Three models for discriminative machine translation using Global Lexical Selection and Sentence Reconstruction

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Complexity of the task

- 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:
  - There are long distance word order variations in English-Hindi unlike English-French.

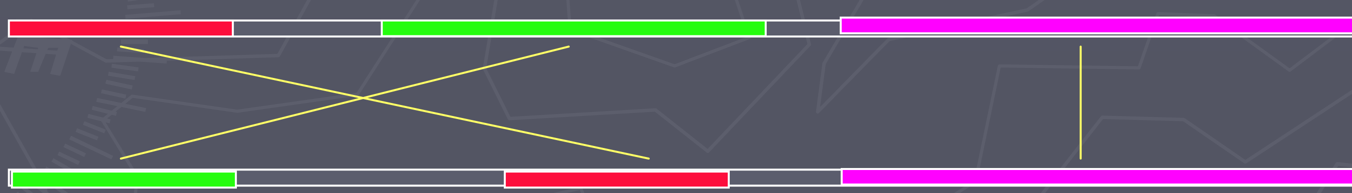
Outline

- Previous Work
- Global Lexical Selection
- Three models
  - Bag-of-Words Lexical Choice Model
  - Sequential Lexical Choice Model
  - Hierarchical Lexical association and Reordering Model
- Results
- Conclusion and Future Work

Previous work on Stat MT.

- Local associations between source and target phrases are obtained.

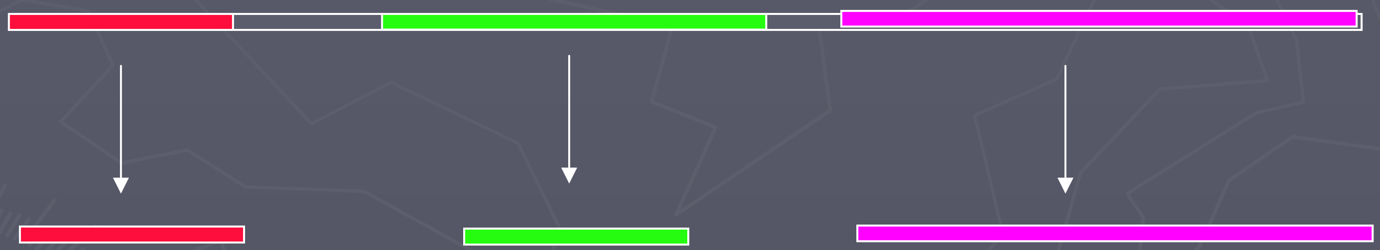
1. GIZA++ is used to align source words to target words.
2. These alignments augmented with target-to-source alignments.
3. Word-alignments are extended to obtain phrase level local associations.



Previous work on Stat MT.

- Translation is done in two steps

1. Local associations of phrases of source sentence are selected.



2. Re-ordering the target language phrases.

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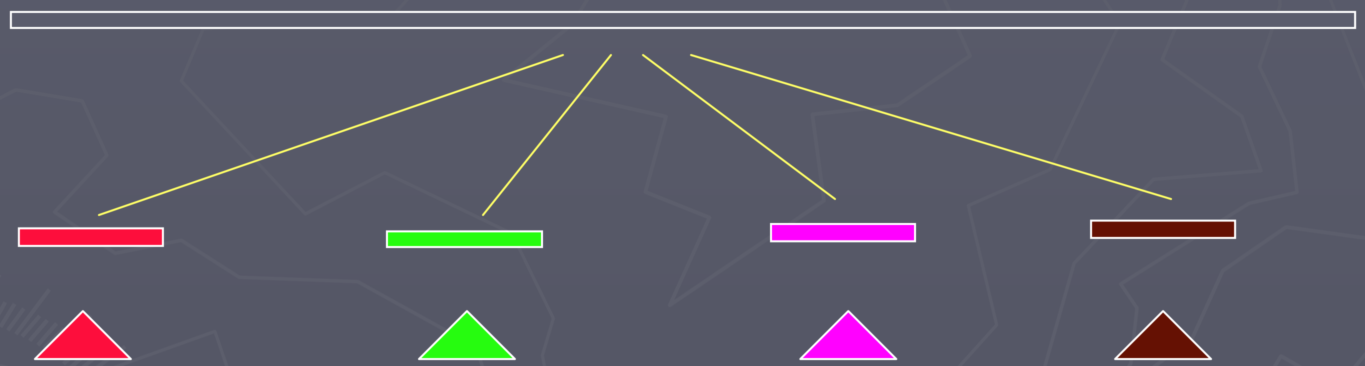
Global Lexical Selection

- In contrast, the target words are associated to the entire source sentence.



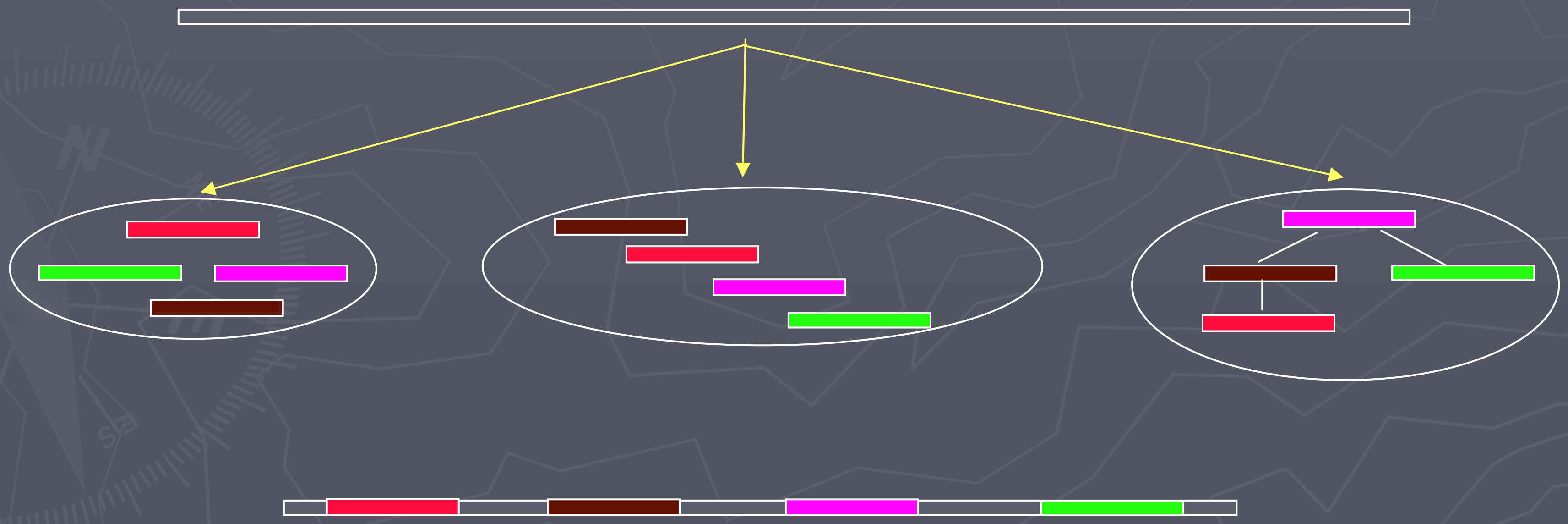
- Intutions
  1. Lexico-syntactic features (not necessarily single words) in source sentence might trigger the presence of target words.

  2. Also predict syntactic cues along with lexical/phrasal units.

Global Lexical Selection

- No longer tight association between source language words/phrases.

- During translation,



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Bag of words model

- Learn: Given a source sentence S, what is the probability that a target word t is in its translation ?

  i.e., estimate p (true | t , S) and p (false | t, S)

- Binary classifiers are built for all words in target language vocabulary.

- Maximum entropy model is used for learning.

Bag of words model - Training

- Training binary classifier for target language word t.

- Example sentences:

s1 True (t exists in translation)

s2 False (t doesn't exists in translation)

s3 False (t doesn't exists in translation)

s4 True (t exists in translation)

- Number of training sentences for each target language word are total number of sentence pairs.

Bag of words model – Lexical selection

- For an input sentence S, first the target sentence bag is obtained.
- Source sentence features considered : N-grams
  - Let, BOgrams(S) be N-grams of source sentence S.
- The bag contains a target word w, if

  $$p\ (\text{true} \mid t, \text{BOgrams}(S)\ ) > \tau\ \ (\text{threshold})$$

- $\text{BOW}\ (T) = \{\ t \mid p\ (\text{true} \mid t, S) > \tau\ \}$

Bag of words model
– Sentence Reconstruction

- Various permutations of words in BOW (T) considered and then ranked by a target language model.

- All possible permutations -- computationally not feasible.

- Reduced by constraining permutations to be within local window of adjustable size (perm) . (Kanthak et al., 2005)

- During decoding, some words can be deleted. Parameter (δ) can be used to adjust length of translated outputs.

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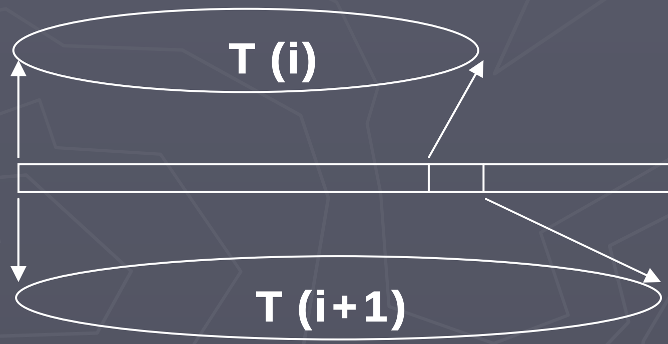
Sequential lexical choice model

- In Previous approach we begin permuting with an arbitrary order of words as start point.
- Better to start with a more definite string.
- During lexical selection, target words are first placed in an order faithful to source sentence words.
- Training same as bag of words model.

Sequential model - Decoding

- Goal: Associate sets of target words with every position in source sentence (S).
- Predict bags of words (T_i) for all prefixes of S.



- Associate a target word t to source position (i+1) if it is present in T_{i+1} but not in T_i .

Sequential model - Decoding

- Intution:
  - Word t associated with position i if some information at i^{th} position triggered it.
- Example:
  - Pay a : दो
  - Pay a visit : मिलो
  - Associate मिलो with the position of **visit** in source sentence.
- **Limitation**
  - **Using moving permutation window can explore only local word reordering.**

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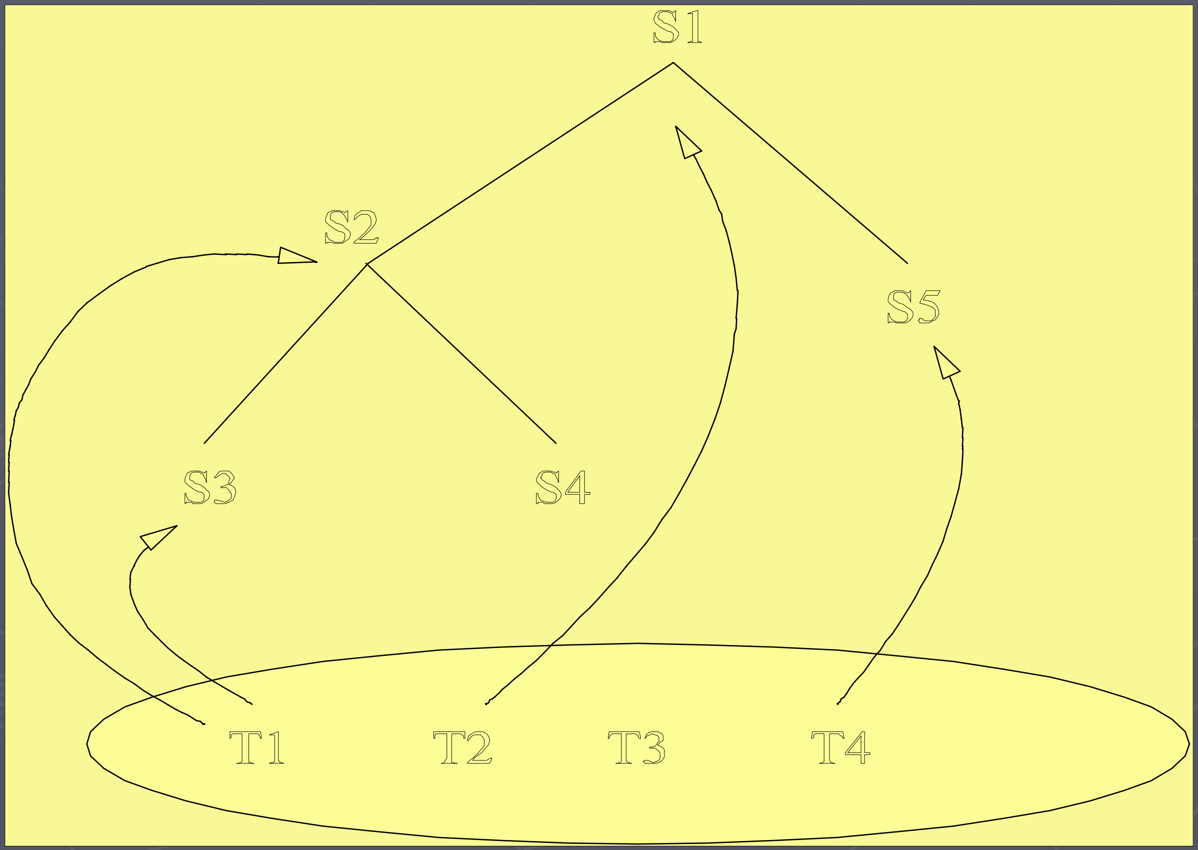
Hierarchical model

- Sequential model expected to work better for language pairs with only local word order variations.
    - May perform poorly for language pairs (English-Hindi) with significant word order variation.
- Previous approach: Associated target words with source positions.
- This approach: Associate target words with nodes of source dependency tree.

Hierarchical model - attachment



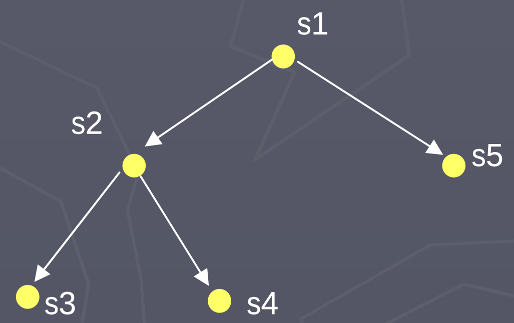
Hierarchical model - decoding

1. Predict the bag-of-words (same as previous models)
   - Given source sentence S and its dependency structure.
2. Attachment to source nodes.
   - Attach words from previous step to various nodes of source dependency structure.
3. Ordering target language words
   - Traverse source dependency structure in bottom-up fashion to obtain best target string.

Predict Bag-of-words

- Same as bag-of-words model except that both n-gram features and dependency features are used.
  - Include t if , p (true| t, f (S)) > τ

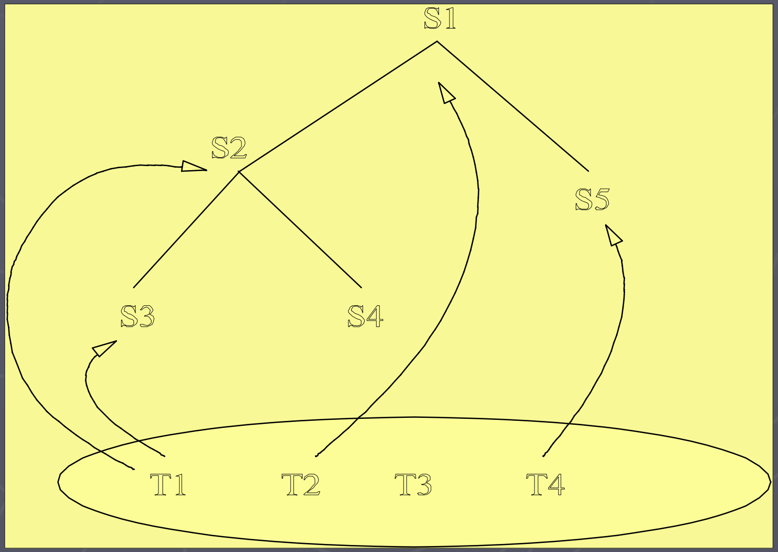
- Features f(S)



  - N-gram features ‘s1’ ‘s2’ ‘s3 s2’ ‘s2 s4 s1’
  - Dependency pairs ‘s2 s1’ ‘s4 s2’
  - Dependency Treelet ‘s3 s2 s5’ ‘s2 s1 s5’

Hierarchical model - attachment

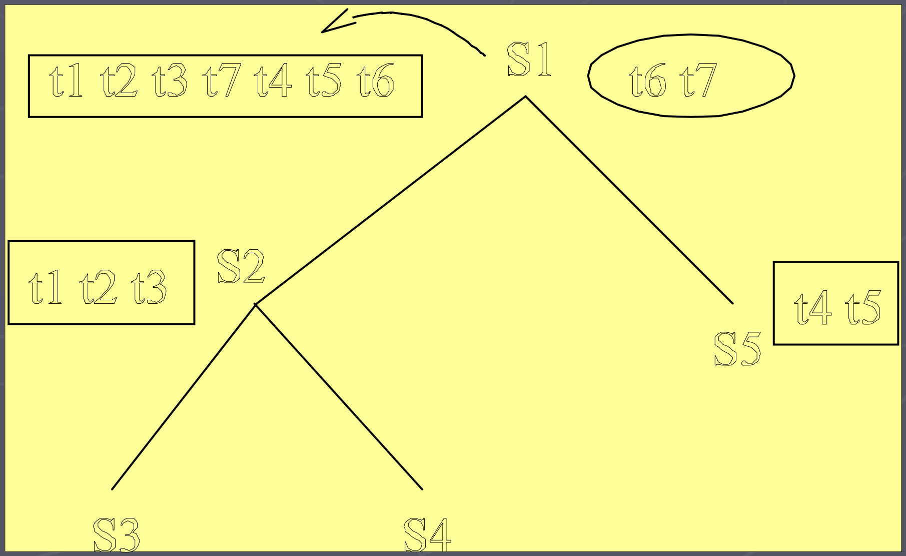
- Every target word t is attached to the source node whose *local features* give the best positive probability for word t.



- If s_t is source node to which target word t is attached to
  - $s_t = \mathrm{argmax}_s\ p(\mathrm{true} \mid t, f_L(s))$.

Hierarchical model - ordering

- Source sentence dependency tree is traversed in a bottom-up fashion.
- The best target string for every sub-tree is determined.



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Experiments - Dataset

- Language pair: English – Hindi (large word-order variations)

- Training set : 37967 pairs
- Development : 819 pairs
- Test : 699 pairs

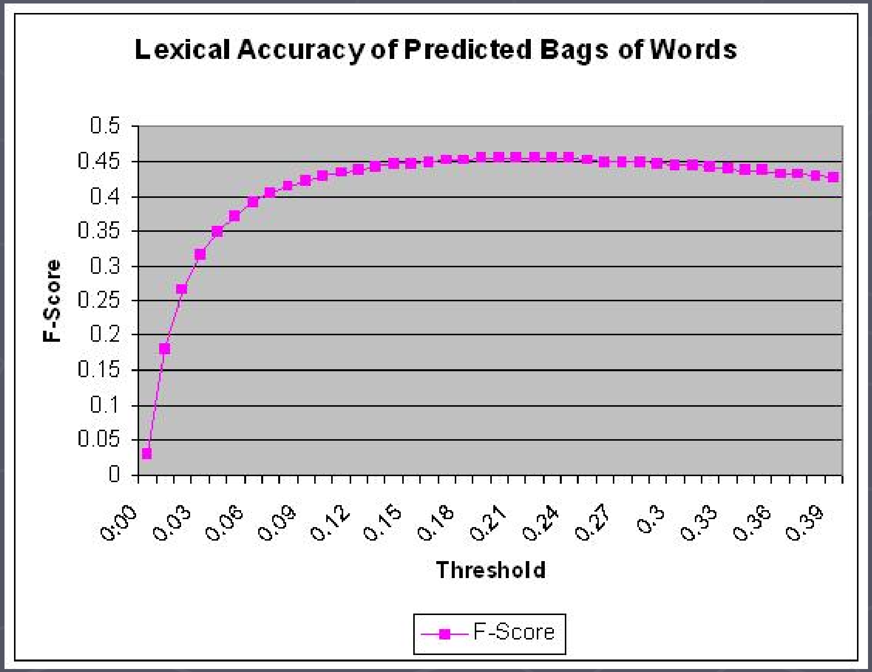
- Maximum sentence length = 30

- Unseen tokens in target side of devel corpus : 13.48%
- Unseen tokens in source side of devel corpus : 10.77%

Results – Bag of words model

- Need to determine the best value of τ, perm and δ .

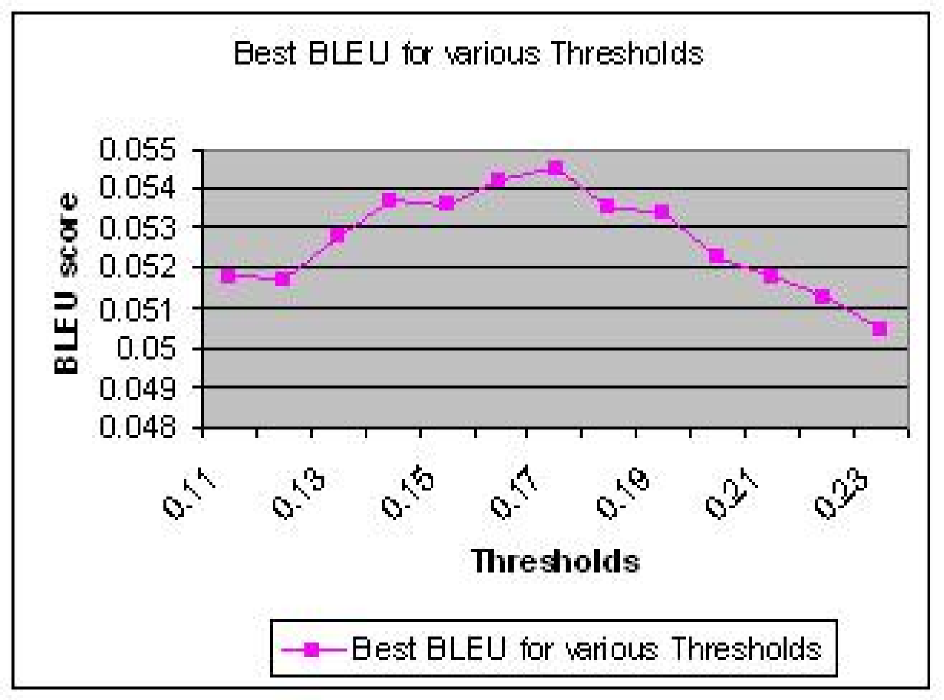
- Quality of bags (Lexical accuracy/F-score) determined by threshold τ. Best LexAcc = 0.455.



Results - Bag of words model

- All the bags obtained using various thresholds are now permuted.

- Best Bleu scores for various thresholds. Best Bleu = 0.0545



Results

		Devel. Set	Test. Set	
		BLEU	LexAcc	BLEU
Bag of words		0.0545	46.20	0.0428
Sequential		0.0586	45.24	0.0473
Hierarchical		0.0650	46.20	0.0498
MOSES (3 → 1)			34.42	0.0381
MOSES (3 → 3)			32.18	0.0440
MOSES (7 → 7) (Untuned)			28.23	0.0222

Conclusion

- Global Lexical selection
  - To Make use of lexico-syntactic features on source.
  - Predict syntactic cues along with lexical/phrasal units.
- Predicted units are semi-aligned with source structures for better target sentence re-construction.
  - Alignment is an inferred step and not a primary step.
- These models give scope for obtaining entirely different structures in target language.

Future work

- Improve hierarchical reordering model.
  - Take K-best target strings for every sub-tree during traversal.

- Handling cases of structural non-isomorphism between source and target sentences

- Consider phrases on target sentence instead of just words.

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