Improved Word Alignments for Statistical Machine Translation

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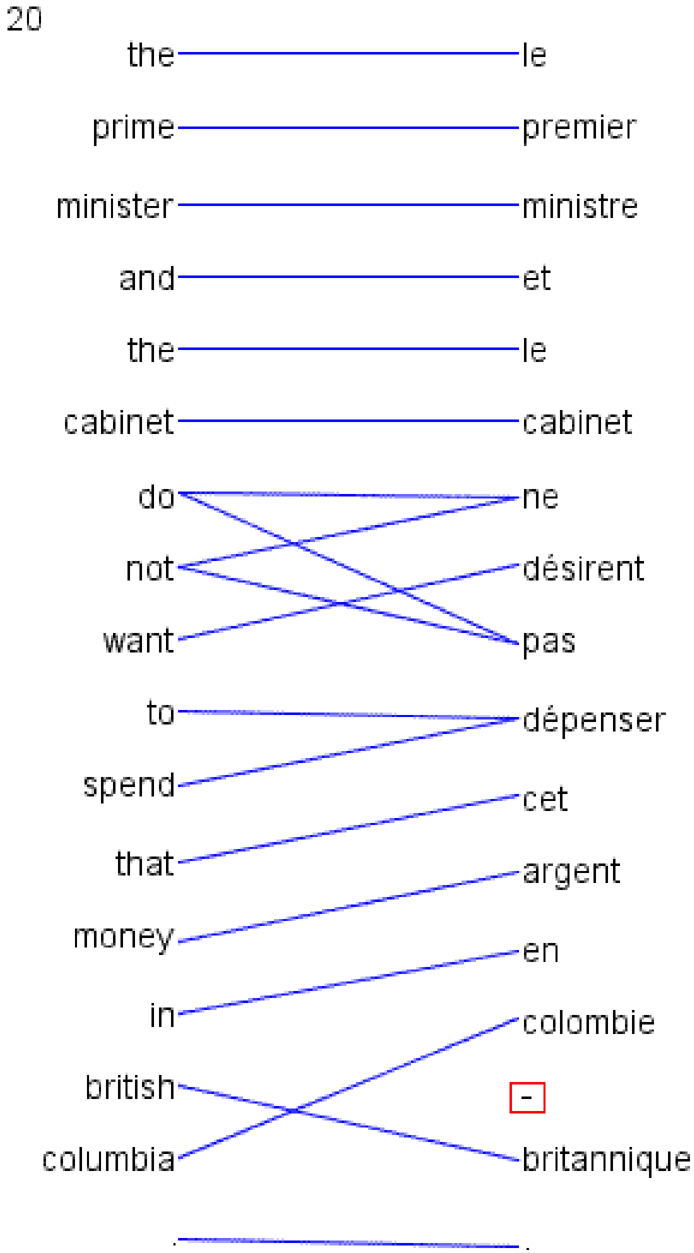
Statistical Machine Translation (SMT)

- Build a model P(e | f), the probability of the English sentence "e" given the French sentence "f"
- To translate a French sentence "f", choose the English sentence "e" which maximizes P(e | f)

$$\operatorname*{argmax}_{e} P(e \mid f) = \operatorname*{argmax}_{e} P(f \mid e)\, P(e)$$

- P(f | e) is the "translation model"
  - Collect statistics from word aligned parallel corpora
- P(e) is the "language model"



Annotation of Minimal Translational Correspondences

- Word alignment is annotation of minimal translational correspondences
- Annotated in the context in which they occur
- Not idealized translations!

(solid blue lines annotated by a bilingual expert)

Overview

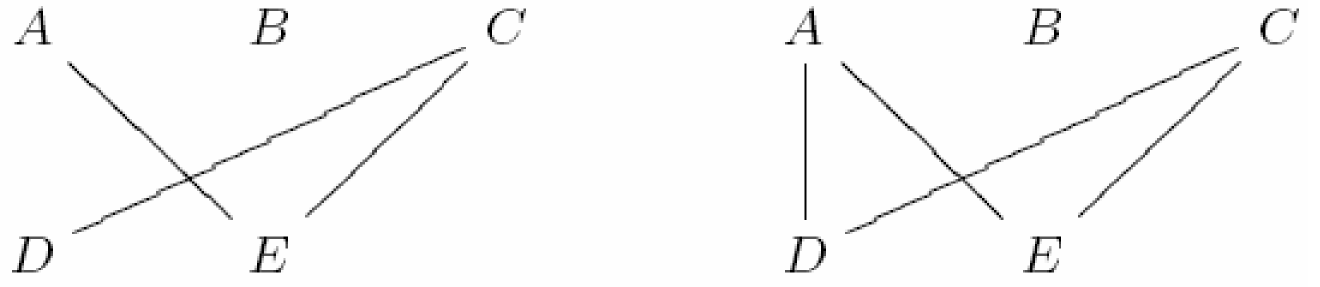
- Solving problems with previous word alignment methodologies
  - Problem 1: Measuring quality
  - Problem 2: Modeling
  - Problem 3: Utilizing new knowledge
  - Joint Work with Daniel Marcu, USC/ISI

Problem 1: Existing Metrics Do Not Track Translation Quality

- Dozens of papers report word alignment quality increases according to intrinsic metrics
- Contradiction: few of these report MT results; those that do report inconclusive gains
- This is because the two commonly used intrinsic metrics, AER and balanced F-Measure, do not correlate with MT performance!

Measuring Precision and Recall

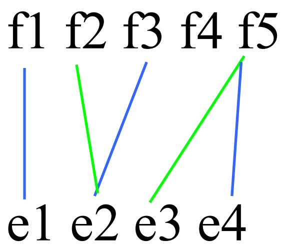
- Start by fully linking hypothesized alignments



- Precision is the number of links in our hypothesis that are correct
  - If we hypothesize there are no links, have 100% precision
- Recall is the number of correct links we hypothesized
  - If we hypothesize all possible links, have 100% recall
- We will test metrics which formally define and combine these in different ways

Alignment Error Rate (AER)

Gold



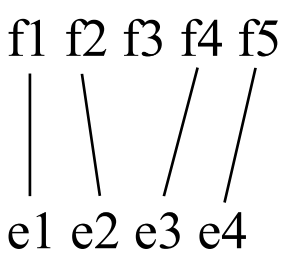
$$\text{Precision}(A,P) = \frac{|P \cap A|}{|A|} = \frac{3}{4}$$

(e3,f4) wrong

$$\text{Recall}(A,S) = \frac{|S \cap A|}{|S|} = \frac{2}{3}$$

(e2,f3) not in hyp

Hypothesis



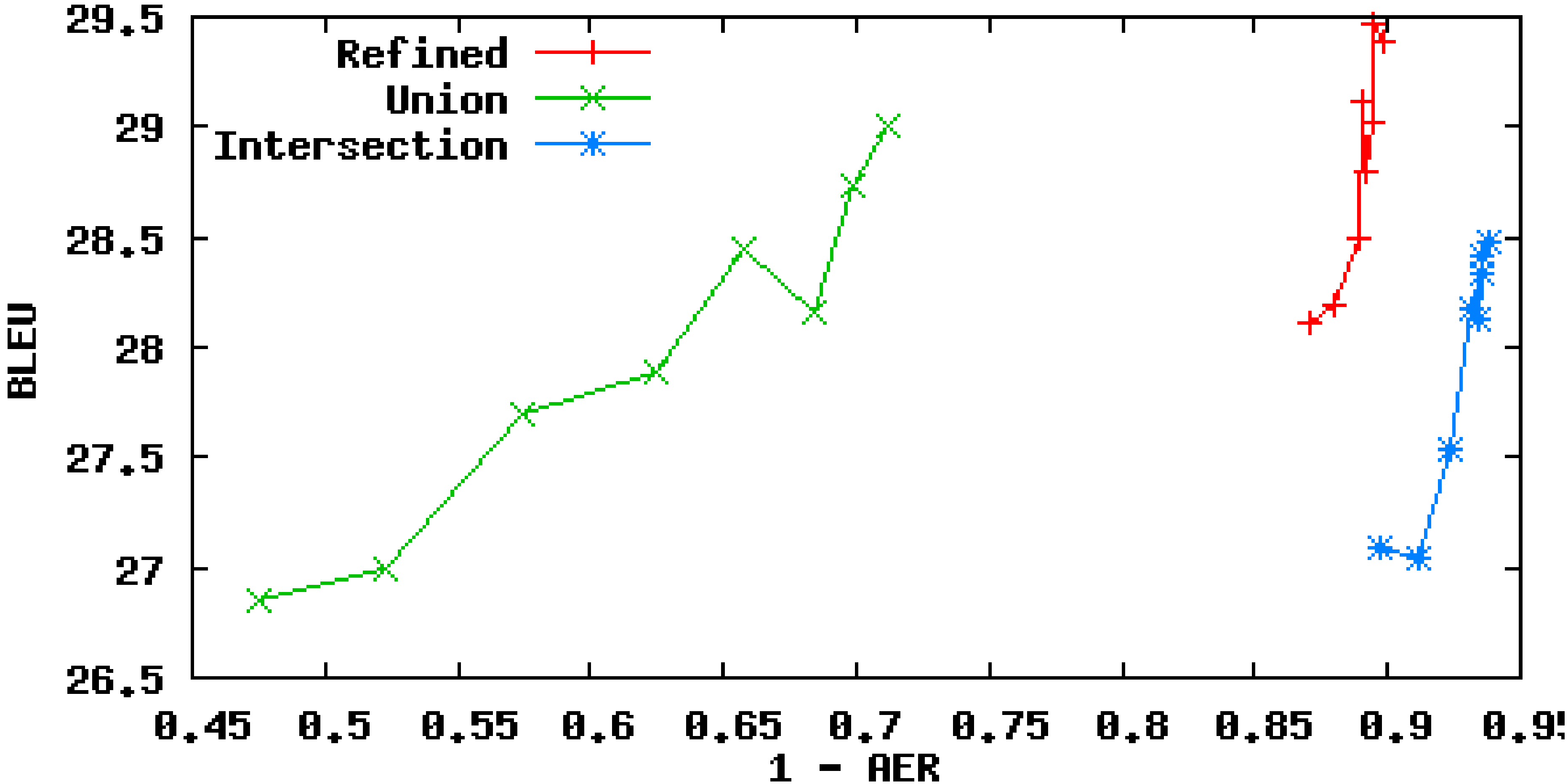
$$\text{AER}(A,P,S) = 1 - \frac{|P \cap A| + |S \cap A|}{|S| + |A|} = \frac{2}{7}$$

BLUE = sure links GREEN = possible links

Experiment

- Desideratum:
  - Keep everything constant in a set of SMT systems except the word-level alignments
    - Alignments should be realistic
- Experiment:
  - Take a parallel corpus of 8M words of Foreign-English. Word-align it. Build SMT system. Report AER and Bleu.
  - For better alignments: train on 16M, 32M, 64M words (but use only the 8M words for MT building).
  - For worse alignments: train on 2×1/2, 4 × 1/4, 8 × 1/8 of the 8M word training corpus.
- If AER is a good indicator of MT performance, 1 – AER and BLEU should correlate no matter how the alignments are built (union, intersection, refined)
  - Low 1 – AER scores should correspond to low BLEU scores
  - High 1 – AER scores should correspond to high BLEU scores

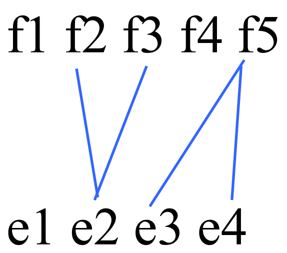
AER is not a good indicator of MT performance



$r^2 = 0.16$

F_α-score

Gold



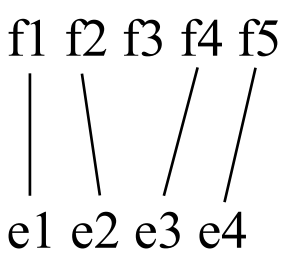
$$\text{Precision}(A,S) = \frac{|S \cap A|}{|A|} = \frac{3}{4}$$

(e3,f4) wrong

$$\text{Recall}(A,S) = \frac{|S \cap A|}{|S|} = \frac{3}{5}$$

(e2,f3)
(e3,f5)
not in hyp

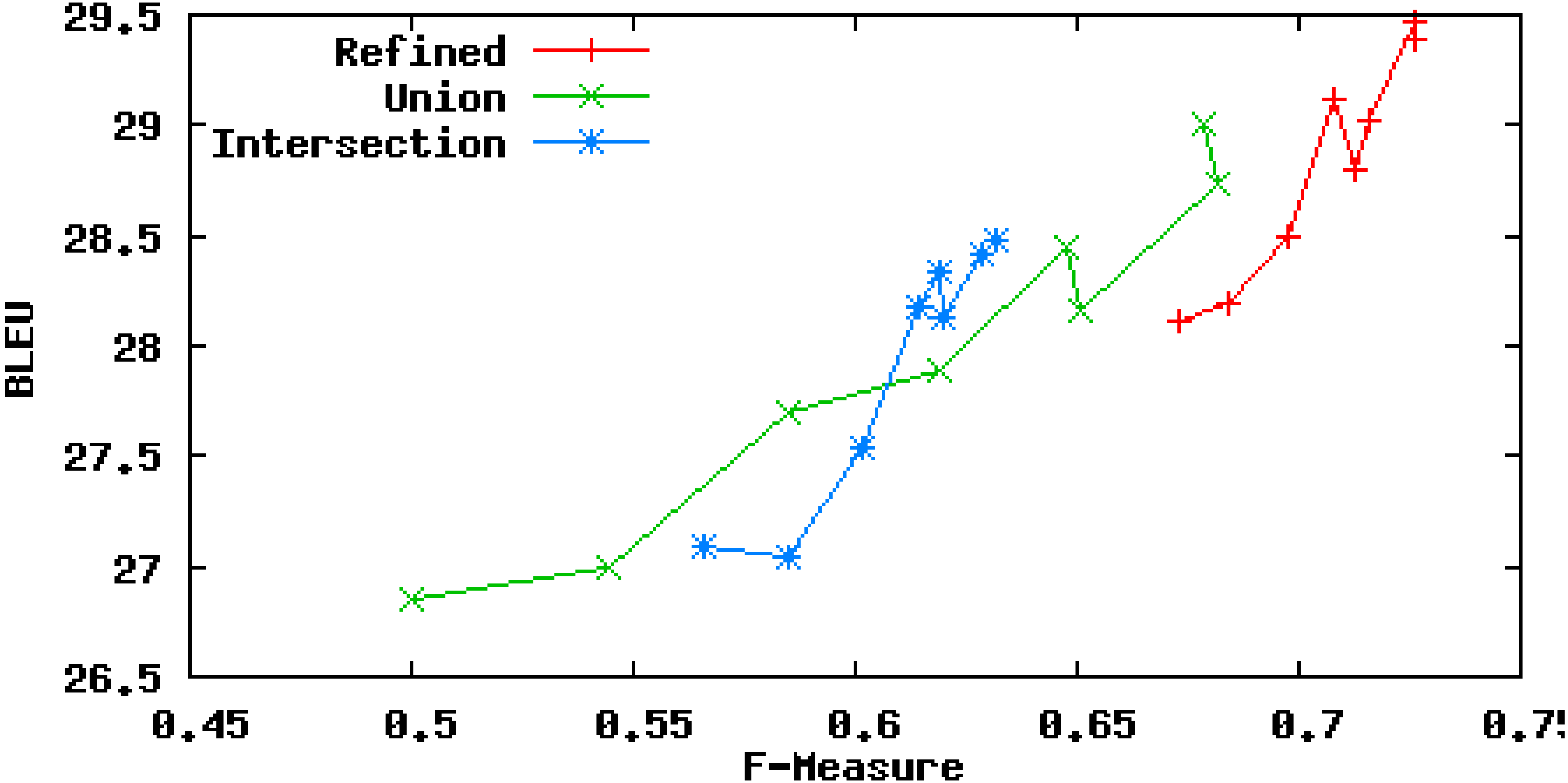
Hypothesis



$$F(A,S,\alpha) = \frac{1}{\dfrac{\alpha}{\text{Precision}(A,S)} + \dfrac{1-\alpha}{\text{Recall}(A,S)}}$$

Called F_α-score to differentiate from ambiguous term F-Measure

F_α-score is a good indicator of MT performance

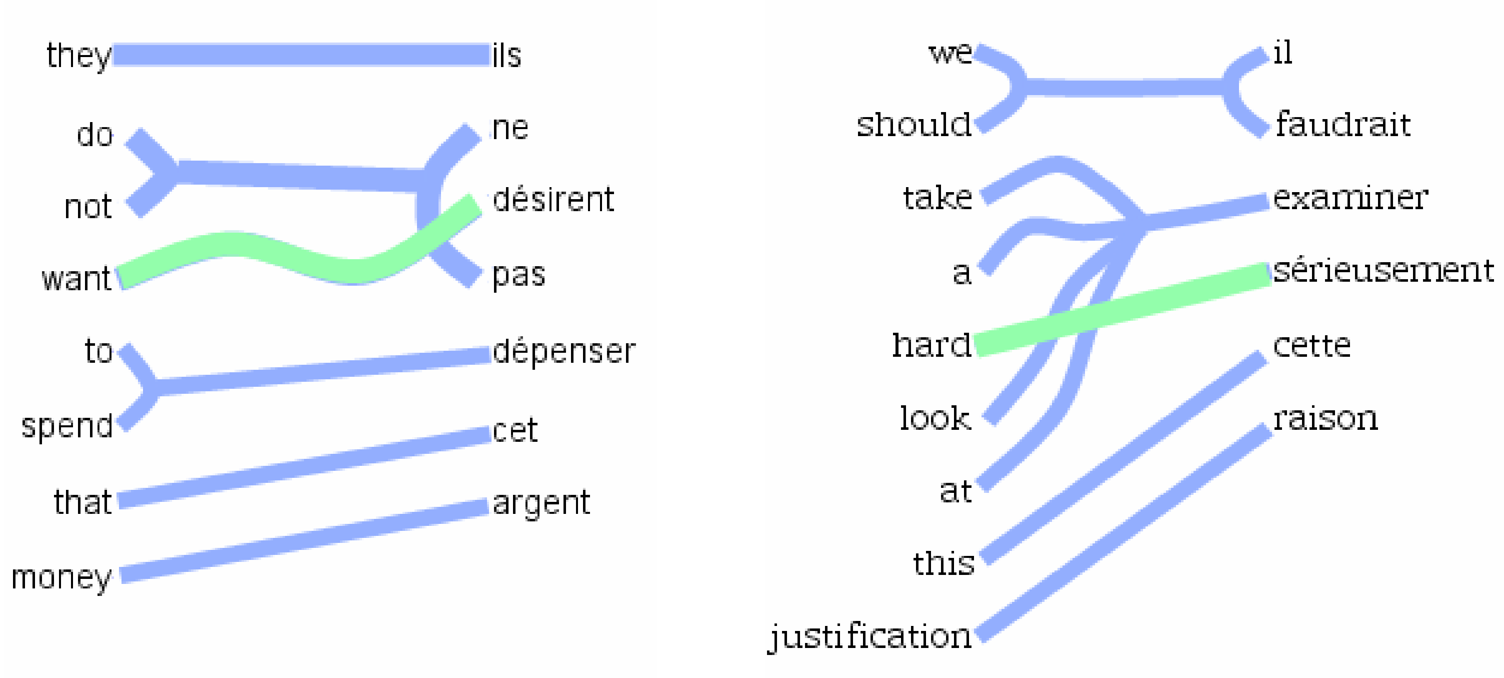


$r^2 = 0.85$ $\alpha = 0.4$

Discussion

- Using F_α-score as a loss criterion will allow for development of discriminative models (later in talk)
- AER is not derived correctly from F-Measure
- For details of experiments see squib in Sept. 2007 Computational Linguistics

Problem 2: Modeling the Wrong Structure



- 1-to-N assumption
  - Multi-word “cepts” (words in one language translated as a unit) only allowed on target side. Source side limited to single word “cepts”.
- Phrase-based assumption
  - “cepts” must be consecutive words

LEAF Generative Story

source	absolutely	[comma]	they	do	not	want	to	spend	that	money	
word type (1)	DEL.	DEL.	HEAD	non-head	HEAD	HEAD	non-head	HEAD	HEAD	HEAD	
linked from (2)			THEY	do	NOT	WANT	to	SPEND	THAT	MONEY	
head(3)			ILS		PAS	DESIRENT		DEPENSER	CET	ARGENT	
cept size(4)			1		2	1		1	1	1	
num spurious(5)	1										
spurious(6)	aujourd'hui										
non-head(7)			ILS	PAS	ne	DESIRENT		DEPENSER	CET	ARGENT	
placement(8)	aujourd'hui		ILS	ne	DESIRENT	PAS		DEPENSER	CET	ARGENT	
spur. placement(9)			ILS	ne	DESIRENT	PAS		DEPENSER	CET	ARGENT	aujourd'hui

- Explicitly model three word types:
  - **Head word**: provide most of conditioning for translation
    - Robust representation of multi-word cepts (for this task)
    - This is to semantics as ``syntactic head word'' is to syntax
  - **Non-head word**: attached to a head word
  - **Deleted source words** and **spurious target words** (NULL aligned)

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- Once source cepts are determined, exactly one target head word is generated from each source head word
- Subsequent generation steps are then conditioned on a single target and/or source head word
- See EMNLP 2007 paper for details

LEAF

- Can score the same structure in both directions
- Math in one direction (please do not try to read):

$$
\begin{aligned}
p(f, a|e) = & [\prod_{i=1}^{l} g(\chi_i|e_i)] \\
& [\prod_{i=1}^{l} \delta(\chi_i, -1) w_{-1}(\mu_i - i|\text{class}_e(e_i))] \\
& [\prod_{i=1}^{l} \delta(\chi_i, 1) t_1(\tau_{i1}|e_i)][\prod_{i=1}^{l} \delta(\chi_i, 1) s(\psi_i|e_i, \gamma_i)] \\
& [s_0(\psi_0|\sum_{i=1}^{l} \psi_i)][\prod_{k=1}^{\psi_0} t_0(\tau_{0k})] \\
& [\prod_{i=1}^{l} \prod_{k=2}^{\psi_i} t_{>1}(\tau_{ik}|e_i, \text{class}_h(\tau_{i1}))] \\
& [\prod_{i=1}^{l} \prod_{k=1}^{\psi_i} D_{ik}(\pi_{ik})]
\end{aligned}
$$

Discussion

- LEAF is a powerful model
- But, exact inference is intractable
  - We use hillclimbing search from an initial alignment
- First model of correct structure: M-to-N discontiguous
  - Head word assumption allows use of multi-word cepts
    - Decisions robustly decompose over words
    - Does not have segmentation problem of phrase alignment models: Probability of alignments of cept "the man" are closely related to probabilities for cept "man"
  - Not limited to only using 1-best prediction

Problem 3: Existing Approaches Can't Utilize New Knowledge

- It is difficult to add new knowledge sources to generative models
  - Requires completely reengineering the generative story for each new source
- Existing unsupervised alignment techniques can not use manually annotated data

Background

- We love EM, but
  - EM often takes us to places we never imagined/wanted to go
- Bayes is always right

$$\underset{e}{\text{argmax}}\ P(e \mid f) = \underset{e}{\text{argmax}}\ P(e) \times P(f \mid e)$$

But in practice, this works better:

$$\underset{e}{\text{argmax}}\ P(e)^{2.4} \times P(f \mid e) \times \text{length}(e)^{1.1} \times KS^{3.7} \ldots$$

Decomposing LEAF

- Decompose each step of the LEAF generative story into a sub-model of a log-linear model
  - Add backed off forms of LEAF sub-models
  - Add heuristic sub-models (do not need to be related to generative story!)
  - Allows tuning of vector λ which has a scalar for each sub-model controlling its contribution

Reinterpreting LEAF

- $g(e_i)$ – source word type sub-model
- $w(\mu_i)$ – source non-head linking sub-model
- $t_1(f_j \mid y(i))$ – head word translation sub-model

- Etc… – many more sub-models

$$p(a, f \mid e) = g \times w \times t_1 \times \text{etc}\ldots$$

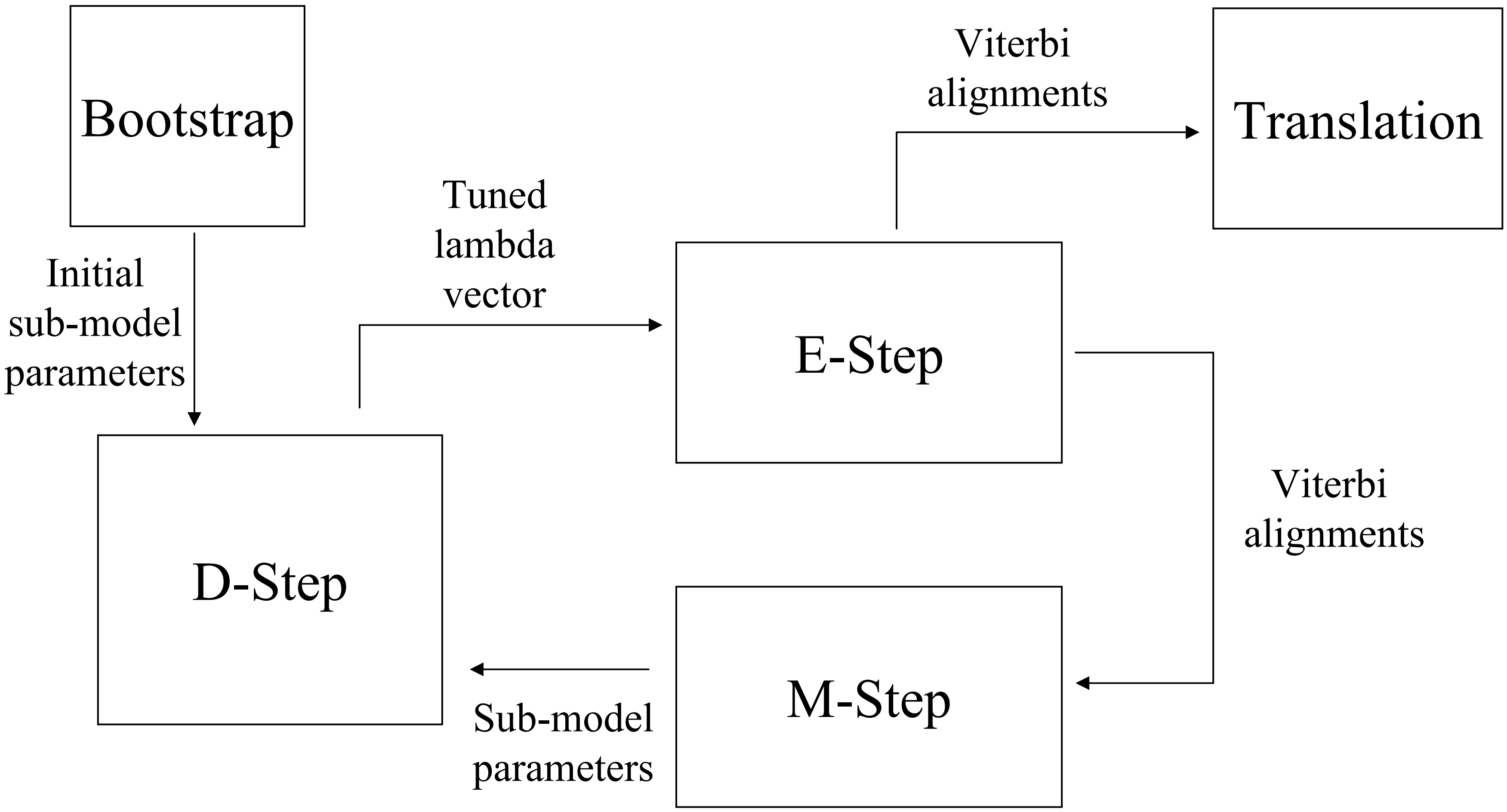
$$p(a, f \mid e) = z^{-1} \times g^{\lambda 1} \times w^{\lambda 2} \times t_1^{\lambda 3} \times \text{etc}\ldots$$

$$p(a, f \mid e) = \frac{\exp \sum_m \lambda_m h_m(f, a, e; \theta_m)}{\exp(Z)}$$

Semi-Supervised Training

- Define a semi-supervised algorithm which alternates increasing likelihood with decreasing error
  - Increasing likelihood is similar to EM
  - Discriminatively bias EM to converge to a local maxima of likelihood which corresponds to "better" alignments
    - "Better" = higher F_{α}-score on small gold standard corpus

The EMD Algorithm



Discussion

- Usual formulation of semi-supervised learning: “using unlabeled data to help supervised learning”
  - Build initial supervised system using labeled data, predict on unlabeled data, then iterate
  - But we do not have enough gold standard word alignments to estimate parameters directly!
- EMD allows us to train a small number of important parameters discriminatively, the rest using likelihood maximization, and allows interaction
  - Similar in spirit (but not details) to semi-supervised clustering

Experiments

- French/English
  - LDC Hansard (67 M English words)
  - MT: Alignment Templates, phrase-based
- Arabic/English
  - NIST 2006 task (168 M English words)
  - MT: Hiero, hierarchical phrases

Results

	French/English		Arabic/English	
System	F-Measure ($\alpha = 0.4$)	BLEU (1 ref)	F-Measure ($\alpha = 0.1$)	BLEU (4 refs)
IBM Model 4 (GIZA++) and heuristics	73.5	30.63	75.8	51.55
EMD (ACL 2006 model) and heuristics	74.1	31.40	79.1	52.89
LEAF+EMD	76.3	31.86	84.5	54.34

Contributions

- Found a metric for measuring alignment quality which correlates with MT quality
- Designed LEAF, the first generative model of M-to-N discontiguous alignments
- Developed a semi-supervised training algorithm, the EMD algorithm
- Obtained large gains of 1.2 BLEU and 2.8 BLEU points for French/English and Arabic/English tasks

Thank You!