

Large-Scale Statistical Machine Translation with Weighted Finite State Transducers

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Source-channel model of Statistical Machine Translation

- ▶ Task is to recover the source sentence $\mathbf{S} = s_1, s_2, \dots, s_l$ that generated the observed target $\mathbf{T} = t_1, t_2, \dots, t_j$
- ▶ Typically decomposed into translation and language model probabilities:

$$\hat{\mathbf{S}} = \operatorname{argmax}_{\mathbf{S}} P(\mathbf{S}|\mathbf{T}) = \operatorname{argmax}_{\mathbf{S}} P(\mathbf{T}|\mathbf{S})P(\mathbf{S})$$

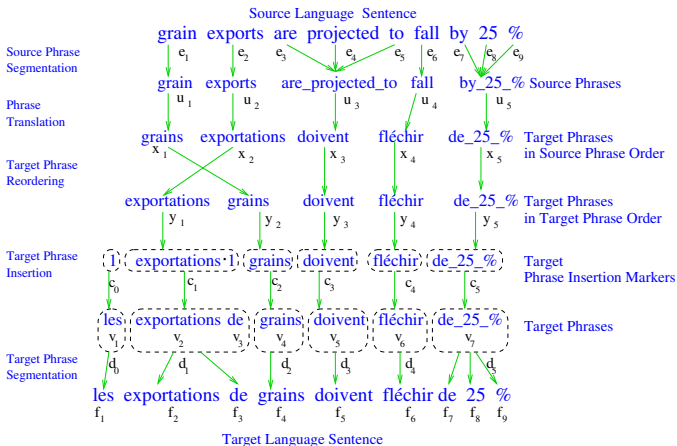
- ▶ These probability distributions are estimated from (word-aligned) parallel and monolingual corpora
- ▶ Minimal translation unit is the phrase

Transducer Translation Model (TTM)

- ▶ The Cambridge University Engineering Department phrase-based SMT system follows the Transducer Translation Model (TTM)
- ▶ Generative model of translation
- ▶ Implemented with Weighted Finite State Transducers (WFST)
 - ▶ WFSTs used for word alignment, language model, word-to-phrase segmentation, phrase translation and reordering
 - ▶ Translation is performed using libraries of [standard FST operations](#)
 - ▶ [No special-purpose decoder](#) required
 - ▶ [Modularity](#). Easy to work on translation components in isolation
 - ▶ [Open Source WFST Toolkit](#) ¹ – www.openfst.org/
- ▶ Incorporates various second-pass lattice rescoring stages

¹C. Allauzen, M. Riley, J. Schalkwyk, W. Skut , and M. Mohri (2007), OpenFst: A General and Efficient Weighted Finite-State Transducer Library. CIAA.

Transducer Translation Model (TTM)



- ▶ Transformations via stochastic models implemented as WFSTs
- ▶ Built with standard WFST operations such as composition and best-path search

TTM Component Models

Basic models:

- ▶ Source first-pass [language model](#) G
- ▶ Source phrase segmentation (unweighted) W
- ▶ [Phrase translation](#) and [reordering](#) R
- ▶ Target [phrase insertion](#) Φ
- ▶ Target phrase segmentation (unweighted) Ω
- ▶ [Word penalty](#) and [phrase penalty](#)

Decoding: A translation lattice is obtained through the series of compositions:

$$L = G \circ W \circ R \circ \Phi \circ \Omega \circ \mathbf{T}$$

where \mathbf{T} is the target sentence to translate.

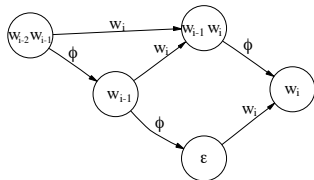
⇒ the most likely translation $\hat{\mathbf{S}}$ is the path in L with least cost (i.e. minimum negative log-likelihood in tropical semiring)

First-pass Language Model (word n -Gram)

Backoff n -gram approximation : $P(s_1^l) \approx \prod_i P(s_i | s_{i-n+1}^{i-1})$

$$P(s_i | s_{i-n+1}^{i-1}) =$$

$$\begin{cases} \rho(s_{i-k+1}^i) & \text{if } c(s_{i-k+1}^i) > \tau \\ \lambda(s_{i-k+1}^{i-1}) P(s_i | s_{i-n+2}^{i-1}) & \text{otherwise} \end{cases}$$



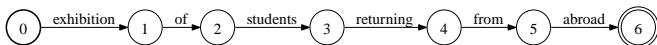
WFSA Trigram²

- ▶ each probability and back-off weight is encoded as a cost on an arc in the grammar WFST
- ▶ ρ and λ can be pre-computed and stored for reasonable sized language models
- ▶ WFST implements backoff n -gram exactly (ϕ is a failure arc) or approximately

For 'reasonable' sized LM training sets, WFST implementations work well

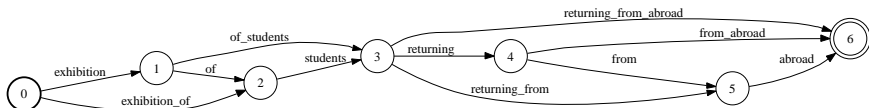
²C. Allauzen et al. 2003. Generalized Algorithms for Constructing Statistical Language Models. Proc. ACL

Phrase Segmentation Transducers



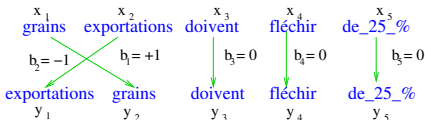
Sentence Acceptor

⇓ Phrase Segmentation Transducer W or Ω



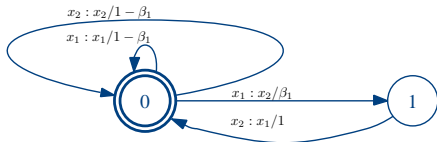
Phrase Sequence Lattice

- ▶ Phrase Segmentation Transducers convert word sequences (or lattices) into phrase lattices according to [Phrase Pair Inventory](#)
- ▶ lattice is unweighted \Rightarrow all segmentations equally likely in first-pass decoding

Phrase Swapping by WFSTs³

Associate a **jump sequence** b_1^K with each sequence y_1^K

$$P(b_1^K | x_1^K, u_1^K, K, s_1^K) = \prod_{k=1}^K \underbrace{P(b_k | b_{k-1}, x_{k-1}, x_k, u_{k-1}, u_k)}_{\text{orientation prob., estimated from alignments}}$$



b_k specify relative offsets

MJ-1 : maximum jump of 1

$$b \in \{0, +1, -1\}$$

Extremely simple, but

→ Properly parameterized

→ Not degenerate

³Kumar, Byrne 2005. Local phrase reordering models for statistical machine translation. HLT-EMNLP.

Grammar constraints as LM acceptor

- ▶ often certain input word sequences are to be passed through the translation system intact

此外, 大约三十个摊位也以各类行动电视手机如 t-dmb (terrestrial digital media broadcasting), s-dmb (satellite digital multimedia broadcasting) 及 dvb-h (digital video broadcasting-handhelds), 提供杜林冬运现场实况转播的画面, 藉以吸引参观者注意。
- ▶ Separate translation of Foreign-language sequences is not ideal, as it prevents long-span translation, reordering and language models from looking across boundaries
- ▶ **Solution:** Compose source language model with an additional constrained grammar
 - ▶ $G' = G \circ C$, where C accepts sequences $V^* \cdot u_1 \cdot V^* \cdot u_2 \cdot V^*$ (V is the source language vocabulary)
- ▶ Useful to impose constraints on output and keep scores based on long-span models
 - ▶ parentheses or quotes properly matched
 - ▶ names correctly transliterated

Minimum Error Training (MET)

- ▶ MET is used to adjust the relevance of each component transducer to the translation metric (BLEU, TER, etc.)
- ▶ Effective in tuning systems to task-specific situations

Additional models for MET:

- ▶ Inverse phrase translation
- ▶ 3 phrase pair count features ⁴

⇒ Total of 10 scaling factors are optimized on development set (typ. 3-4 iterations)

- ▶ weights are assigned to WFST likelihoods for test translation

⁴O. Bender, E. Matusov, S. Hahn, S. Hasan, S. Khadivi, and H. Ney (2007). The RWTH Arabic-to-English Spoken Language Translation System. ASRU.

Large Language Model Rescoring

Stupid backoff zero cut-off 5-gram language model ⁵

Directly build sentence-specific LMs:

- ▶ Counts are extracted beforehand from all monolingual English data
- ▶ 5-grams are extracted from first-pass lattices
- ▶ All observed n-grams are kept and backoff weight α is fixed for all orders:

$$S(s_i | s_{i-n+1}^{i-1}) = \begin{cases} \frac{\#(s_{i-n+1}^i)}{\#(s_{i-n+1}^{i-1})} & \text{if } \#(s_{i-n+1}^i) > 0 \\ \alpha S(s_i | s_{i-n+2}^{i-1}) & \text{otherwise} \end{cases}$$

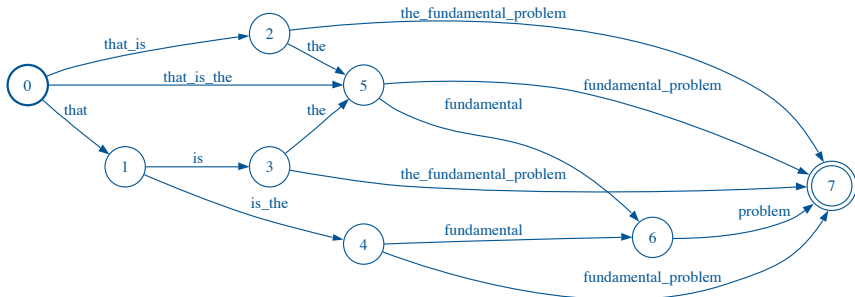
- ▶ equal weight interpolation with first-pass 4-gram LM
- ▶ exact search with OpenFST libraries in second-pass lattice rescoring

⁵T. Brants et al. 2007. Large Language Models in Machine Translation. EMNLP

Phrasal Segmentation Model Rescoring

Assign probability to sequences of English phrases

- ▶ phrases are translatable word sequences
- ▶ complement word-based N-grams



Source phrase segmentation transducer assigns 'bigram' probabilities:

$$P(u_1^K | s_1^I) = \prod_k P(u_k | u_{k-1}, s_1^K)$$

Model-1 Lattice-to-String Alignment Scores

IBM Model-1 is the simplest model of word alignment used in text alignment:

$$P_{M1}(t_1^J, a_1^J, J | s_1^J) = P_L(J | I) \frac{1}{J} \prod_{j=1}^J p_T(t_j | s_{a_j})$$

It is not powerful enough to guide translation, but is useful to rank competing translation hypotheses

- ▶ Finding the max. likelihood alignment is straightforward via dynamic programming
- ▶ For a fixed target sentence \mathbf{T} and a translation lattice L , we can simultaneously find the best alignment of every lattice path to the target string
- ▶ This is done with non-WFST based lattice-to-string alignment procedures to keep compact lattice representation intact

Minimum Bayes Risk Decoding⁶

Taking the goal as BLEU maximization

- ▶ A baseline translation model to give the probabilities over translations: $P(\mathbf{S}|\mathbf{T})$
- ▶ A set \mathcal{N} of N-Best Translations of T
- ▶ A Loss function $L(\mathbf{S}', \mathbf{S})$ that measures the the quality of \mathbf{S}' relative to \mathbf{S}

MBR Decoder

$$\hat{\mathbf{S}} = \operatorname{argmin}_{\mathbf{S}' \in \mathcal{N}} \sum_{\mathbf{S} \in \mathcal{N}} -\text{BLEU}(\mathbf{S}', \mathbf{S})P(\mathbf{S}'|\mathbf{T})$$

$\hat{\mathbf{S}}$ is sometimes called the ‘consensus hypothesis’

- ▶ picks from the middle of the similar, relatively likely translation hypotheses
- ▶ must be done over an N-Best list

Rationale is to balance estimation criteria (e.g. MLE) with translation criteria (e.g. BLEU)

⁶S. Kumar W. Byrne. 2004. Minimum Bayes-risk decoding for statistical machine translation. HLT-NAACL

Task Description

NIST 2008 Arabic-English MT task ⁷

- ▶ development set (*mt02-05-tune*): odd-numbered sentences of the NIST MT02 through MT05 evaluation sets
- ▶ validation set (*mt02-05-test*): even-numbered sentences of the NIST MT02 through MT05 evaluation sets
- ▶ test sets: MT06 (with newswire and newsgroup subsets) and MT08

TTM system trained on all available Arabic-English data for NIST MT08

- ▶ ~ 6M sentences, ~ 150M words
- ▶ word-aligned using MTTK

English Language Model data includes:

- ▶ first-pass 4-gram: parallel corpus + subset from English GigaWord Third Edition (~ 965M words)
- ▶ second-pass zero-cutoff 5-gram: ~ 4.7B words (newswire text)
- ▶ phrasal segmentation model: ~ 1.8B word subset of the above text

⁷nist.gov/speech/tests/mt/2006 nist.gov/speech/tests/mt/2008

Results (1)

MET and successive lattice rescoring steps

- ▶ Reordering model is MJ1 with orientation probabilities

Lowercase BLEU/TER scores over five test sets from 2002 through 2008:

Method	mt02-05-tune	mt02-05-test	mt06-nist-nw	mt06-nist-ng	mt08-nist
TTM+MET	50.9 / 42.8	50.3 / 43.3	48.1 / 44.3	37.5 / 53.5	43.1 / 49.5
+5g	53.5 / 41.8	52.4 / 42.4	49.6 / 43.9	39.0 / 54.0	43.7 / 49.3
+PSM	53.9 / 42.1	53.3 / 42.7	50.1 / 44.3	39.0 / 54.7	44.3 / 49.3
+MBR	54.0 / 41.7	53.7 / 42.2	51.0 / 43.9	39.4 / 54.1	45.0 / 48.9

- ▶ Important gains from lattice rescoring (improved fluency)
- ▶ Phrasal segmentation model complements 5-gram rescoring with further (yet smaller) gains
- ▶ Minimum Bayes Risk on the 1000-best list produces consistent gains
- ▶ Ranks among the group of top single-system entries in NIST 2008 official results

Results (2)

Impact of orientation probabilities in reordering model

- ▶ Comparison with vs without orientation probs. (flat β_1 distribution)

Lowercase BLEU/TER scores over development and validation sets:

Method	with orientation probs.		without orientation probs.	
	mt02-05-tune	mt02-05-test	mt02-05-tune	mt02-05-test
TTM+MET	50.9 / 42.8	50.3 / 43.3	50.4 / 43.3	50.0 / 43.8
+5g	53.5 / 41.8	52.4 / 42.4	53.0 / 42.2	52.2 / 42.8
+PSM	53.9 / 42.1	53.3 / 42.7	53.4 / 42.5	53.1 / 43.1

- ▶ Degradation of around 0.4 BLEU in MET results, sustained after rescoring
- ▶ More informed phrase reordering model produces better MET lattice
- ▶ Further improvements in reordering model expected to benefit even more from large rescoring

Results (3)

Impact of phrase pair count features included in MET

- ▶ Comparison with vs without phrase pair counts feats. (10 vs 7 MET parameters)

Lowercase BLEU/TER scores over development and validation sets:

Method	with phrase pair cnt.		without phrase pair cnt.	
	mt02-05-tune	mt02-05-test	mt02-05-tune	mt02-05-test
TTM+MET	50.9 / 42.8	50.3 / 43.3	48.9 / 43.8	48.6 / 44.1
+5g	53.5 / 41.8	52.4 / 42.4	51.5 / 42.2	51.5 / 42.7
+PSM	53.9 / 42.1	53.3 / 42.7	52.6 / 42.3	52.6 / 42.7

- ▶ Significant contribution of phrase pair count features
- ▶ Simple features produce a very useful phrase selection effect
- ▶ Better quality MET lattice \Rightarrow better quality after rescoring

Results (4)

Impact of Model-1 rescoring and order of rescoring steps

- ▶ Comparison of two different rescoring orders (without phrase pair counts feats.)

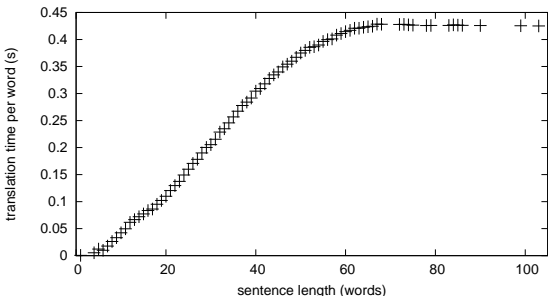
Lowercase BLEU/TER scores over development and validation sets:

Method	mt02-05-tune	mt02-05-test	Method	mt02-05-tune	mt02-05-test
TTM+MET	48.9 / 43.8	48.6 / 44.1	TTM+MET	48.9 / 43.8	48.6 / 44.1
+MOD1	50.5 / 42.5	50.4 / 43.0	+5g	51.5 / 42.2	51.5 / 42.7
+5g	52.2 / 41.6	52.1 / 42.3	+PSM	52.6 / 42.3	52.6 / 42.7
+PSM	52.9 / 41.9	52.6 / 42.6	+MOD1	53.0 / 41.8	52.6 / 42.5

- ▶ Model-1 is beneficial when directly rescoring MET lattice
 - ▶ No real improvement if applying it after 5-gram and phrasal segmentation
- ⇒ each of the rescoring techniques is a useful source of information
- ⇒ applying all techniques to the same MET lattice does not always provide gains
- ⇒ integration in MET prior to generating lattice would be helpful

Efficiency Considerations

- ▶ Efficiency/Parallelization via WFSTs with sentence-specific model parameters
- ▶ Memory requirements under $\sim 4\text{Gb}$ for most sentences
- ▶ Pruning for longest sentences (~ 100 words) prior to LM composition is required
 - ▶ rather than via standard cost-based pruning, via minimum number of phrases
 - ▶ affects around 2% of the sentences
- ▶ *mt02-05-tune* ($\sim 60\text{k}$ words) translated in 420 minutes (12s/sent on average, parallelizable)
- ▶ Translation time per word:



Conclusion and future work

Summary:

- ▶ CUED SMT system formulates translation as a series of transformations encoded in WFSTs
- ▶ Decodes using standard FST operations
- ▶ Able to efficiently handle very large quantities of data
- ▶ Good performance on 2008 NIST MT Arabic-English task
- ▶ Easy to apply to translation of ASR lattices

Future Work

- ▶ Integration of phrasal segmentation model and Model-1 into MET
- ▶ Focus on reordering model (current MJ1 model does not allow long-range reordering)

Thanks!
Questions and comments welcome.



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