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IMEANT

Better semantic frame based MT evaluation via inversion transduction grammars

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what makes a translation useful

how well is

who did what to whom, for whom, when, where, why and how

preserved in translation?

surface MT metrics (BLEU, NIST, ...)

how well do
n-grams
match

between reference and machine translations?

semantic MT metrics (MEANT, ...)

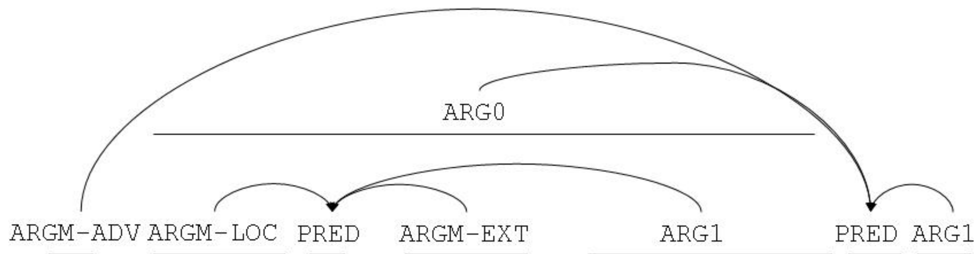
how well do

semantic frames

match

between reference and machine translations?

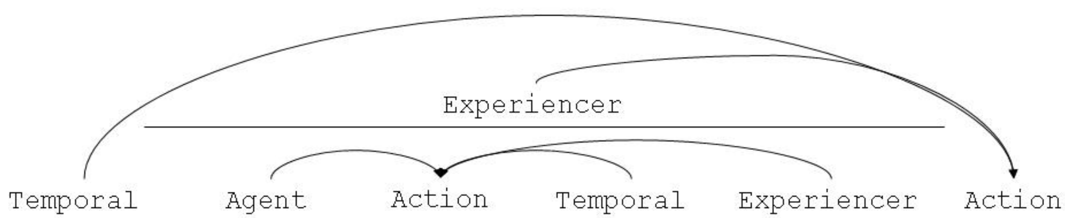
HMEANT
Human semantic MT evaluation via SRL



[IN] 至此， 在 中国 内地 停售 了 近 两 个 月 的 ＳＫ－ＩＩ 全线 产品 恢复 销售 。

[REF] Until after their sales had ceased in mainland China for almost two months , sales of the complete range of SK – II products have now be resumed .

[MT1] So far , nearly two months sk - ii the sale of products in the mainland of China to resume sales .



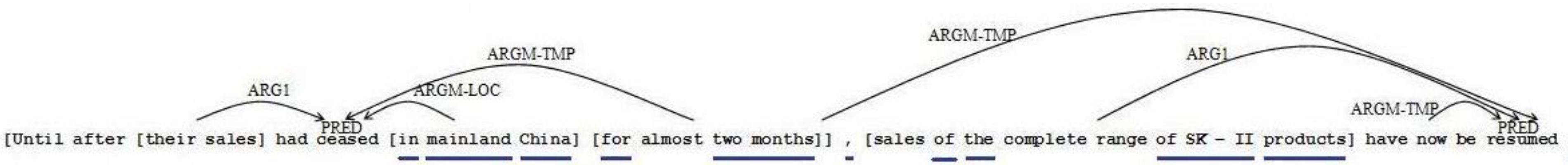
[MT2] So far , in the mainland of China to stop selling nearly two months of SK - 2 products sales resumed .

[MT3] So far , the sale in the mainland of China for nearly two months of SK - II line of products .

Example: a less useful translation

Fewer SRL matches ☺

but more N-gram and syntax-subtree matches! ☹

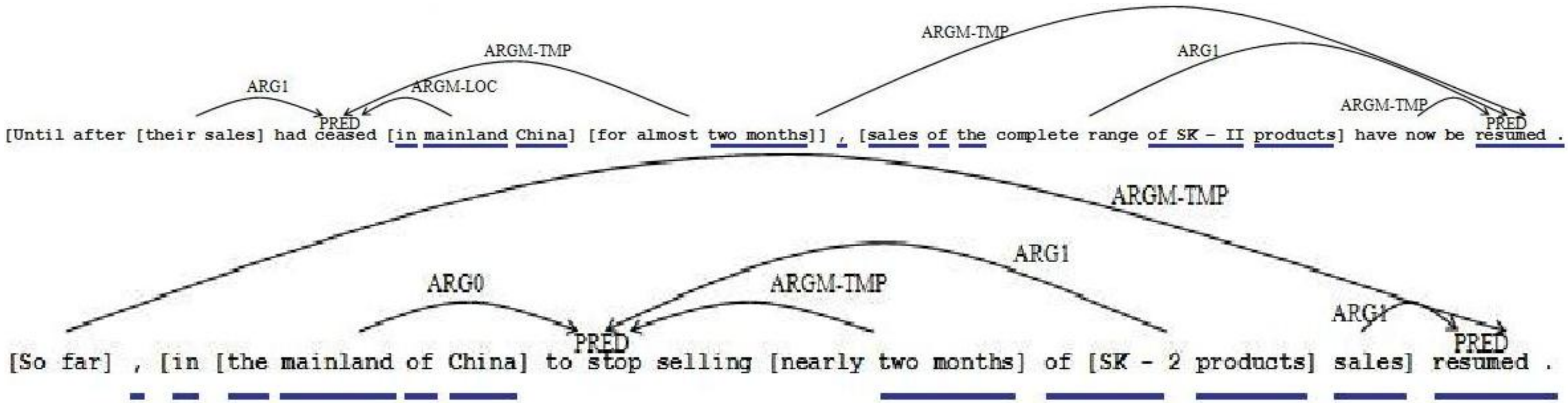


So far , the sale in the mainland of China for nearly two months of SK - II line of products .

N-gram		Syntax-subtree		SRL	
1-gram matches:	15	1-level subtree matches:	34	Predicate matches:	**0**
2-gram matches:	4	2-level subtree matches:	**8**		
3-gram matches:	**3**	3-level subtree matches:	**2**		
4-gram matches:	**1**	4-level subtree matches:	0		

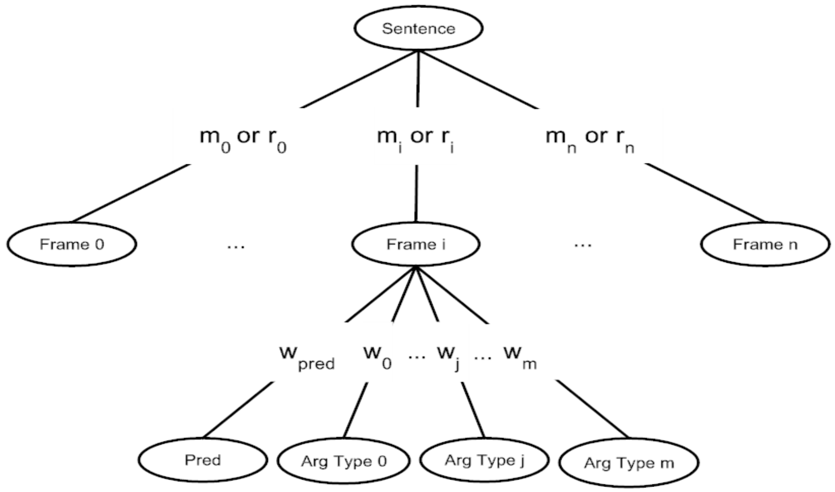
Conversely: a more useful translation

More SRL matches ☺
but fewer N-gram and syntax-subtree matches! ☹



N-gram		Syntax-subtree		SRL	
1-gram matches:	15	1-level subtree matches:	35	Predicate matches:	**2**
2-gram matches:	4	2-level subtree matches:	**6**	Argument matches:	**1**
3-gram matches:	**1**	3-level subtree matches:	**1**		
4-gram matches:	**0**	4-level subtree matches:	0		

HMEANT is just an f-score on semantic frame match (with a tiny number of weights)



$$m_i \equiv \frac{\text{\# word tokens filled in Frame i}}{\text{total\# word tokens in MT}}$$

$$r_i \equiv \frac{\text{\# word tokens filled in Frame i}}{\text{total\# word tokens in REF}}$$

$$\text{precision} \equiv \frac{\sum_i m_i \frac{w_{\text{pred}} + \sum_j w_j (C_{i,j} + w_{\text{partial}} P_{i,j})}{w_{\text{pred}} + \sum_j w_j M_{i,j}}}{\sum_i m_i}$$

$$\text{recall} \equiv \frac{\sum_i r_i \frac{w_{\text{pred}} + \sum_j w_j (C_{i,j} + w_{\text{partial}} P_{i,j})}{w_{\text{pred}} + \sum_j w_j R_{i,j}}}{\sum_i r_i}$$

- **sentence accuracy:** avg translation accuracy over all frames of a sentence
  sentence precision (or recall) = frame precision (or recall) averaged across the total number of frames in MT (or REF)
- **frame accuracy:** avg translation accuracy over all roles of a frame
  frame precision (or recall) = weighted sum of # correctly translated arguments, normalized by the weighted sum of # arguments in MT (or REF)
- **frame importance:** weight each frame by its span coverage ratio
- **role importance:** weight each type of role
  by maximizing HMEANT's correlation with HAJ using a human ranked training corpus

HMEANT, MEANT, UMEANT a family of semantic frame based MT evaluation metrics

- **HMEANT** human [Lo & Wu, ACL, IJCAI, SSST 2011]
  - assesses MT utility via semantic frames with high representational transparency
  - needs only unskilled humans to annotate and align semantic frames
  - correlates with human adequacy judgment better than HTER at lower labor cost
  - applies easily on any language pair
- **MEANT** automatic [Lo, Tumuluru & Wu, WMT 2012]
  - outperforms all commonly used automatic MT evaluation metrics
    - replaces human SRL with automatic shallow semantic parsing
    - replaces human semantic frame alignment with automatic alignment
  - simple & transparent – preserves Occam's razor spirit of HMEANT
  - now in both English and Chinese
  - top 4 in WMT2013 metrics track evaluation
- **UMEANT** unsupervised automatic [Lo & Wu, SSST 2012]
  - eliminates any dependency on a corpus with human ranked MT output
    in training the weights of semantic role labels
    by estimating them via the relative frequency of the labels in the reference
  - good for resource-sparse languages
  - top 3 in WMT2013 metrics track evaluation

the first ever

directly semantically trained SMT systems

- **why tune MT against MEANT?**
  - produces more robustly adequate translations than tuning against BLEU or TER
    - across genres (newswire, web forum, TED)
    - across output languages (English, Chinese)
    - accros MT paradigms (phrase based, hierarchical phrase based)
  - constrains the MT system to make more accurate lexical and reordering choices
    - preserving the meaning of the translation as captured by semantic frames right in the training process
- the first time in 25 years of history that SMT has ever been directly trained **to maximize preserving who did what to whom, for whom, when, where, how, why** (a bit scary!)

XMEANT a cross-lingual semantic frame based MT evaluation metric

- **XMEANT** cross-lingual MEANT [Lo, Beloucif, Saers & Wu, ACL 2014]
  - eliminates the need for expensive reference translations …
    yet correlates with human adequacy judgment even more closely than MEANT!
  - since words come from different vocabularies for input and output languages, can't use MEANT's word vector similarities to align role fillers any more; instead use translation probabilities plus **language-independent BITGs constraints** (Wu 1997; Zens & Ney 2003; Saers & Wu 2009)
  - a new generation of Wu & Fung's (NAACL, EAMT 2009) cross-lingual score …
    that exploits all our recent advances on monolingual MEANT
- well, if BITG constraints work so well for cross-lingual XMEANT… could they also improve ordinary monolingual MEANT?

IMEANT *new!* an ITG-based semantic frame based MT evaluation metric

- **further improves** MEANT's correlation with human adequacy judgment which was already high

- achieved by using **bracketing ITGs** to biparse the semantic role fillers in both reference and machine translations

- shows that ITGs
  - appropriately constrain the allowable permutations between the compositional segments across the reference and machine translations
  - score the phrasal similarity of the semantic role fillers more accurately than the simple heuristics like bag-of-word alignment or maximum alignment

MEANT

1. apply automatic shallow semantic parsing to the reference and machine translations

2. apply maximum weighted bipartite matching to align the semantic frames between the reference translation and the machine translation, according to the lexical similarity of the semantic predicates

3. for each pair of aligned semantic frames, apply maximum weighted bipartite matching to align arguments between the reference translation and the machine translation, according to the lexical similarity of the semantic role fillers

4. compute the weighted f-score over the matching role labels of these aligned predicates and role fillers

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$$
\begin{aligned}
q^0_{i,j} &\equiv \text{ARG j of aligned frame i in MT} \\
q^1_{i,j} &\equiv \text{ARG j of aligned frame i in REF} \\
w^0_i &\equiv \frac{\text{\#tokens filled in aligned frame i of MT}}{\text{total \#tokens in MT}} \\
w^1_i &\equiv \frac{\text{\#tokens filled in aligned frame i of REF}}{\text{total \#tokens in REF}} \\
w_{\text{pred}} &\equiv \text{weight of similarity of predicates} \\
w_j &\equiv \text{weight of similarity of ARG j} \\
s_{i,\text{pred}} &\equiv \text{predicate similarity in aligned frame i} \\
s_{i,j} &\equiv \text{ARG j similarity in aligned frame i} \\
\text{precision} &= \frac{\sum_i w^0_i \frac{w_{\text{pred}} s_{i,\text{pred}} + \sum_j w_j s_{i,j}}{w_{\text{pred}} + \sum_j w_j |q^0_{i,j}|}}{\sum_i w^0_i} \\
\text{recall} &= \frac{\sum_i w^1_i \frac{w_{\text{pred}} s_{i,\text{pred}} + \sum_j w_j s_{i,j}}{w_{\text{pred}} + \sum_j w_j |q^1_{i,j}|}}{\sum_i w^1_i} \\
\text{MEANT} &= \frac{2 \cdot \text{precision} \cdot \text{recall}}{\text{precision} \cdot \text{recall}}
\end{aligned}
$$

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IMEANT

1. apply automatic shallow semantic parsing to the reference and machine translations
2. apply maximum weighted bipartite matching to align the semantic frames between the reference translation and the machine translation, according to the lexical similarity of the semantic predicates
3. for each pair of aligned semantic frames, apply maximum weighted bipartite matching to align arguments between the reference translation and the machine translation, according to the lexical similarity of the semantic role fillers **aggregated under ITG-constrained alignments**
4. compute the weighted f-score over the matching role labels of these aligned predicates and role fillers

MEANT

$$q^0_{i,j} = ARG\ j \text{ of aligned frame } i \text{ in MT}$$
$$q^1_{i,j} = ARG\ j \text{ of aligned frame } i \text{ in REF}$$
$$w^0_i = \frac{\#\text{ tokens filled in aligned frame } i \text{ of MT}}{\text{total }\#\text{ tokens in MT}}$$
$$w^1_i = \frac{\#\text{ tokens filled in aligned frame } i \text{ of REF}}{\text{total }\#\text{ tokens in REF}}$$
$$w_{pred} = \text{weight of similarity of predicates}$$
$$w_j = \text{weight of similarity of } ARG\ j$$
$$\boldsymbol{e}_{i,pred} = \text{pred string of the aligned frame } i \text{ of MT}$$
$$\boldsymbol{f}_{i,pred} = \text{pred string of the aligned frame } i \text{ of REF}$$
$$\boldsymbol{e}_{i,j} = \text{role fillers of } ARG\ j \text{ of the aligned frame } i \text{ of MT}$$
$$\boldsymbol{f}_{i,j} = \text{role fillers of } ARG\ j \text{ of the aligned frame } i \text{ of REF}$$
$$s(e,f) = \text{lexical similarity of token } e \text{ and } f$$

$$prec_{\boldsymbol{e},\boldsymbol{f}} = \frac{\sum_{e\in\boldsymbol{e}} \max_{f\in\boldsymbol{f}} s(e,f)}{|\boldsymbol{e}|}$$
$$rec_{\boldsymbol{e},\boldsymbol{f}} = \frac{\sum_{f\in\boldsymbol{f}} \max_{e\in\boldsymbol{e}} s(e,f)}{|\boldsymbol{f}|}$$
$$s_{i,pred} = \frac{2 \times prec_{\boldsymbol{e}_{i,pred},\boldsymbol{f}_{i,pred}} \times rec_{\boldsymbol{e}_{i,pred},\boldsymbol{f}_{i,pred}}}{prec_{\boldsymbol{e}_{i,pred},\boldsymbol{f}_{i,pred}} + rec_{\boldsymbol{e}_{i,pred},\boldsymbol{f}_{i,pred}}}$$
$$s_{i,j} = \frac{2 \times prec_{\boldsymbol{e}_{i,j},\boldsymbol{f}_{i,j}} \times rec_{\boldsymbol{e}_{i,j},\boldsymbol{f}_{i,j}}}{prec_{\boldsymbol{e}_{i,j},\boldsymbol{f}_{i,j}} + rec_{\boldsymbol{e}_{i,j},\boldsymbol{f}_{i,j}}}$$

$$precision = \frac{\sum_i w^0_i \frac{w_{pred}s_{i,pred}+\sum_j w_j s_{i,j}}{w_{pred}+\sum_j w_j |q^0_{i,j}|}}{\sum_i w^0_i}$$
$$recall = \frac{\sum_i w^1_i \frac{w_{pred}s_{i,j}+\sum_j w_j s_{i,j}}{w_{pred}+\sum_j w_j |q^1_{i,j}|}}{\sum_i w^1_i}$$
$$MEANT = \frac{2\times precision\times recall}{precision+recall}$$

IMEANT

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$$G \equiv \langle\{\mathrm{A}\}, \mathfrak{W}^0, \mathfrak{W}^1, \mathfrak{R}, \mathrm{A}\rangle$$
$$\mathfrak{R} \equiv \{\mathrm{A} \to [\mathrm{A\ A}], \mathrm{A} \to \langle\mathrm{A\ A}\rangle, A \to e/f\}$$
$$p([\mathrm{A\ A}]|\mathrm{A}) = p(\langle\mathrm{A\ A}\rangle|\mathrm{A}) = 1$$
$$p(e/f\,|\mathrm{A}) = s(e,f)$$
$$s_{i,pred} = lg^{-1}\left(\frac{\lg\left(P\left(A \xrightarrow{+} \boldsymbol{e}_{i,pred}/\boldsymbol{f}_{i,pred}\,|G\right)\right)}{max\left(|\boldsymbol{e}_{i,pred}|, |\boldsymbol{f}_{i,pred}|\right)}\right)$$
$$s_{i,j} = lg^{-1}\left(\frac{\lg\left(P\left(A \xrightarrow{+} \boldsymbol{e}_{i,j}/\boldsymbol{f}_{i,j}\,|G\right)\right)}{max\left(|\boldsymbol{e}_{i,j}|, |\boldsymbol{f}_{i,j}|\right)}\right)$$

$$precision = \frac{\sum_i w^0_i \frac{w_{pred}s_{i,pred}+\sum_j w_j s_{i,j}}{w_{pred}+\sum_j w_j |q^0_{i,j}|}}{\sum_i w^0_i}$$
$$recall = \frac{\sum_i w^1_i \frac{w_{pred}s_{i,j}+\sum_j w_j s_{i,j}}{w_{pred}+\sum_j w_j |q^1_{i,j}|}}{\sum_i w^1_i}$$
$$IMEANT = \frac{2\times precision\times recall}{precision+recall}$$

IMEANT
outperforms the most recent version of MEANT

- IMEANT shows a 3 point improvement over MEANT on GALE-A
- IMEANT is tied with MEANT in correlation with HAJ on GALE-B

Table 1. Sent-level correlation with HAJ on GALE P2.5 data

	GALE-A	GALE-B
HMEANT	0.53	0.37
IMEANT	**0.51**	**0.33**
XMEANT	**0.51**	0.20
MEANT	0.48	**0.33**
METEOR 1.5 (2014)	0.43	0.10
NIST	0.29	0.16
METEOR 0.4.3 (2005)	0.20	0.29
BLEU	0.20	0.27
TER	0.20	0.19
PER	0.20	0.18
CDER	0.12	0.16
WER	0.10	0.26

IMEANT
outperforms cross-lingual XMEANT

- IMEANT is tied with XMEANT on GALE-A
- IMEANT correlates with HAJ much better than XMEANT on GALE-B

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IMEANT
outperforms any of the others

- IMEANT produces much higher HAJ correlations than any of the other metrics on both GALE-A and GALE-B

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IMEANT
even closes the gap with HMEANT

- IMEANT even comes within a few points of the human upper bound established by HMEANT

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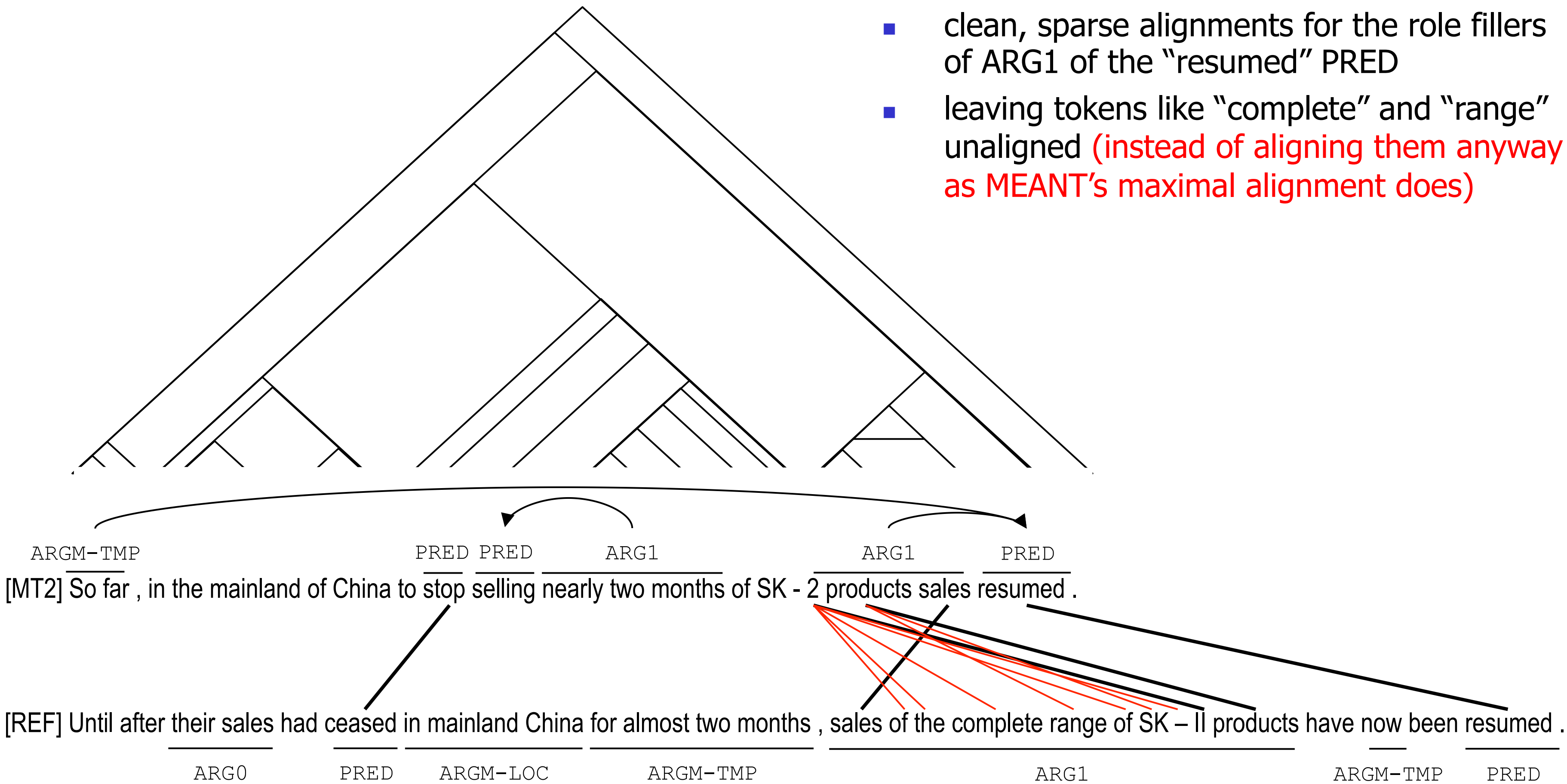
observation
how ITG constraints help IMEANT

- empirically, we see
  - ITGs produce significantly more accurate phrasal similarity aggregation
  - compared to MEANT's standard bag-of-words based heuristics
- **permutation** and **bijectivity** constraints enforced by the ITG
  - offer better leverage to reject inappropriate token alignments
  - compared to the maximal alignment approach which tends to be rather promiscuous

example
how ITG constraints help IMEANT

- clean, sparse alignments for the role fillers of ARG1 of the "resumed" PRED
- leaving tokens like "complete" and "range" unaligned (instead of aligning them anyway as MEANT's maximal alignment does)



semantic MT evaluation
the MEANT viewpoint

- **simple** Occam's razor: easy to define, easy to implement, easy to use
- **representationally transparent** can look at a score and understand scientifically why it was high or low
  - eg, MEANT's degree of match between semantic frames
  - who did what to whom, for whom, when, where, why and how
- **tunable** support fast scoring of massive numbers of hypotheses for tuning/training
- **discriminating** fine-grained scores (not just ranking or "good/bad" binary classification)
- **language independent** methodology that works across all language pairs
  - eg, IMEANT and XMEANT's incorporation of language universal ITG biases
- **stable** high HAJ correlations without retraining

conclusions

- **IMEANT** – our newest 2014 version of MEANT is based on ITGs
- **achieves highest correlation** with HAJ among all variants of MEANT as well as other common MT evaluation metrics
- aligns and scores semantic frames via a simple, consistent BITG which provides **informative permutation and bijectivity biases**
  - replaces MEANT's maximal alignment and bag-of-words heuristics
- retains MEANT's characteristics of **Occam's Razor style simplicity** and **representational transparency**