Discriminative word alignment by learning the alignment structure and syntactic divergence between a language pair

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Outline

- Word Alignment - English-Hindi Language Pair
- Related approaches
- Discriminative Re-ranking approach
  - Features
  - Parameter optimization using MIRA
  - Results
- Future Work and Conclusion

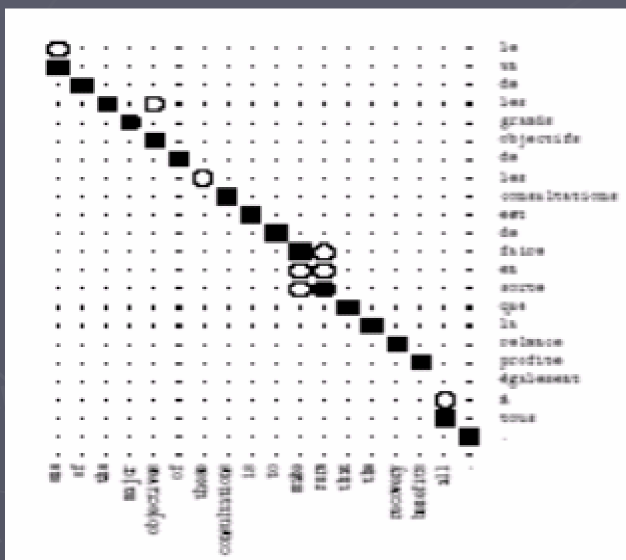
Word-Alignment

- People of these islands have adopted Hindi as a means of communication .

- इन द्वीपों के लोगों ने हिंदी भाषा को एक संपर्क भाषा के रूप में अपना लिया है .
- These islands of people hindi language a commu. language in form of adopted-take-be

- Primary Observation:
  - The alignment between English-Hindi is largely non-monotonic, unlike the alignment between English-French.

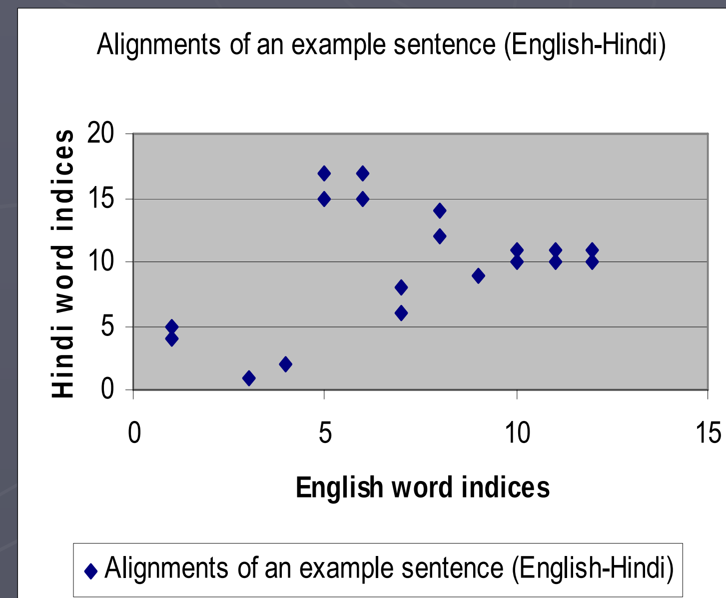
Comparison



French

English

Hindi



English

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Related approaches

- Generative models
  - IBM Models, HMM models (Implemented in Giza++)
- Discriminative models
  - (Taskar et al., 2005)
  - (Moore et al., 2005)

Generative models - Limitations

- Difficult to add new Parameters.
  - The generative story needs to be modified appropriately to incorporate the new parameters.
- Parameters are not optimized.
  - All the parameters used have equal weights. For example, translation probabilities have the same importance as distortion probabilities.
  - As more complex features are added to the model, the parameters need to be optimized appropriately.

(Taskar et al., 2005) - Limitations

- The alignment search and optimization requires that the features are local to the alignment link.
- There is 0^{th} order correlation with other alignments links in an alignment.
- (Lacoste-Simon et al., 2006) include first-order features (similar to HMM Parameter) and fertility but still there isn't much room for more complex global features required for aligning diverse language pairs such as English-Hindi.

(Moore et al., 2006) - Limitations

- Structural features are applied on partial structures (ie.., every time a new alignment link is considered)
  - May lead to ruling out good alignments at an early stage.
  - Restricts us from using more complex syntactic features.
    (As it is a left to right search).

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Discriminative Re-ranking Approach

- The best alignment $\hat{a}$ = argmax score(a | e, h)

- Here, **e** is the english and **h** is the hindi sentence.

- $score(a \mid e, h) = score_{La}(a \mid e, h) + score_{S}(a \mid e, h)$

Alignment search (Discriminative Re-ranking)

- Three main steps
  - Populate the Beam
    - Use local features to determine K-best alignments of source words with words in the target sentence.
  - Re-order the Beam
    - Re-order the above alignments using structural features.
  - Post-processing
    - Extend alignments to include other links that can be inferred using simple rules.

Alignment search (Discriminative Re-ranking)

Populate the Beam

- Obtain K-best candidate alignments using local scores .
- Local score is computed by looking at the features of the individual alignment links independently.
- $score_L(e_j, h_k) = W. f_L(e_j, h_k)$
- $score_{La}(a \mid e, h) = \sum score_L(e_j, h_k)$

Populate the Beam - 2

- Task: Populate the beam in the decreasing order of $score_{La}(a \mid e, h)$.
- Compute the local score of each source word with every target word (including NULL).
- Top-k alignment links of each source word are chosen.

Populate the Beam - 2

- Populating K-best alignments
  - Implemented using Priority Queues.
- Initial State of Priority Queue
  - One entry representing the best alignment (set of best alignment links).
- At every iteration
  - Pop the best entry from the PQ.
  - Add it's k successor entries back into the PQ.

Re-order the Beam

- Structural scores are now added to the local scores of the alignments in the beam in order to re-order the beam.
  - $score_S(a) = W \cdot f_S(a)$
- Overall score $= score_{La}(a) + score_S(a)$
- Structural features look at properties of the entire alignment structure instead of individual alignment links.

Post-processing

- Previous two steps produce alignments which contain one-to-one and many-to-one mappings.

- Goal is to include the best alignment structure from previous step to include other alignment links of one-to-many/many-to-many types.

- New alignment links are added while processing source words in the breadth first order of the **dependency structure**.

Post-processing

- Algorithm:
- Let w be next word considered. pw = parent (w).
  - If w , pw linked to one or more common words.
    Align w to all words already aligned with pw.
  - Else, Use simple target-specific rules to extend alignments of w.
- Recursively consider all the children of w

Post-processing

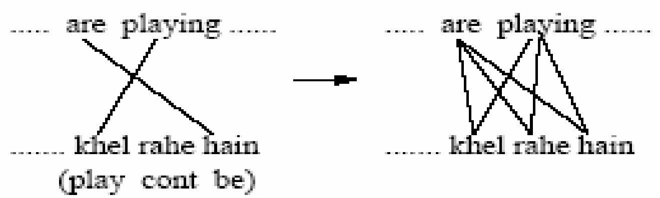

Figure 1: Inferring the many-to-many alignments of verb and auxiliaries

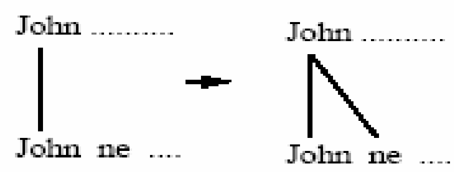

Figure 2: Inferring the one-to-many alignment to case-markers in Hindi

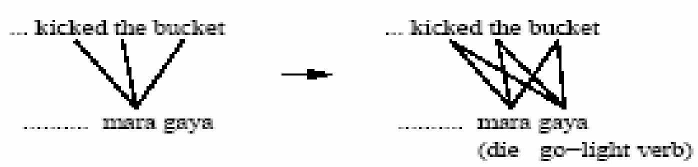

Figure 3: Inferring many-to-many alignment for source idioms

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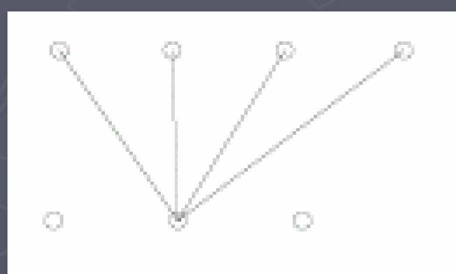
Features - Local

- DiceWords (Taskar et al., 2005)
- DiceRoots : Lemmatized forms of e_j and h_k .
- Dict : Whether there exists an entry from source word e_j to target word h_k.
- Null(POS) : Binary feature which is active when a source word with a particular part-of-speech tag is aligned with NULL.

Structural Features

- Overlap
  - This feature considers the instances in a sentence pair where a source word links to a target word which is a participant in more than one alignment link.



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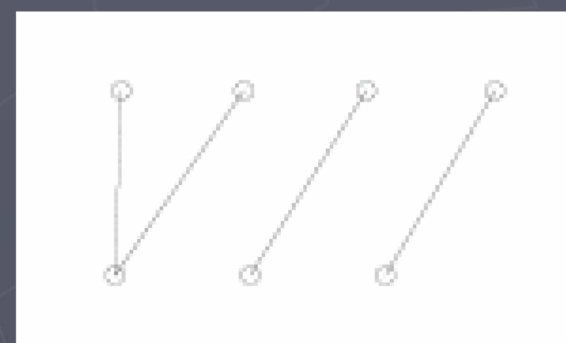


$$Overlap(\bar{a}) = \frac{\sum_{h_q \in T, Fert(h_q)>1} Fert^2(h_q)}{\sum_{h \in T} Fert(h)}$$

Structural Features

- Null Percent

  - This feature measures the percentage of words in target sentence with zero fertility.

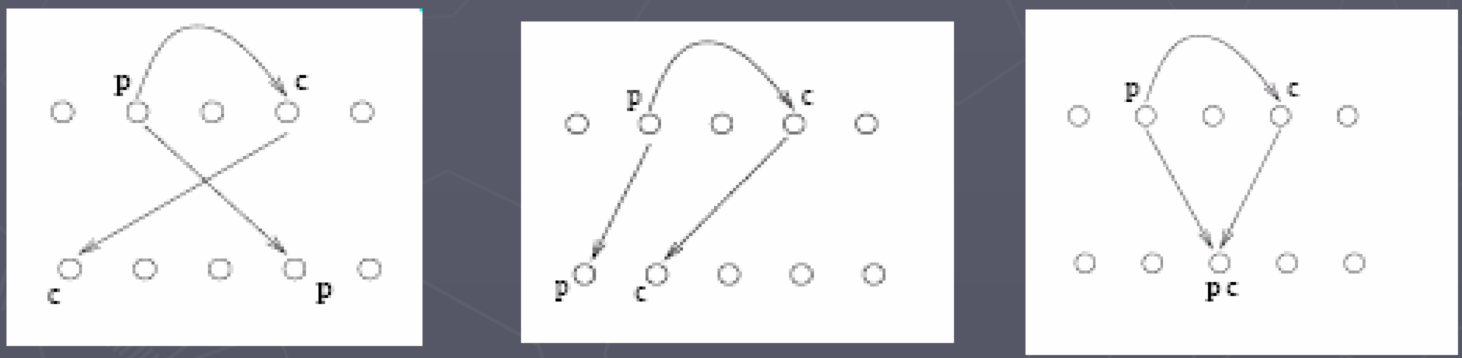
$$NullPercent = \frac{|h_q|_{h_q \in T, Fertility(h_q)==0}}{|h|_{h \in T}}$$

Structural Features

- Direction of Dependency Pair
  - Captures first order interdependence between the alignments links connected to two sources connected by a dependency relation.
  - One way to measure such interdependence is by noting the order of target sentence words the child and the parent of a source sentence dependency relation.
  - Three possible orders (next slide).

Structural Features

- Direction of Dependency Pair



- The feature thus captures a simple divergence between the source and target dependency structures.

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Online large margin Training using MIRA

- For parameter optimization, we used online-large margin algorithm called MIRA (Crammer and Singer, 2005; McDonald et al., 2005).

- If $T = \{ (x_i, y_i) \}^m$ be gold data, where x_i is the i^{th} sentence pair, y_i is the corresponding gold alignment. The task is to learn the weight vector W such that,

Online large margin Training using MIRA

- For a sentence pair, the weight should be optimized in the following fashion.

Minimize $|| w_{i+1} - w_i ||$

Such that

w. f(xi, yi) - w. f(xi, y'i) >= loss (yi, y'i)

For all, (xi,yi) E T , y'i E K-best Predictions (xi)

- Online training algorithm.

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Data

- Unsupervised data: 50,000 sentence pairs

- Supervised data
  - Training : 4252 sentence pairs
  - Testing : 100 sentence pairs

GIZA++ results

Mode	*Prec.*	*Rec.*	*F-meas.*	*AER*
Normal: Eng-Hin	47.57	40.87	43.96	**56.04**
Normal: Hin-Eng	47.97	38.50	42.72	57.28
Normal: Inter.	88.71	27.52	42.01	57.99
Lemma.: Eng-Hin	53.60	44.58	48.67	**51.33**
Lemma.: Hin-Eng	53.83	42.68	47.61	52.39
Lemma.: Inter.	86.14	32.80	47.51	52.49

Table 3: Giza++ Results

Results using local features

Features	Precision	Recall	F-measure	AER
Dicewords + Diceroots	41.49	38.71	40.05	59.95
+ Null_POS	42.82	38.29	40.43	59.57
+ Dict	43.94	39.30	41.49	58.51
+ Word pairs	46.27	41.07	43.52	56.48

Results after adding Global features

Features	Precision	Recall	F-measure	AER
Local feats.	46.27	41.07	43.52	56.48
Local feats. + Overlap	48.17	42.76	45.30	54.70
Local feats + Direct_Deppair	47.93	42.55	45.08	54.92
Local feats + All struct. feats	48.81	43.31	45.90	54.10

Adding structural features to Giza transition probabilities

Features	Precision	Recall	F-measure	AER
IBM Model-4 Pars. + Local feats.	48.85	43.98	46.29	52.71
Local feats. + All struct. feats	48.95	50.06	49.50	50.50

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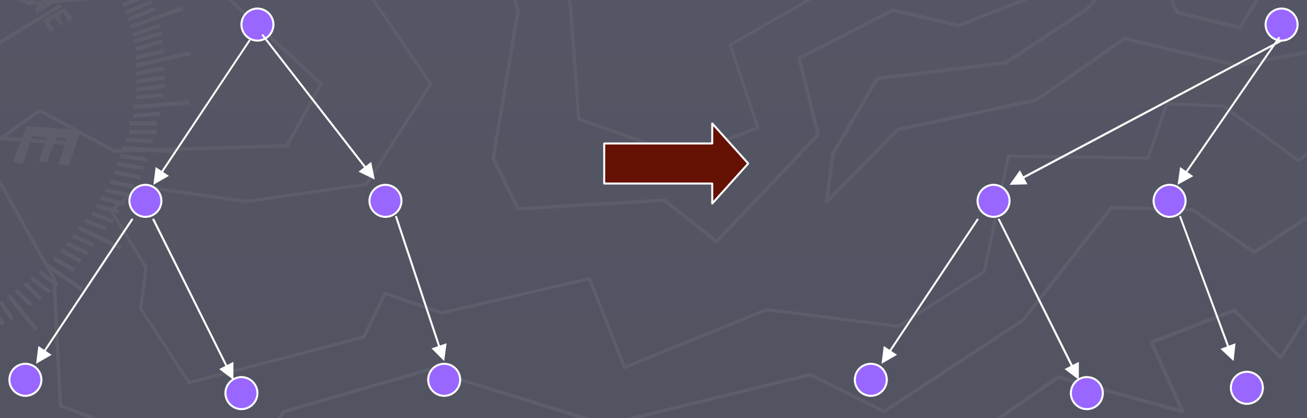
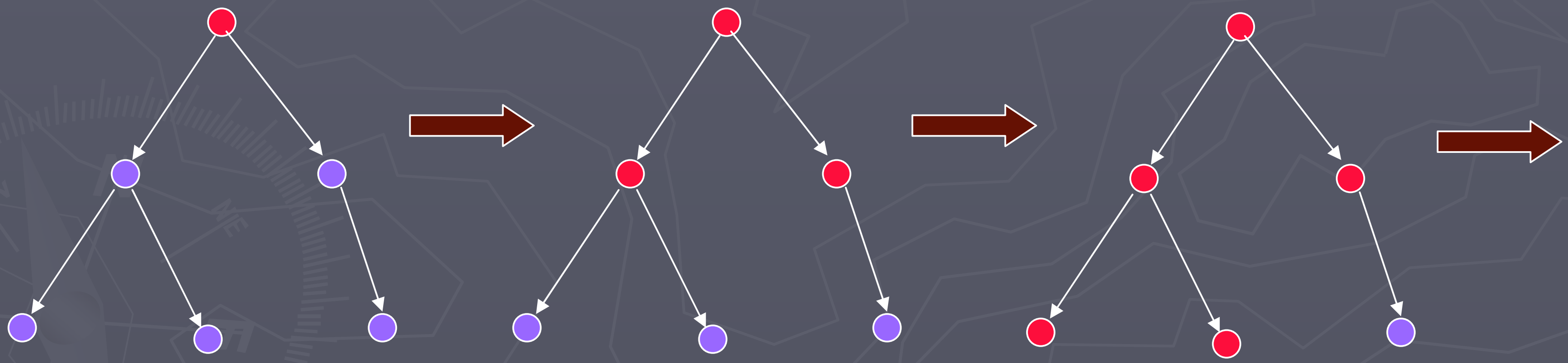
Future work

- Experiment with more sophisticated structural features.
- Design an transducer (dependency based) which uses parameter weights learnt by our approach and the LM.



Future work

- Merge the two alignment search steps to make better use of structural features.



THANK YOU

Questions and Suggestions ?