Minimum Bayes-Risk Decoding for Statistical Machine Translation

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**Introduction**

- Statistical Machine Translation systems can be evaluated using a variety of metrics
  - Different aspects of translation quality: BLEU, NIST, WER, PER, ..
  - Application specific criteria: usefulness for IR, summarization etc
- Maximum Likelihood techniques are used in decision processes of most current Statistical MT systems
  - Do not explicitly take into account evaluation criteria
- **Minimum Bayes-Risk Decoding**
  - Automatic systems tuned for desired evaluation criteria
  - Formulation in Statistical Machine Translation
  - Will show performance gains by matching decoder to the evaluation criterion
Minimum Bayes-Risk (MBR) Decoding Framework

- Decision processes optimized for specific loss functions
  - Automatic Speech Recognition (Goel and Byrne CSL ’00)
  - Bitext Word Alignment (Kumar and Byrne EMNLP ’02)
- MBR decoding for two translation scenarios
  - Loss functions derived from evaluation metrics
  - Design of specialized loss functions to incorporate desired characteristics such as syntactic structure
Outline

- Hierarchy of Translation Loss functions with different levels of lexical and syntactic Information
- MBR decoding framework
- Experiments
- Conclusions and Future Work
Translation Loss Functions

For a sentence $F$ in the foreign language with parse-tree $T_F$

- Hypothesis Translation $E'$ with word alignment $A'$ and parse tree $T_{E'}$
- Reference Translation $E$ with word alignment $A$ and parse tree $T_E$
- Loss Function $L((E, A, T_E), (E', A', T_{E'}); F)$ measures quality of the hypothesis translation against the reference

Hierarchy of Loss functions

- Lexical Loss functions: $L(E, E')$
- Target Language Parse Tree Loss functions: $L(T_E, T_{E'})$
- Bilingual Parse Tree Loss functions: $L((T_E, A), (T_{E'}, A'); T_F)$
Competing English translations for a Chinese sentence

- \( E_1 \): the first two months of this year Guangdong’s high-tech products 3.76 billion US dollars
- \( A_1 \)
- \( F \): jin-nian qian liangyue guangdong gao xinjishu chanpin chukou sanqidianliuyi meiyuan
- \( A_2 \)
- \( E_2 \): the first two months of this year Guangdong exported high-tech products 3.76 billion US dollars

Reference translation

- \( E \): export of high-tech products in Guangdong in first two months this year reached 3.76 billion US dollars
- \( A \)
- \( F \): jin-nian qian liangyue guangdong gao xinjishu chanpin chukou sanqidianliuyi meiyuan
Lexical Loss Functions

- $L((E, A, T_E), (E', A', T_{E'}); F)$ simplifies to $L(E, E')$
- Loss function depends only on word strings
- Examples
  - Sentence-level BLEU score
    \[
    \text{BLEU}(E, E') = \exp \left( \sum_{n=1}^{N} \log \frac{p_n(E, E')}{N} \right) \ast \text{Brev. Penalty}(E, E')
    \]
    \[
    L_{\text{BLEU}}(E, E') = 1 - \text{BLEU}(E, E')
    \]
  - Word Error Rate (WER)
  - Position Independent Word Error Rate (PER)
    Minimum # of edit operations to transform $E$ into any permutation of $E'$
  - Other examples: NIST score, Precision-Recall Measure (Melamed 2003)
Target Language Parse-Tree Loss Functions

- Information from parse-trees of the two translations
- \( L((E, A, T_E), (E', A', T_{E'}); F) \) simplifies to \( L(T_E, T_{E'}) \)

- Examples
  - Tree-edit distance between parse trees
  - String-edit distance between event representation of parse trees
    (Tang, Luo and Roukos ’03)
  - Tree Kernel (Collins ’02)

- No experiments involving these loss functions in this talk

- Problem can be simplified if we have a third tree in the foreign language with node-to-node alignments relative to \( T_E \) and \( T_{E'} \)
Bilingual Parse-Tree Loss Functions

- Word alignments and parse-trees from English and foreign language strings
- \( L((E, A, T_E), (E', A', T_{E'}); F) \) simplifies to \( L((T_E, A), (T_{E'}, A'); T_F) \)

Example BiTree Loss Function

- Alignment of Parse-Trees
  - Use MT word alignments to obtain node-to-node alignments between nodes
    \( n \in T_F \) to nodes \( m \in T_E \) and \( m' \in T_{E'} \)
  - Subtree \( t_n \) (in \( T_F \)) mapped to \( t_m \) (in \( T_E \)) and \( t_{m'} \) (in \( T_{E'} \))
- Loss Computation between Aligned Parse-Trees
  - \( \bar{N}_F \) is the subset of nodes in \( T_F \) which have corresponding nodes in both \( T_E \) and \( T_{E'} \)
  - \( \text{BiTreeLoss}((T_E, A), (T_{E'}, A'); T_F) = \sum_{n \in \bar{N}_F} d(t_m, t_{m'}) \)
$T_F$ : Chinese Sentence

$T_1$ : English Hypothesis Translation 1
$T_F$ : Chinese Sentence

$T_2$ : English Hypothesis Translation 2
Comparison of Loss Functions

| Loss Functions            | \(L(E, E_1)\) | \(L(E, E_2)\) |
|---------------------------|---------------|---------------|
| BLEU (%)                  | 26.4          | 26.4          |
| WER (%)                   | 70.6          | 70.6          |
| PER (%)                   | 23.5          | 23.5          |
| BiTree Error Rate (%)     | 92.3          | 65.4          |

- BLEU, WER and PER are identical
- Parse-trees for the two translations differ substantially and BiTree Loss is quite different for the two translations
- Example of a loss function that can capture properties of translation that string based loss functions are unable to measure
Outline

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- Minimum Bayes-Risk decoding framework
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Decoding in Statistical MT as a classification problem

- Map a foreign sentence $F$ into its English translation $E'$ with word alignment $A'$
  $$\delta(F) = (E', A')$$

- Given the reference translation $(E, A)$, the Decoder Performance is measured by the Loss Function $L((E, A), \delta(F))$

- Goal: Find the decoder with the best performance over all translations

- Bayes-Risk: Expected Loss of a hypothesis under the true distribution
  $$P(E, A, F): \mathbb{E}_{P(E, A, F)}[L((E, A), \delta(F))]$$

- Decision Rule that minimizes Bayes-Risk is: MBR Decoder
  $$\delta(F) = \arg\min_{E', A'} \sum_{E, A} L((E, A), (E', A'); F)P(E, A|F)$$
MBR Decoders

- Consensus Translation: Select the hypothesis that is closest to other hypotheses
- MAP decoder is an MBR decoder under 0-1 loss function
- Implementation on an N-best List
  - N-Best List of Translations \((E_i, A_i)\) from a baseline system
  - True distribution \(P(E, A|F)\) is approximated using a baseline MT system (translation model and language model)
  - MBR Decision Rule via N-best Rescoring

\[
\hat{i} = \arg\min_{i \in \{1,2,\ldots,N\}} \sum_{j=1}^{N} L((E_j, A_j), (E_i, A_i))P(E_j, A_j|F) \\
\delta(F) = (E_{\hat{i}}, A_{\hat{i}})
\]
Baseline MT system from JHU Summer Workshop WS ’03 group on Syntax for Statistical Machine Translation

Test Set: 993 sentences from Eval01 + 878 sentences from Eval02

1000-best lists for each Chinese sentence

| Decoder               | BLEU (%) | mWER(%) | mPER (%) | mBiTree Error Rate(%) |
|-----------------------|----------|---------|----------|-----------------------|
| MAP(baseline)         | 31.2     | 64.9    | 41.3     | 69.0                  |
| MBR                   |          |         |          |                       |
| BLEU                  | 31.5     | 65.1    | 41.1     | 68.9                  |
| WER                   | 31.3     | 64.3    | 40.8     | 68.5                  |
| PER                   | 31.3     | 64.6    | 40.4     | 68.6                  |
| BiTree Loss           | 30.7     | 64.1    | 41.1     | 68.0                  |
Observations

- In most cases MBR decoder under a loss function performs best under the corresponding error metric.
- MAP decoder is not optimal in any of the cases.
- Performance under BLEU can be improved by using MBR relative to MAP.
- Affinity among loss functions.
- Useful to tune decoding procedures to the performance criterion of interest.
Conclusions

- MBR decoding: Build special purpose decoders from general purpose MT models.

- Applicability to two MT scenarios
  - Given an MT evaluation metric (e.g. BLEU), MBR decoding can improve well trained statistical MT models by tuning translation to the particular evaluation metric
  - Suppose we have desiderata e.g. syntactic well-formedness to incorporate in the baseline MT system
    - Design a loss function to incorporate the desired criterion
    - Use MBR decoding to optimize performance under this loss function
    - Bitree loss function is an example of this type of loss function - we have not yet measured any correlations with human judgements
MT evaluation is active area of research.

- MBR decoding can be used to optimize existing MT systems for new metrics
- Compensate mismatch between decoding criterion of MT systems and their evaluation criterion

Loss functions can also incorporate task-based error criteria
e.g. precision/recall for IR

Extension of search space of MBR decoders to translation lattices.
Thank you!