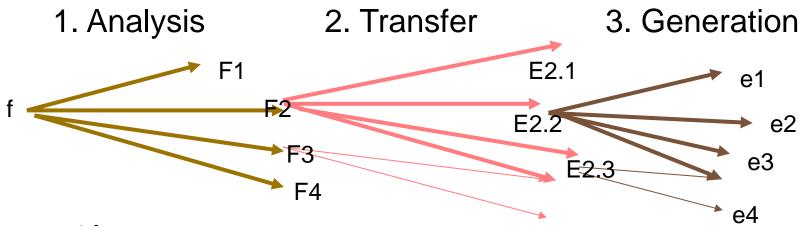
Better:

- Inspired by parse ranking
- Developed on the basis of a parse bank

Extract features	model	exact match	five-best	WA
Max-ent learning	BNC LM	53.24	78.81	0.882
Better results!	Log-Linear	72.28	84.59	0.927



- Should have been conditional probabilities:
 - The probability of an English MRS given a Norwegian MRS:
- Only included absolute probabilities:
 The probability of an English MRS



□ Alternatives

- 1. First $\arg \max_{i} P(F_i | f)$, say F_{2} , then $\arg \max_{j} P(E_j | F_2)$ etc
- 2. The most likely path

 $\underset{i,j,k}{\operatorname{arg\,max}} P(e_k \mid E_j) P(E_j \mid F_i) P(F_i \mid f)$

3. The most likely translation $\arg \max_{e} \sum_{F_i} \sum_{E_j} P(e_k | E_j) P(E_j | F_i) P(F_i | f)$



- 1. First $\arg \max_{i} P(F_i | f)$, say $F_{2,}$ then $\arg \max_{j} P(E_j | F_2)$ etc \Box Theoretically sound:
 - The best parse is in principal independent of the translation, etc.



- 2. The most likely path $\underset{i,j,k}{\operatorname{arg\,max}} P(e_k | E_j) P(E_j | F_i) P(F_i | f)$
- □ Might yield better results:
 - When we see that the translation is unlikely, we may detect mistakes earlier in the process



3. The most likely translation

 $\arg\max_{e} \sum_{F_i} \sum_{E_j} P(e_k \mid E_j) P(E_j \mid F_i) P(F_i \mid f)$

Might yield better results:

- Ambiguities in source language may be the same in target language, e.g. PP-attachement
 - Jeg så mannen i parken med kikkerten
 - I saw the man in the park with the binoculars
 - The same 5 way ambiguity in Norw. and English

End-to-end reranking

- Adding an end-to-end-reranker
 - Goal: rank all the candidates end-to-end towards a modified, sentence-based BLEU-score
- □ Why?
 - Possibly correct the individual modules
 - Include more information than the three modules e.g.
 - Lexical trans. probabilities
 - Word order etc.
 - Can be considered a refinement/extension of the model 3 on last slide

Results

set	#	chance	first	LL	top	judge
JHd	1391	34.18	40.95	44.10	49.89	_
$\mathbf{JH}_{\mathbf{t}}$	115	30.84	35.67	38.92	45.74	46.32

Table 4: BLEU scores for various re-ranking configurations, computed over only those cases actually translated by LO-GON (second column). For all configurations, BLEU results on the training corpus are higher by about four points.

- □ 'first' is the first strategy
- □ LL is the end-to-end reranker, strategy 3+
- Top/judge is human selection of best from all alternatives

Today

□ Hybrid translation: Linguistic rule-based + probability ranking Linguistic information in STATMT Morphology Word/order - syntax □ State of the art: alternatives Tree-based translation Neural networks

STATMT vs linguisitcs

- □ The STATMT model works best if there is
 - A 1-1 relationship between words in source sentence and target sentence
 - Same word order
- □ Not always the case!

STATMT vs linguisitcs

- Linguistic challenges for STATMT
 - Morphology:
 - One source word many alternative translations
 - STATMT is particularly designed to handle that one word may have alternative translations, but
 - Different forms of the same lexeme is a challenge
 - Not a word-to-word relationship
 - Phrase-based STATMT is designed to meet this, but
 - Synthetic languages (many morphemes in a word) a challenge
 - **Syntax:**
 - Larger differences in word order is a problem

Different forms of the same lexeme

- English has a poor morphology
- □ Other languages:
 - Inflection of verbs in person and number
 - Inflection in case and gender: nouns, relative pronouns, determiners, ...
- □ Problems:
 - Sparse training data: a form may not have been seen
 - Challenge to choose the corret form

Morphology

□ One possibility:

- Analyze the training data, replace a fullform with the lemma form and morphological information
- Learn translation probabilities on lemma pairs
- Process morphology information separately

f			е
bil	bil+SG+IND	car+SG	car
bilen	bil+SG+DEF	car+SG	car
biler	bil+PL+IND	car+PL	cars
bil	bil+PL+DEF	car+PL	cars

Translating the morphology



- Some features should be translated:
 - Number
- □ Other features are ignored:
 - Norw: definiteness (into english)
 - German: case (into Norw. Or english)
- □ Or determined by the source language (model)

A statistical model

$$p(s_e, m_e|s_f, m_f) = p(s_e|s_f, m_f) p(m_e|s_e, s_f, m_f)$$
$$\simeq p(s_e|s_f) p(m_e|m_f)$$

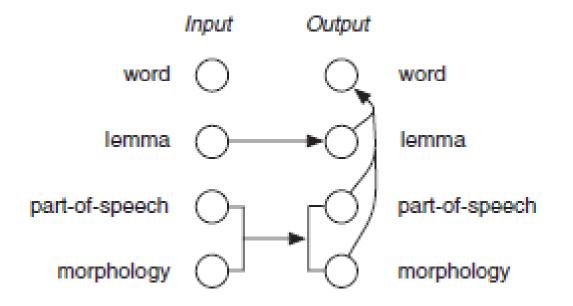
(s_e is stem of e, m_e is morpholgoy of e, similarly for f)
 But a word may have more than one analysis

$$p(e|f) = \sum_{(s_e, m_e)} p(e|s_e, m_e) \sum_{(s_f, m_f)} p(s_e, m_e|s_f, m_f) p(s_f, m_f|f)$$

- □ Not in use in this form in SMT, but
- motivating factored translation

Factored translation

- Consider a source language word a set of features
- □ Factor out what should depend on what



häuser

- Translation: Mapping lemmas
 - haus → house, home, building, shell
- 2. Translation: Mapping morphology
 - NN|plural-nominative-neutral → NN|plural, NN|singular
- 3. Generation: Generating surface forms
 - house|NN|plural → houses
 - house|NN|singular → house
 - home|NN|plural → homes



häuser

Translation: Mapping lemmas

{?|house|?|?, ?|home|?|?, ?|building|?|?, ?|shell|?|? }

2. Translation: Mapping morphology

{?|house|NN|plural, ?|home|NN|plural, ?|building|NN|plural, ?|shell|NN|plural, ?|house|NN|singular, ... }

3. Generation: Generating surface forms

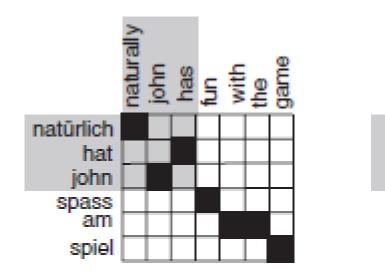
{houses|house|NN|plural, homes|home|NN|plural, buildings|building|NN|plural, shells|shell|NN|plural, house|house|NN|singular, ... }

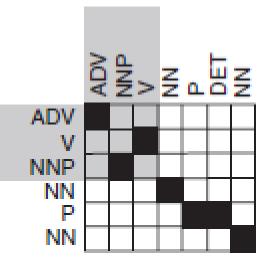
.

Learning factored model

□ Try to learn on the basis of bitext:

- 1. Word/phrase-align
- 2. Parse/tag both languages separately
- 3. (1)+(2) yields:
 - 1. category/tag alignment
 - 2. morphology alignment





Decoding factored models

- □ The book is sparse on details
- Basically the same algorithm as for phrase-based translation

Today

□ Hybrid translation: Linguistic rule-based + probability ranking Linguistic information in STATMT Morphology Word/order - syntax □ State of the art: alternatives Tree-based translation Neural networks

Word order

- How to handle word-order better?
- □ Alt 1: Preprocessing
 - Reorder the source sentences in the corpus before word-alignment
- □ Alt 2: Postprocessing

Add rules that reorder the output of the STATMT-system

Syntactic restructuring

□ Approach:

- 1. Analyze f sentence
- 2. Restructure f-sentence to e word order
- 3. Use SMT (phrase trans prob.s+LM+dist.)
- \Box Example (German \rightarrow English):
 - 1. Move head verb first
 - 2. Move subject in front of head verb
 - 3. etc.

Reordering

- □ Hand-written rules, or
- □ Try to learn on the basis of bitext:
 - 1. Word/phrase-align
 - 2. Parse/tag both languages separately
 - 3. (1)+(2) yields category/tag alignment
 - 4. Try to extract rules
 - 5. Test the reliability of rules

Tag or parse?

Tagger

- Always succeeds
- Rules like:

■ V VINF VMFIN → VMFIN V VINF



■ VAFIN X* VVFIN → VAFIN VVFIN X*



- □ The X*-s are hard to match
 - Many possible candidates
 - Time consuming
- □ Want to locate HEADVERB, SUBJ, ...
- SUBJ VAINF OBJ* VVFIN → SUBJ VAINF VVFIN OBJ*
- Reorders a local tree

(daughters of the same mother)

Try to keep the alternatives

Syntactic post-editing

- □ Use syntactic features in the post-editing reranking
- \Box E.g.
 - Number agreement source target
 - Agreement Verb Subject
- □ Use a parser to rerank:
 - Grammatical output better than ungrammatical

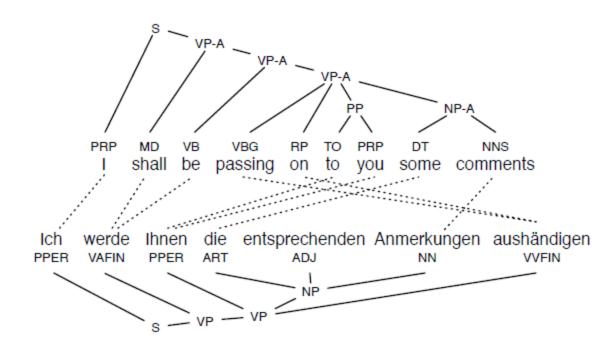
Today

□ Hybrid translation: Linguistic rule-based + probability ranking Linguistic information in STATMT Morphology Word/order - syntax □ State of the art: alternatives Tree-based translation Neural networks

Tree-based models

- □ A different approach to statistical MT.
 - Instead of aligning words or phrases
 - Aligning trees
- □ Conceiving the difference:
 - Word-based STATMT can be considered a combination of traditional direct approach + probabilities
 - Tree-based STATMT can be considered a combination of syntactic transfer + probabilities

Aligned Tree Pair



Phrase structure grammar trees with word alignment (German–English sentence pair.)

Tree-based

- We will not consider the tree-based models
 - Too much
 - In flux

What Works Best?

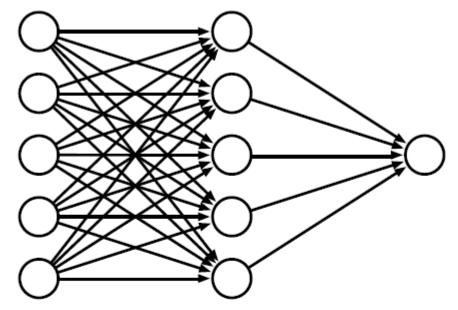


- WMT evaluation campaign
- Winner English–German (with official ties)

System	2008	2009	2010	2011	2012	2013	2014	2015	2016
rule	X	X		Х	Х	Х			
phrase			Х	Х	Х	Х	Х		
syntax							Х	Х	
neural								Х	Х

• For other language pairs, phrase-based systems dominated longer





- Real valued vector representations
- Multiple layers of computation
- Non-linear functions

 $\vec{h} = \text{sigmoid}(W\vec{x})$ $\vec{y} = \text{sigmoid}(V\vec{h})$

Deep learning: neural nets

- A large shift towards nural network models in the 2010s
- Great success:
 - Image reconition
 - Speech recognition
- Tested for all types of NLP tasks
 - Including MT
 - Will probably have to be included in future curriculum