Machine Translation

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Summary

- Human Translation
- Goals of Modern Day Machine Translation
- History of Machine Translation
- Parallel Corpora and their Role in MT
- Aligning Sentences of Parallel Corpora
- Manual Transfer Approaches and Systran
- Statistical Machine Translation
- Adding Structure to SMT
- MT using Deep Learning
- Evaluation

Translation: Human vs. Machine

- Humans do a really good job, very slowly
  - A craft, learned and perfected over centuries
  - NOT directly based on innate human abilities
  - Must understand cultural context of source & target
- Computers are faster and do a bad job
  - Many methods require much computer time to "train"
  - Best translations are literal and awkward
  - Good for tasks where error is tolerated

Human Translation from Source to Target

- Preserve meaning
  - Find idiomatic expressions with similar connotations
  - Explain/remove background knowledge required by one community, but not the other
    - Adding/subtracting whole sentences or parts of sentences
  - Change order to reflect natural order of target language
  - Dynamic (intended) rather than literal (word-for-word) meaning
- Create well-written target language text
  - Obey stylistic conventions of target language
  - Match conventions, e.g., rhyme/meter in poetry
  - Fill in "missing" information required grammatically
    - Missing gender, pronouns, politeness conventions, etc.

Examples of Translations with Glosses

- Example 1
  - *Aquí se habla español* **[Spanish]**
  - *Here one speaks Spanish* **[English gloss]**
  - *Spanish is spoken here* **[English translation]**
- Example 2
  - *Todos los libros me gustan* **[Spanish]**
  - *All the books me please* **[English gloss]**
  - *I like all the books* **[English translation]**
- Example 3
  - *Quiero unas tapas* **[Spanish]**
  - *(I) want some tapas* **[English gloss]**
  - *I want some samplings of small dishes* **[English translation 1]**
  - *I want some assorted appetizers* **[English translation 2]**
  - *I want some (Spanish) Dim Sum* **[English translation 3]**
  - *I want some tapas.* **[English translation 4]**

Computer-Aided Translation

- Translation Memory Systems
  - Professional translators of commercial text may have access to sentence/translation pairs
  - Each translation can be based on a similar instance in translation memory
  - Requires aligned parallel sentences and a similarity measure
- Using MT as a first pass, depending on quality
  - High Quality MT output can be edited by a good writer in the target language.
  - Medium Quality MT output can be edited by a professional translator.
  - Lousy MT output would take longer for a translator to fix than it would take to translate from the original text.

Goals of Modern Day MT

- Gisting
  - Provide an imperfect, but informative translation
    - Identify articles worth translating professionally
    - Multi-lingual Information Extraction or Information Retrieval
- Translating Structured Input
  - Translating forms and tables
  - Translating Controlled/Limited Languages
    - Caterpillar Manuals, Microsoft Help Text
- Literal translation
- Mostly formal language and correspondence
- Literature (esp poetry) is basically impossible

An Abbreviated History of MT

- 1947 – Warren Weaver mentions the possibility of automatic translation in a memo to Norbert Weiner
- 1954 – The Georgetown Experiment automatically translates about 60 Russian sentences to English
- 1966 – ALPAC report admits that MT is really hard and that progress has been slow: funding is cut sharply
- 1968—1976 – Commercially successful manual MT systems
  - Systran, Logos, Meteo
- 1980s – Statistical MT (IBM) & Example-based MT (Nagao)
- 1990 – 2000 – Combining /developing statistical and example-based
- 2000 – Present – adaption of SMT to deal with syntax
  - Phrased-based Statistical Methods (Och, Koehn, …)
  - Tree to String (Yamada, Knight, …) & sometimes more structured input
- 2013 – Present – Deep Learning MT (Kalbrenner, Blunsom, Sutskever, Cho ...)

Parallel, Near Parallel and Comparable Corpora

- A **bitext** is a pair of texts such that one is a translation of the other.
- A **tritext** is a triple of texts such that they are each a translation of the others.
- **Parallel** corpora include bitexts, tritexts, and any set of N texts, such that each is a translation of the others.
- **Parallel corpora tend towards literal translations.**
- **Comparable** corpora are sets of text about the same topic.
- A **Near-parallel** corpus is a text and one or more very dynamic translations of that text.
- **Examples:** Wikipedia pages of the same topic in multiple languages vary a lot with respect to these categories.

Uses of Parallel/Comparable Corpora

- Acquiring bilingual dictionaries
  - All types of parallel to comparable corpora
- Creating sentence-aligned bitexts
  - parallel corpora
- Statistical MT and Example-based MT
  - Sentence-aligned bitexts
  - Bilingual dictionaries
- Answer Keys for Automatic MT evaluation
  - Sentence-aligned bitexts
- Translation Memory for Manual Translation
  - Sentence-aligned bitexts

Aligning Sentences of Bitexts

- Problem: Given a parallel bitext, determine which sentences of the SOURCE language aligns with which sentences of the TARGET
- Possible mappings between source/target sentences
  - 1 to 1 X translates as X'
  - N to 1 X_1, X_2, … X_N in combination translate as X'
  - 1 to N X translates as X_1', X_2', … X_M' combined
  - N to N X_1, X_2, … $X_N \leftrightarrow X_1'$, X_2', … X_M'
  - 1 to 0 Source Sentence is not translated
  - 0 to 1 Target Sentence is added information
- Scrambling: Source/Target sentences may be ordered differently

Gale and Church 1993

- "A Program for Aligning Sentences in Bilingual Corpora," Computational Linguistics, 19:1, pp. 75-102
  - http://www.aclweb.org/anthology/J93-1004
- Uses character lengths of sentences and dynamic programming to assign probability scores to matching sentences
- First uses this method to align paragraphs, then aligns sentences within matching paragraphs
- Uses a training corpus of manually aligned sentences
- Incorporates edit distances for differences in alignments
  - deletions, scramblings, N to 1, etc.

Quick Definitions of Standard Statistical Concepts

- Variance = average of the squares of deviations from the mean
- Standard Deviation = square root of variance
- These are used to represent values that are distributed with a normal distribution.
- Distance Measures based on Standard Deviation are on the next slide

Gale and Church 2

- Probability that two units match calculated from manually aligned sentences
  - c = average number of characters in L1 per characters in L2
  - s^2 = variance between number of characters in corresponding $[1_1,1_2]$ sentence pairs.
  - $\delta = \frac{l_1 - (l_2 \times c)}{\sqrt{l_1 s^2}}$
    - Approximately the number of standard deviations from the expected length
  - $P(match|\delta) = constant \times P(\delta|match) \times P(match)$
- Probability of different types of matches
  - P(1 to 1) = .89
  - P(1 to 0 or 0 to1) = .0099
  - P(2 to 1 or 1 to 2) = .089
  - P(2 to 2) = .011
- Distance is calculated to penalize deletions, mergers and scramblings
- These probabilities are combined (details omitted)
- Alignments for English/French and English/German were about 96% correct
  - Hansards Corpus (English/French Canadian Parliament proceedings)
  - Economic Reports from Union Bank of Switzerland (English/German & English/French)

Meyers, Kosaka and Grishman 1998

- "A Multilingual Procedure for Dictionary-Based Sentence Alignment", Proceedings of AMTA'98"
  - http://nlp.cs.nyu.edu/publication/papers/meyer_multi98.ps
- Sentence Similarity score based on morphological analysis and bilingual dictionary
- Analyzes sentence alignment as a variant of the stable marriage problem. Uses a solution based on the Gale-Shapey algorithm
- Assumes that alignments occur in 10 sentence windows
  - Large gaps can throw off alignment unless some other technique (paragraph alignment) is used in addition
- Handles 1 to 1, 1 to 0, 0 to 1, N to 1 and 1 to N alignments, not N to N
  - Assumes N < 4
- Results
  - Span/Eng 1-1: 97.8/93.5/95.6 Prec/Rec,/F, 1-2/2-1: 20/100/33 Prec/Rec/F
  - Jap/Eng 1-1: 90.9/72.3/80.5 Prec/Rec/F, 1-2/2-1: 13.6/42.9/20.7 Prec/Rec/F

1 to 1 version

- Fill a 10 X 10 array with similarity scores between the first 10 source and first 10 target sentences
- Select the best alignment mapping from source to target using a version of the Gale-Shapey algorithm
  - An alignment is a set of source/target pairs
- From this alignment, keep the pairs that include source sentence 1 and target sentence 2 (this can be 0, 1 or 2 pairings).
- Remove the paired sentences from consideration and advance the window, so it is 10 X 10 again.
- Repeat until all sentences are aligned

Some Details

- N to 1 algorithm for some maximal N
  - Enlarge array for N to 1 & 1 to N matches, N = 1, 2 or 3
  - Only consecutive sentences are considered
  - Thus for 10 sentences, the array is 27 X 27 = 729 cells
    - 10 sentences + 9 sequences of 2 + 8 sequences of 3 = 27
- Constraint: matched sentences are at most 6 apart
  - Source sentences 1 and 10 compete for target sentence 5
- Similarity based on source (S) & target (T), words
  - $Dice = \frac{2 \times |Match(S,T)|}{|S| + |T|}$
- A source and target word match if
  - Any pair of morphological forms matches bilingual dictionary
  - Dictionary can be supplemented automatically by co-occurrance of unmatched words (requires second pass)
  - Morphological forms can be generated generously by removing any possible ending (erroneous forms won't match anything)

Gale Shapey Algorithm

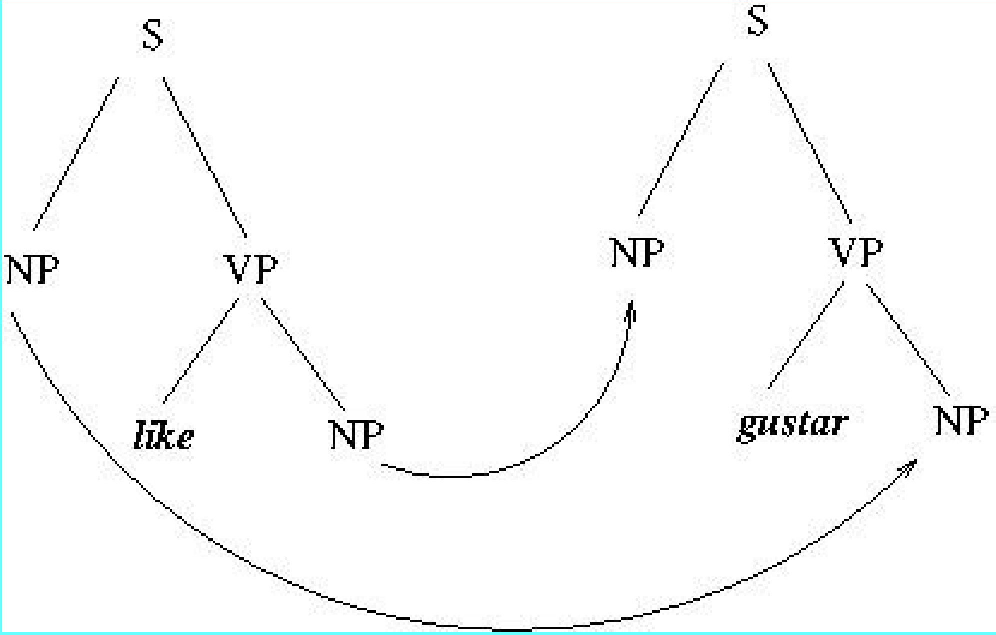
- Stable Marriage Problem
  - N potential husbands, each with a ranking of N potential wives
  - N potential wives, each with a ranking of N potential husbands
  - A stable matching is a set of [husband,wife] pairings such that there is no two pairs [h_1,w_1], [h_2, w_2] such that: h_1 prefers w_2 to w_1 and w_2 prefers h_1 to h_2
- Gale Shapey algorithm chooses a set of 1-1 pairs, optimizing either for husband preferences or the wife preferences
  - Applications: applicants to law schools, dating services, and obviously, **sentence alignment**
  - Complexity = $O(n^2)$
- Gale Shapey Algorithm, optimizing for source sentences:
  - Repeat the following step until there are no more unmatched source sentences:
    - Match a source sentence **S** with its most preferred available target sentence **T**
    - **T** is available if:
      - **T** is currently unmatched or
      - **T** is matched, but prefers **S** to its current match **S' (Then S' becomes unmatched)**
- We run once optimized for source, once for target, then keep intersection and select conflicting cases based on score
- N-to-1 matches: modified definition of match conflicts and preferring 1 to 1

Direct Transfer Manual MT

- Separate Morphological from Lexical Components
  - *John likes ice cream sandwiches* →
    John like+3rd_sing ice_cream sandwich+plural
- Translate words
  - Juan gustar+3rd_sing helado sándwich+plural
- Apply transfer rules, reorder and apply morphology
  - * letter indices: translations, number indices: per/num/gen agree
  - X_i $like_i$ Y → X' $gustar_j$ Y_j'
  - $noun_1$ $noun_2$ → $noun_2$' de $noun_1$'
  - plural noun → $\textit{el/la}_i$ + plural + $noun_i$ + plural
  - *Juan gustan los sándwiches de helado*

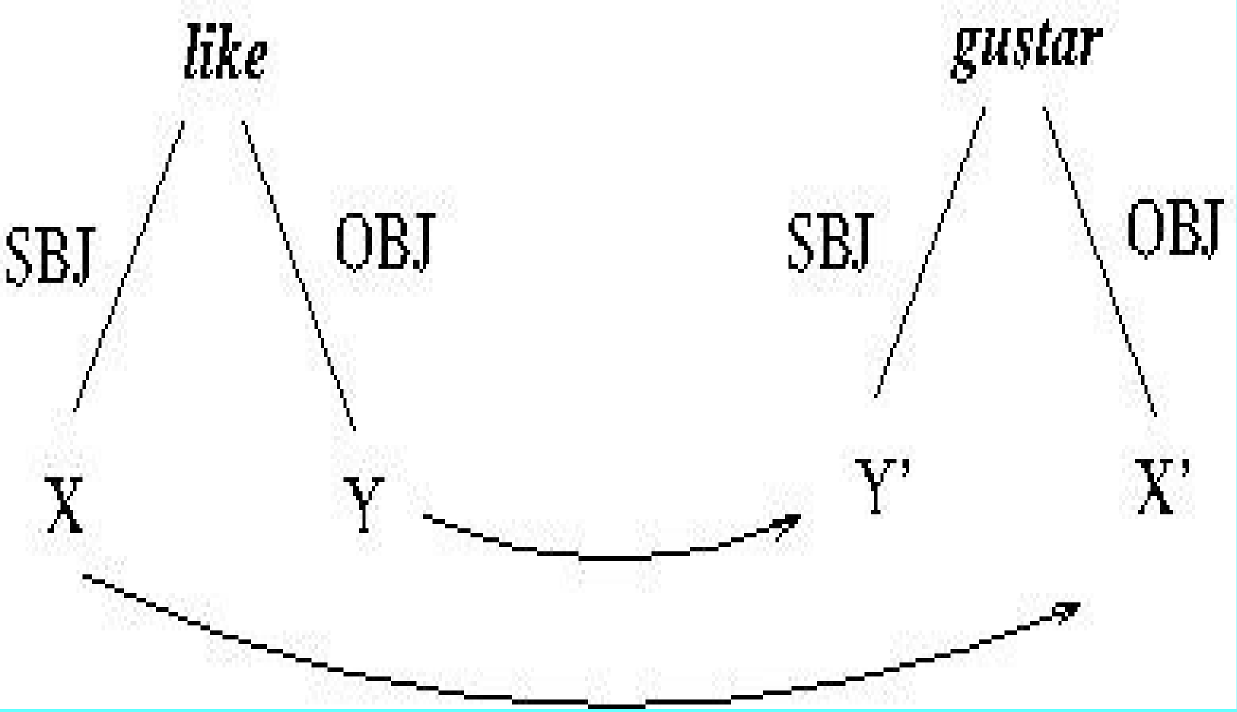
Syntactic Transfer

- Transfer Rules Based on Parse Trees
  - Idiosyncratic to parsing/semantic system assumed
  - Semi-standardization of parsing to Penn Treebank is recent and not uncontroversial
- *like* → *gustar*
- More precise than direct transfer



“Deeper” Level Transfer

- Can incorporate more generalizations
  - Example: morphological agreement with the subject can occur after transfer



Systran

- History
  - Oldest Commercial MT system
    - company founded 1968
    - descendant of Georgetown University system from 1950s
  - Most successful manual transfer system
  - Some current Systran systems are hybrid manual/statistical systems
  - The Engine Behind Yahoo!'s BabbleFish translation service before it was replaced by Bing translate in 2012 (current version at:
    - https://www.systransoft.com/lp/text-translation/
- Languages
  - Many language pairs to/from English or French
- Multiple dictionaries for each language: idioms, morphology, compound nouns, …
- Many components are language independent, but have language specific modules
- Description taken from: Hutchins and Somers (1992) *Introduction to Machine Translation.* Academic Press

Hutchins & Somers 1992 Systran Diagram

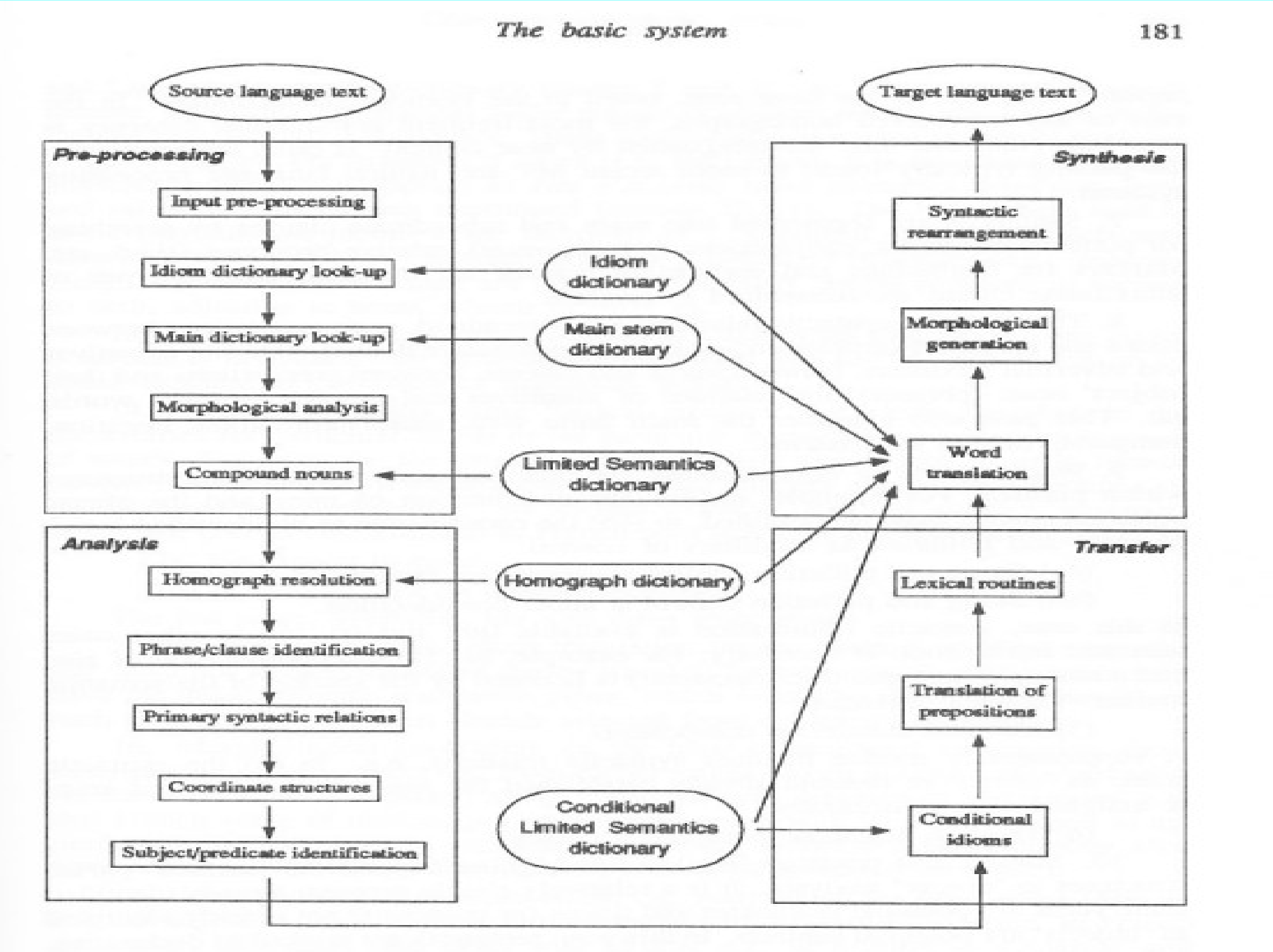


Figure 10.1 Systran translation process

Systran: Source Language Pre-Processing

- Lookup in 3 bilingual dictionaries
  - Idioms and compound nouns – fixed multi-word dictionaries
    - *with respect to, ice cream, tip top, so so, good for nothing, blow drier*
  - Words – Main dictionary
- Morphological analysis
  - Nothing for English
  - For languages like Russian, stems and affixes looked up separately in Dictionaries
  - Some category info inferred from endings of OOV words

Systran 2nd Stage: Source Language Analysis

- Homograph resolution (same spelling/different word)
  - Manual rules using adjacent POS – default: most frequent POS
- Phrase and Clause Identification:
  - A sort of shallow parsing, but looking for larger units than chunks
  - Clues: subordinate conjunctions (*because*), punctuation, pronouns, …
- Identify Syntactic Relations:
  - Also like shallow parsing, but more like chunking/head identification
- Coordination and other "enumerations"
  - E.g., scope in: ***zinc and aluminum components***
- Identify Subjects, Predicates and semantic roles (deep cases)
  - Use special analytic dictionaries to deal with rare structures

Systran 3rd Stage: Transfer

- Translate conditional idioms (other idioms stage 1)
  - English passive ***agreed*** is translated as French ***convenir***
  - Otherwise, *forms of* ***agree*** are translated as ***être d'accord***
- Translate prepositions/postpositions
  - Previous stages needed – require syntactic/semantic info
- Lexical Routines: rules triggered by lex items
  - English ***as*** translates as many different French words depending on context

Systran 4rth Stage: Synthesis

- Word Translation (for words not handled by more specific rules)
- Morphological generation
  - Gender, number, tense, etc.
    - Previous rules allow agreement to be handled properly
- Syntactic Rearrangement
  - English Adj/Noun order → Spanish Noun/Adj order
- Result: Translated Sentence

How many MT Systems for N languages?

- N (N-1) transfer systems
  - English to Spanish, Spanish to English, English to German, German to English, Spanish to German, …
  - 10 languages → 180 systems (both directions)
- 2 X N Interlingua Systems
  - English to Interlingua, Interlingua to English, Spanish to Interlingua, Interlingua to Spanish, German to Interlingua, Interlingua to German, …
  - 10 languages → 20 systems

The Interlingual Approach

- Translate source language into Interlingua
  - Usually similar to automatic semantic analysis (from parse to semantics)
- Generate target language
  - Natural Language Generation
- What does an Interlingua Look Like?
  - A logical representation with standard primitives, e.g.,
    - Structure like a programming language OR
    - Feature structure (or similar datastructure) OR
    - Logical formulas
  - Some Pivot Language
    - English, Sanskrit, Esparanto, …
- Mostly toy systems – approach less successful than others
  - Except for resource-poor languages

Statistical Machine Translation (SMT)

- Word Based Models
  - based on translating individual words
  - allow for deletions, reorderings, etc.
  - Analogous to manual direct transfer systems
- Phrase Based Models (2nd most popular)
  - based on translating blocks of words (may not be conventional phrases) and then words within those blocks
  - allows for deletions, reorderings, etc.
- Models using structured text
  - tree to string
  - synchronous grammars
  - tree to tree
- Neural Networks (Newest and most popular)
  - based on functions from source text to hidden layer(s) (encoding) and functions from hidden layer(s) to target text

Word Alignment

- A 1st step in training most statistical MT systems
- Map source words to target words, before various statistics are recorded (translation, distortion, etc.)
- Many systems implement other components, but use Giza++ or Berkeley word alignment programs
- Simple Example from Microsoft help text

	Excel	vuelve	a	calcular	valores	en	libro	de	trabajo
Excel	X								
recalculates		X	X	X					
values					X				
in						X			
workbook							X	X	X

Word Alignment Discussion

- Use some of Birch and Koehn slides
  - http://www.mt-archive.info/MTMarathon-2010-Birch-ppt.pdf
- Slides 1 to 19: Introduces the IBM Model 1 and how to use with HMM (Model 1 assumes only 1 to 1 matches)
- **Pigeon Hole Principle (Dirchlet)**: If items in **A** are matched to items in **B**, such that **A** has **N** items **B** has **N+1** items, at least 1 item of **A** matches 2 items in **B**.
  - B & K interpret this to favor aligning unaligned items first.
- Go back to these slides for a detailed EM walk through
- We will go back and forth for a bit.

Simplified Example of EM model

- Given
  - 4 French words: ***la***, ***maison***, ***bleu***, and ***fleur***
  - 4 English words: ***the***, ***house***, ***blue*** and ***flower***
  - We only allow 1 to 1 alignments
- Starting assumption
  - Each French word has a .25 chance of being translated as a given English word

Initial Alignment Probs for 3 E/F pairs

- ***la maisson* → *the house*** [***la/the*** (.25), ***maisson/the*** (.25), ***la/house*** (.25), ***maisson/house*** (.25)]
  - ***la/the*** X ***maisson/house*** = $.25^2$ = .0625
  - ***maisson/the*** X ***la/house*** = $.25^2$ =.0625
- ***la maisson bleu* → *the blue house***
  - ***la/the*** X ***maisson/house*** X ***bleu/blue*** = $.25^3$ = .015625
  - ***la/the*** X ***maisson/blue*** X ***bleu/house*** = $.25^3$ =.015625
  - ***la/house*** X ***maisson/the*** X ***bleu/blue*** = $.25^3$ =.015625
  - ***la/house*** X ***maisson/blue*** X ***bleu/the*** = $.25^3$ =.015625
  - ***la/blue*** X ***maisson/house*** X ***bleu/the*** = $.25^3$ =.015625
  - ***la/blue*** X ***maisson/the*** X ***bleu/house*** = $.25^3$ =.015625
- ***La fleur* → *the flower***
  - ***la/the*** X ***fleur/flower***= $.25^2$ = .0625
  - ***fleur/the*** X ***la/flower*** = $.25^2$ = .0625

Maximum Liklihood Estimates (MLE)

- For each e/f pair and for each sentence, add up the probabilities of alignments that contain that pair and regularize to 1 (initially: all prob=.25)
- Sum these scores and divide by the number of instances of f.
- Translations from X to ***the***
  - ***la/the***: .5 of the first set of alignments, .33 of the second set and .5 of the 3rd
    - (.5 + .33 + .5) / 3 = **.44**
  - ***maisson/the:*** .5 of the 1st + .33 of the 2nd , 0 in the 3rd
    - (.5 + .33)/3 = **.28**
  - ***bleu/the***: 0 in the 1st + .33 of the 2nd + 0 in the 3rd
    - .33/3 = **.11**
  - ***fleur/the:*** 0 in the 1st and 2nd, .5 in the 3rd
    - .5/3 = **.17**
- ***house***: ***la/house***=.42, ***maisson/house***=.42, ***bleu/house***=.17, ***fleur/house***=0
- ***blue***: ***la/blue***=.33, ***maisson/blue***=.33, ***bleu/blue***= .33, ***fleur/blue=0***
- ***flower: la/flowe***r=.5 ***maisson/flower***=0, ***blue/flower***=0, ***fleur/flower***= .5

Expectation: Rescore Alignments

- ***la maisson*** → ***the house***
  - ***la/the*** X ***maisson/house*** = .1848
  - ***maisson/the*** X ***la/house*** = .1176
- ***la maisson bleu*** → ***the blue house*** (all possible alignments)
  - ***la/the*** X ***maisson/house*** X ***bleu/blue*** = .06098
  - ***la/the*** X ***maisson/blue*** X ***bleu/house*** = .02468
  - ***la/house*** X ***maisson/the*** X ***bleu/blue*** = .03881
  - ***la/house*** X ***maisson/blue*** X ***bleu/the*** = .01525
  - ***la/blue*** X ***maisson/house*** X ***bleu/the*** = .01525
  - ***la/blue*** X ***maisson/the*** X ***bleu/house*** = .01571
- ***La fleur*** → ***the flower***
  - ***la/the*** X ***fleur/flower***= .22000
  - ***fleur/the*** X ***la/flower*** = .08500

Iteration of EM

- The Expectation and Maximization steps alternate until there is convergence (the probabilities do not change noticeably from iteration N to iteration N+1)
- Some of the details of scoring, e.g., presence of NULL, are omitted from example
- In the 1st EM step, alignments are weighted equally
- For subsequent steps, the probabilities of previous alignments are used as weights, e.g., pairs in ***la maisson*** → ***the house*** have weights of .1848/(.1848+.1176) = .61 and .1176/(.1848+.1176) = .39

IBM Models 1 to 5 for calculating translation probabilities for each sentence

- From Candide Project in 1980s and 1990s
- IBM model 1: Based on translation probability of each source word to each target word
- IBM model 2: Adds in distortion, probability of alignment given positions of source/target words and lengths of sentences
- IBM model 3: Adds fertility model, probability that each source word will correspond to N target words
- IBM model 4: Adds relative alignment model (modifies 2 to account for the fact that chunks move together)
- IBM model 5: Accounts for inaccuracies in 3 and 4 by only considering "vacant positions" when assigning probabilities

Phrase-Based Models

- Performance similar to that of (most popular) Neural Network-based MT
  - Evaluation varies by type of example and by evaluation metric
- In training, N to N words are aligned, not just single words
- These chunks of N words are often called “phrases”
  - But they need not be linguistic phrases
- Example alignment
  - ***natuerlich hat john*** [***<u>spass am</u>***] ***spiel***
  - [***<u>of course</u>***] ***john has*** [***<u>fun with the</u>***] ***game***
  - P. 128 of Koehn, P. (2010) “Statistical Machine Translation”, Cambridge University Press
- Phrase table acquired from alignments is used for translation
- Deletions and insertions become unnecessary

Phrase-Based Alignment

- Record all possible N to N mappings that:
  - are compatible with word alignment
  - N to N mappings are desirable (if frequent)
- It is therefore OK to have reliable mappings in which not all the words are aligned
- One popular technique:
  - Intersection of source-target & target-source word alignments
- Birch and Koehn slides 34 and 35
- It is OK to add unaligned blocks to adjacent aligned blocks
- The more probable phrase translations will be identified by an iterative process and highly ranked in the phrase table
- To limit computation, max phrase length (e.g., 6) often assumed

Decoding for IBM models & Phrasal MT

- Find the most probable translation Ê, given:
  - Probability of translating F to a given E (a candidate Ê)
  - The probability of a particular E (the language model).
- $\hat{E} = \underset{E \in English}{argmax}\, P(F|E) \times P(E)$
- P(F|E) is derived from probabilities trained
  - IBM Models: e.g., from previous slide
    - ***(la/the) .44*** X (***maisson/house) .28*** X ***(bleu/blue) .11*** = .012
  - Phrase Model: probabilities from phrase table
- P(E) is based on language model
  - e.g., multiplying unigram, bigram, etc.

Translating sample sentence

- Input: ***La maissan bleu***
- Translation probabilities (hypothetical):

		English			
French		*the*	*blue*	*house*	*flower*
	la	.70	.10	.15	.05
	maisson	.24	.26	.50	0
	bleu	.25	.41	.22	.12
	fleur	.19	.17	.01	.63

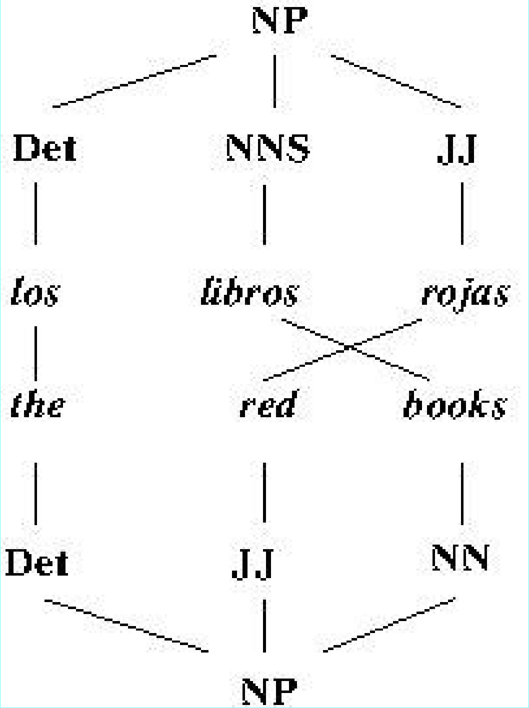
- Unigram probabilities (count in WSJ ÷ 1 million)
  - ***the*** = .035, ***blue*** = 1.3×10^{-4}, ***house*** = 6.7×10^{-4}, ***flower*** = 6×10^{-6}
- The most probable translation would be:
  - ***the house blue*** = translation-prob X language prob = 4.37×10^{-10}
    - translation-prob = .70 X .41 X .50 = .1435
    - Lang-prob = $.035 \times 6.7 \times 10^{-4} \times 1.3 \times 10^{-4} = 3.05 \times 10^{-9}$

More Details About Decoding

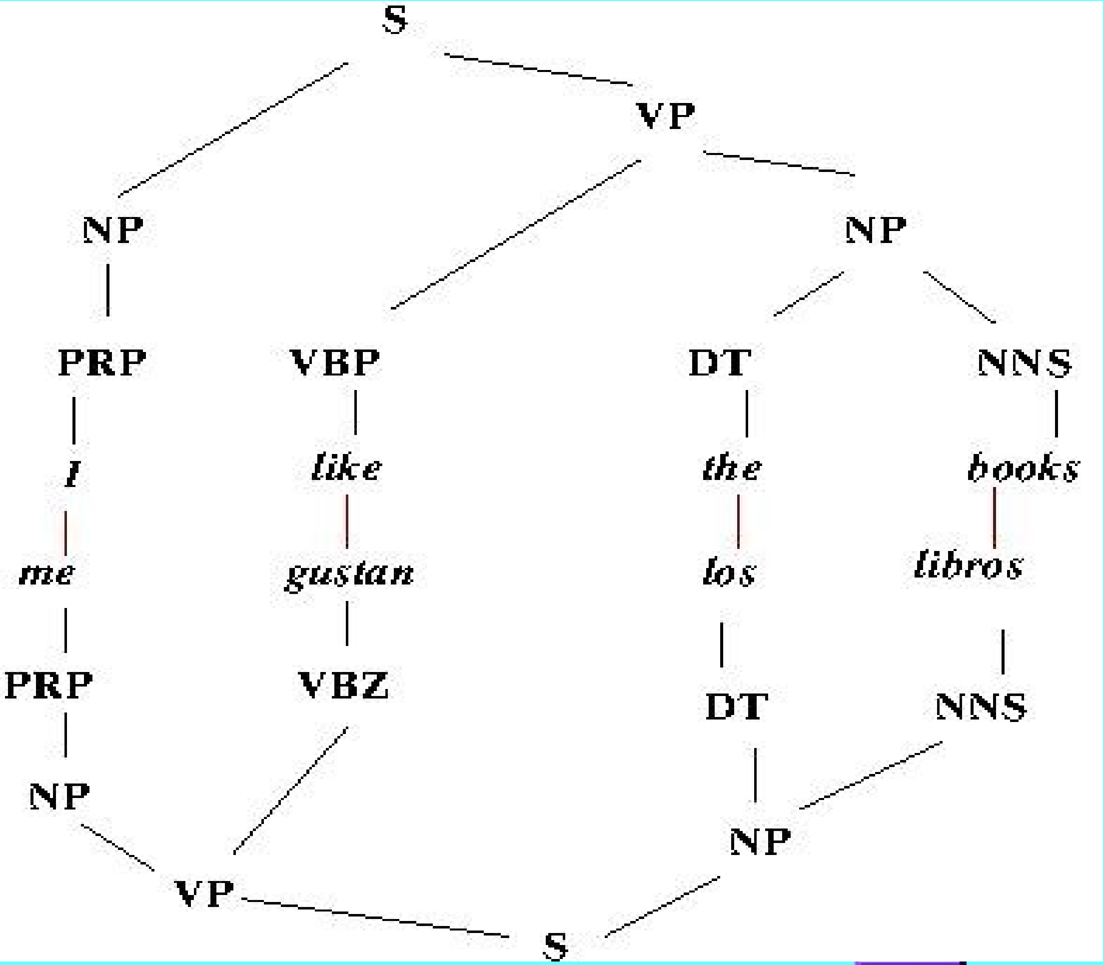
- The translation on the previous slide is the most probable, in part, because we only allow 1 to 1
  – more words → lower probabilities for all translations
  – N words implies N words in the translation
- Other models use additional components:
  – translation to/from NULL, distortion, fertility, ...
- Typically, generate K most likely translations
  – For different applications K can equal 1, 10, 1000, etc.

Tree-based Models

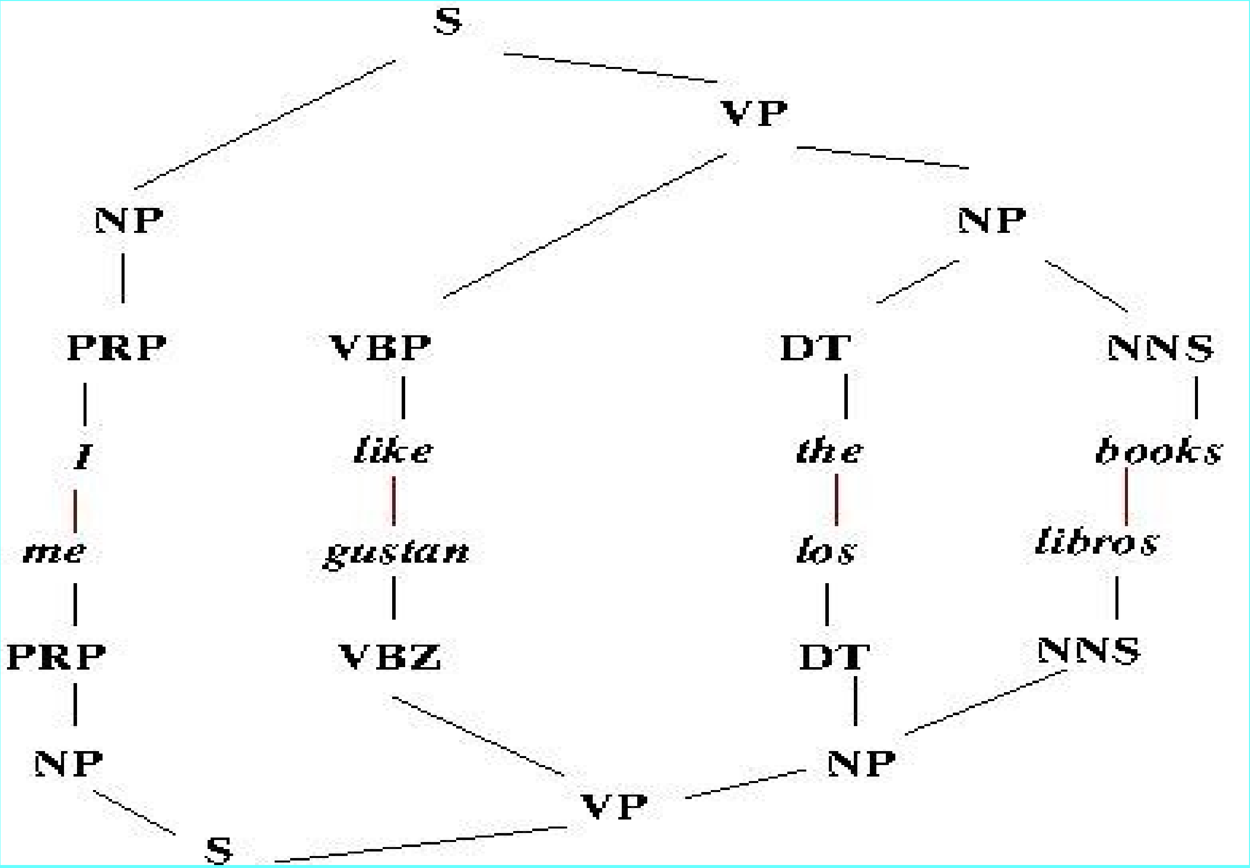
- So far the most successful Tree-based Models assume an isomorphism between source & target
- Sample Rule: NP $\rightarrow$ $\text{Det}_1\ \text{NN}_2\ \text{JJ}_3 \mid \text{Det}_1\ \text{JJ}_3\ \text{NN}_2$
- Tree:



Problematic Tree: No VP rule



Solution: Change Grammar so VPs align



- Note: this change is biased towards English grammar

One Phrase Structure with 2 Strings

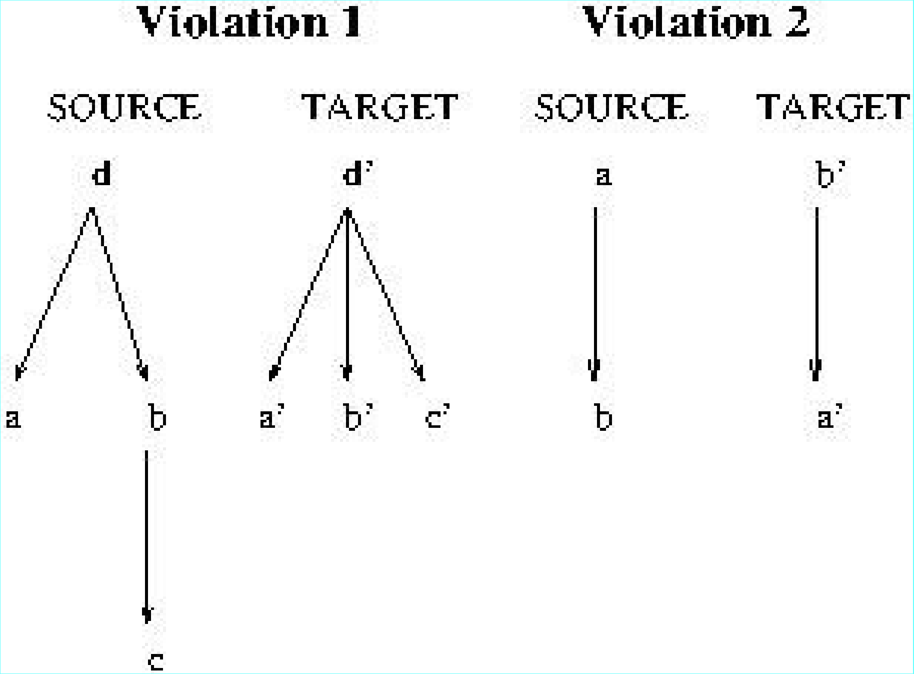
- String to Tree Machine Translation
  - Parser in one language is aligned with the tokens in the other language (biased to source or target)
  - More common method
  - K. Yamada and K. Knight (2001). *A Syntax-based Statistical Translation Model*, ACL 2001
  - M. Galley, M. Hopkins, K. Knight and D. Marcu (2004). *What's in a translation rule?* NAACL 2004
- Synchronous parsing
  - A synchronous grammar is induced from the pair of source and target language texts
  - I. D. Melamed (2004). *Statistical Machine Translation by Parsing*, ACL 2004
  - D. Chang (2005). *A hierarchical phrase-based model for statistical machine translation*. ACL 2005.

What about Tree to Tree alignment?

- Given N source nodes and N target nodes
  - alignment i=set of pairs of source target nodes
  - O(N!) 1 to 1 alignments (and more N to 1, 1 to N, etc.)
- Reasonable constraints shrink the search space
- If synchronous grammars is to strict (1 to 1 partial mapping). What about weaker constraints?
- We did some experiments at NYU using logic dependency graphs (rooted DAGs, tree-like) using a dominance-preserving constraint
  - Motivation: There are cases (long distance dependencies) where linguistic analysis should work better than statistics (allowing displacements of N tokens)
  - Meyers, Yangarber, Grishman, Kosaka, and others: 1996, 1998, 2000
    - 2 Stage Manual Rule Parsers
  - Meyers, Kosaka, Liao, Xue (2011) *Improving Word Alignment Using Aligned Multi-Stage Parses,* in SSSST2011
    - Using GLARF as 2nd stage

Dominance Preserving Constraint

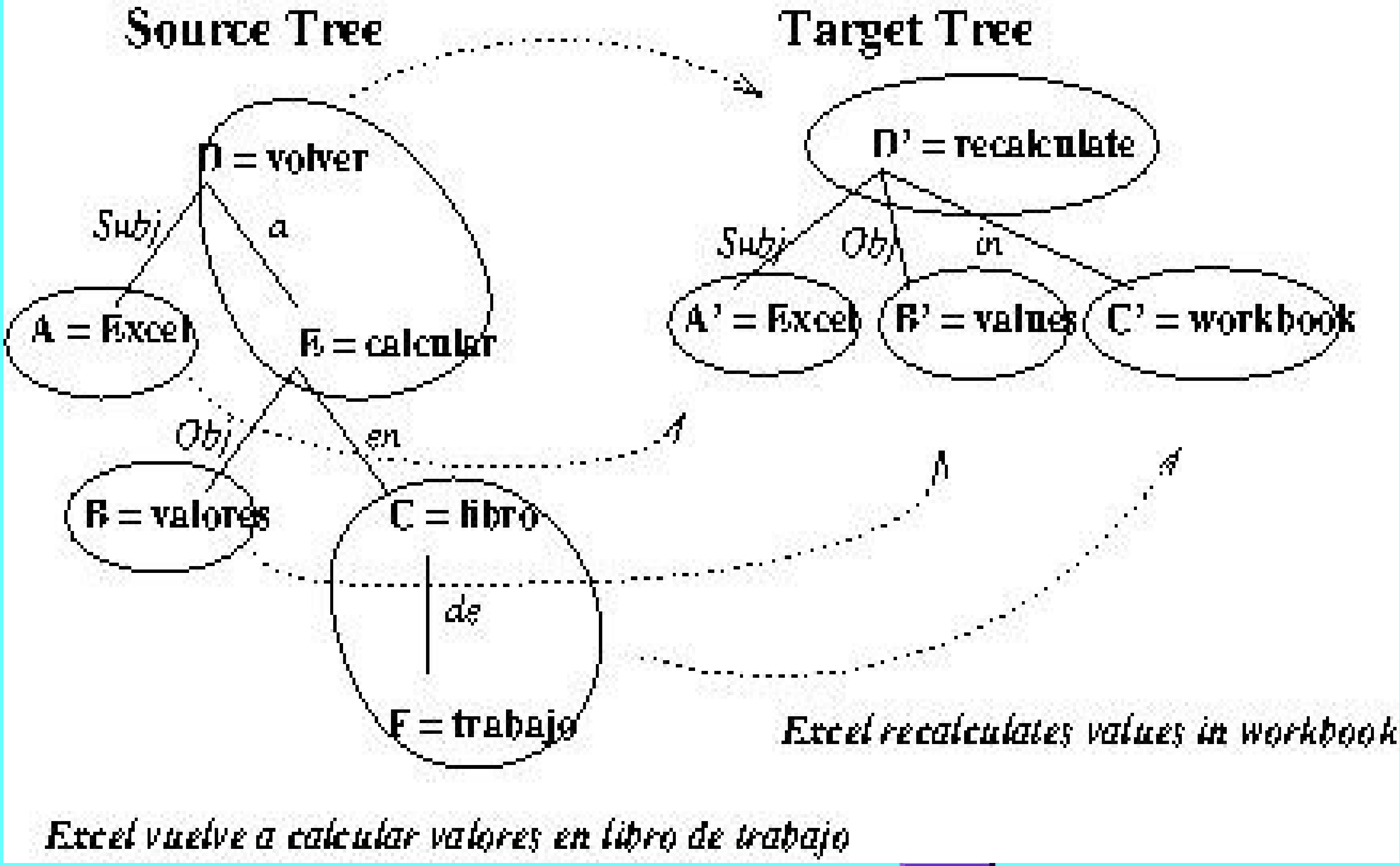
- **Given** alignment **A** including source nodes S_1 and S_2 and target nodes T_1 and T_2
- **If** Dominates(S_1,S_2), **then** Dominates(T_1,T_2)



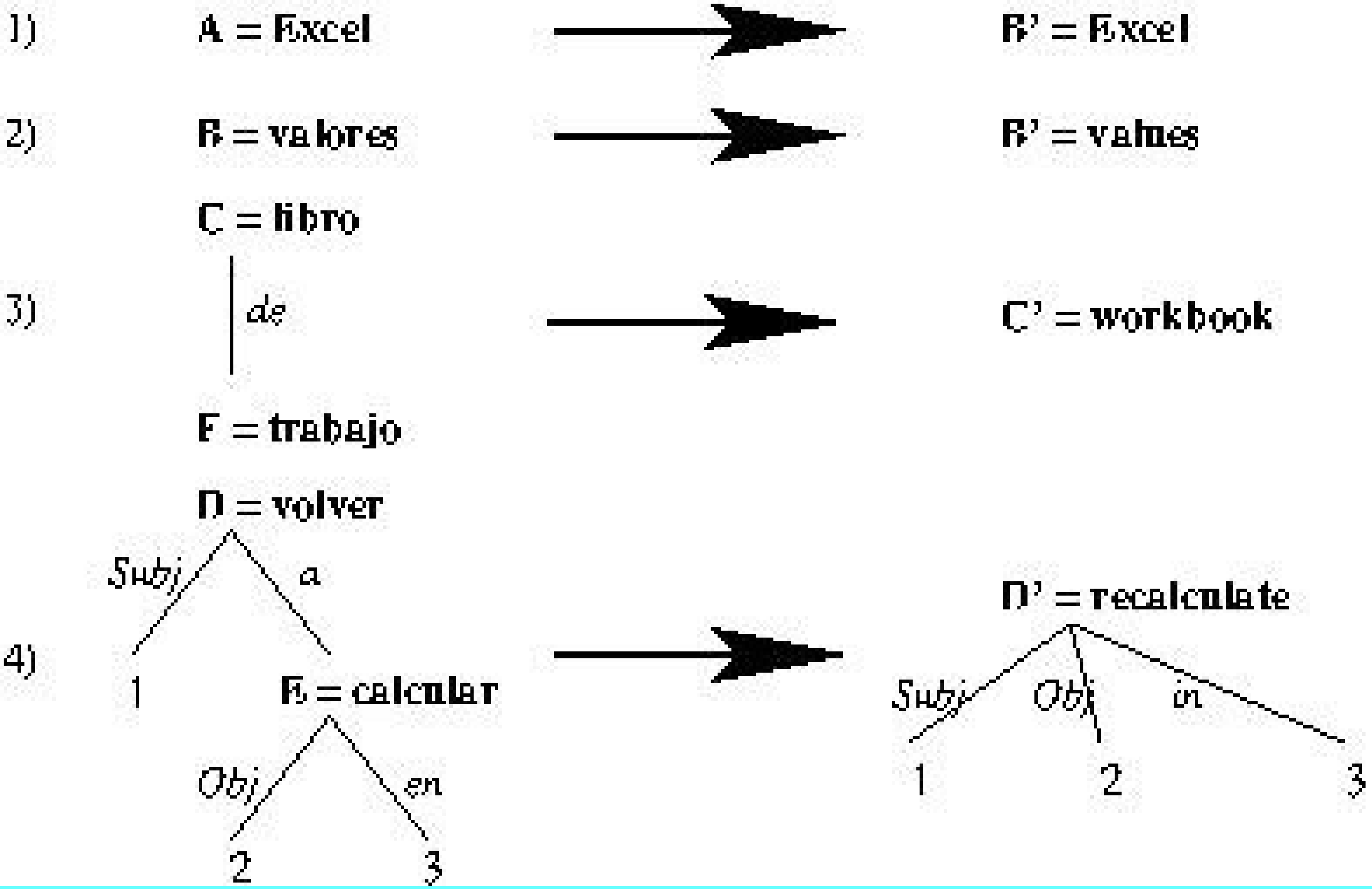
Dominance-Preserving Alignment Algorithm

- Assume that Source and Target Roots are aligned
- Compute the score of the source/target pair using the following recursive routine
- Score(X,Y) = lexical score(X,Y) + highest scoring pairing of the children of X and the children of Y.
  - Lexical scores require a bilingual dictionary, which can be supplemented by automatic procedures to acquire missing (previously unaligned pairs)
- Also allow X to be aligned with one of the children of Y or Y to be aligned with one of the children of X
  - Without this step, the algorithm would be restricted to a least common ancestor preserving alignments, a subset of dominance-preserving alignments

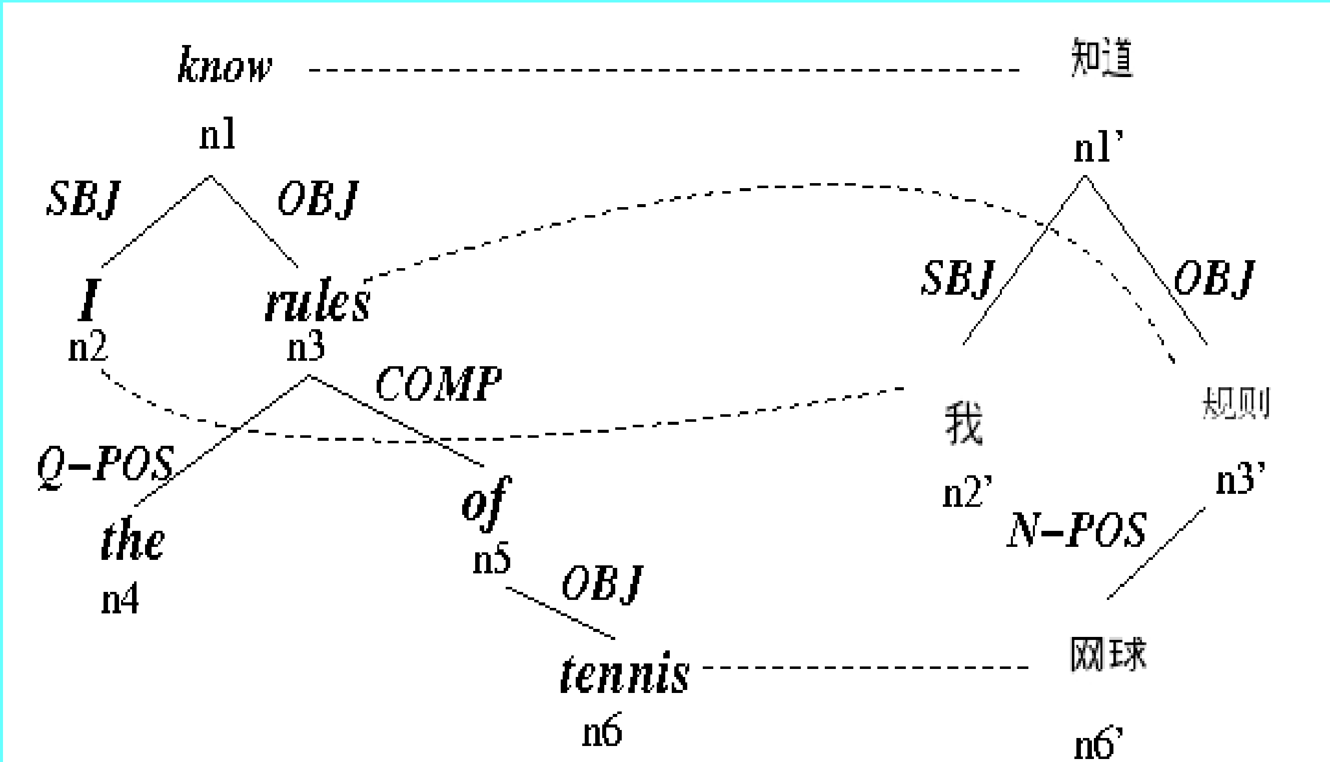
Tree to Tree Alignment



Transfer Rules Derived From Alignment



A simple reordering based on Logic1 node alignment



I know the rules of tennis ↔ 我 知道 网球 规则

English in Chinese order: ***I know the (of) tennis rules***

NYU Systems Using Dependency Graph Alignment

- Why: There are some cases (long distance dependencies) where linguistically motivated analysis should help MT
- 1996-2000
  - Toy systems for Spanish/English and Japanese/English
  - Using 2 stage parsers with manual rules
- 2010
  - Use GLARF on output of state of the art treebank parsers
  - Reordering English sentences to be like Chinese
  - Then run standard word alignment program (Giza++)
  - Achieved 1.5% improvement in Word Alignment
    - Most of the benefit from reordering large noun modifiers
  - Incremental step in larger goal:
    - use reordered English with state-of-the-art MT systems

Dominance-Preserving Constraint is too strong

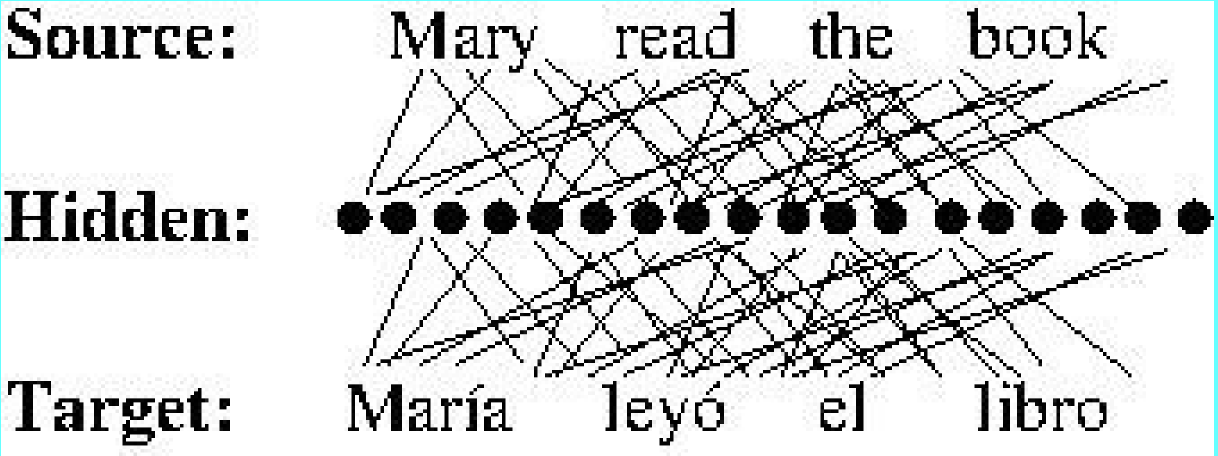
- Weaker than synchronous grammar
- There are real cases for violations 1 and 2
- Violation 1 does not handle unclear modifier attachment
  - ***Mary sent out a letter*** [***to John***]
    - [***sent out*** [***a letter to John***]]
    - [***sent out*** [***a letter***] **[*to John*]**]
- Violation 2 ignores so-called head-switching phenomena
  - ***Er tanzt gerne*** [German]
  - ***He dances with-pleasure*** [English gloss]
  - ***He likes to dance.*** [English translation]
- Both violations are often found in parsing errors
- Common violation 2 instances for Chinese/English
  - Quantifier/transparent noun, e.g.,  → ***series of***

MT using Deep Learning

- Relatively new and very popular
- NYU's Prof. Kyunghyun Cho is one of the leading researchers in this area:
- https://devblogs.nvidia.com/parallelforall/introduction-neural-machine-translation-with-gpus/
- Brief introduction in the next few slides

Source to Hidden to Target

- Lines represent functions from source to hidden layer, and from hidden layer and target
- Hidden Vector contains parameters for functions



- The parameters are initialized randomly and modified incrementally by training the system on parallel text

Hidden Layer is Like an Inter-Lingua

- Hidden layer of fixed number of nodes assumed between source and target words.
- Lots of connections are assumed between source and hidden layer and between hidden layer and target.
- Training the system results in:
  - Encoder translating source sentence to hidden layer
  - Decoder translating hidden layer to target sentence
- Some systems attempt to use the same hidden layer for multiple language pairs (in theory, like an inter-lingua)
  - https://arxiv.org/pdf/1601.01073.pdf
  - This is interesting, but speculative

Deep Learning MT (Last Slide)

- Decoder translates incrementally using N source words (e.g., N=4) to predict the next target words in the translation
- Results comparable to phrase based MT.
- Advantages cited include:
  - Not necessary to manually design feature sets
  - Somewhat better quality

Human Evaluation of MT

- Human Evaluation: Effective & Expensive
- Method 1: Rate translations on several dimensions:
  - fluency – how intelligible is output
    - Includes clarity and naturalness
  - Fidelity – does translation contain all and only information from source
    - Includes adequacy, informativeness
- Method 2: How much editing is required to render the machine output into a good translation?
  - Track this in dollars, time or numbers of key strokes

Automatic Evaluation

- Automatic Methods: inexpensive, predominant, imperfect
  - At minimum, an evaluation metric shows improvement:
    - If a system improves, the score improves
    - If a system degrades, the score degrades
  - Output is rated on its "closeness" to the human translations
- Bleu: proposed statistical definition of "closeness to human translation"
  - Many benchmarks are Bleu scores for particular test sets
  - Multiple human translations are provided for test set
  - Precision of n-grams in system output found in reference translations
    - N-gram is correct if in any of the references
  - Penalizes shorter output
  - Criticized for favoring statistical systems over manual (Systran) despite human evaluations to the contrary

MEANT: Automatic Evaluation Based on Semantic Role Labeling

- Chi-kiu Lo, Anand Karthik Tumuluru and Dekai Wu. "Fully Automatic Semantic MT Evaluation". 7th Workshop on Statistical Machine Translation (at NAACL 2012). Montreal: Jun 2012.
    - http://www.cs.ust.hk/~dekai/library/WU_Dekai/LoTumuluruWu_Wmt2012.pdf
- Steps
    - Step 1: Run SRL system for Answer Key and System Output and represent each as a graph
    - Step 2: Align graphs
    - Step 3: Measure similarity between graphs (based on F-score)
- These authors show a higher correlation with manual evaluation using this metric than other automatic metrics
- Previous papers by Wu's group describe evaluation incorporating manual input
- Subsequent papers describe improvements to the system

Summary

- The best statistical systems currently use the phrase-based and neural network approaches
  - These are arguably the best systems overall
- Systran is a (proprietary) competitive system that is probably uses a combination of approaches including many manual rules and dictionaries
  - May be competitive with statistical approaches (unclear because the most commonly used score is arguably biased)
- There is research in alternatives using more linguistically motivated analysis
  - Sometimes in conjunction with statistical systems

Additional Information

- There has been some research on translating poetry, e.g., by Google:
  - http://research.google.com/pubs/archive/36745.pdf
- Interlingua and Pivot systems are sometimes used for resource-poor languages (other methods not possible for practical reasons)
  - http://www.mt-archive.info/EMNLP-2009-Nakov.pdf

Readings

- Required: J & M Chapter 25
- Various Optional Readings mentioned throughout slides