Non-linear n-best list reranking with few features

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Talk Plan

1. **Motivation**
2. **Non-linear score functions**
3. **Features**
4. **Experiments**
5. **Conclusion & Future Work**

Performance discrepancy in SMT

In SMT we are:

1. using linear scoring (max-entropy) $p(\mathbf{e}|\mathbf{f}) \propto e^{\bar{\lambda}\cdot\bar{g}(\mathbf{e},\mathbf{f})}$
2. MAP inference $e^* = \arg\max_{\mathbf{e}} \bar{\lambda} \cdot \bar{g}(\mathbf{e}, \mathbf{f})$
3. happy with **0.5-1** BLEU increase...

... until we search for oracle e (knowing reference):

measure	found by decoder	lattice oracles
BLEU (fr2en)	~ 28	~ 50
BLEU (de2en)	~ 22	~ 38
BLEU (en2de)	~ 16	~ 30

potentially **two-fold** improvement

Performance discrepancy in SMT

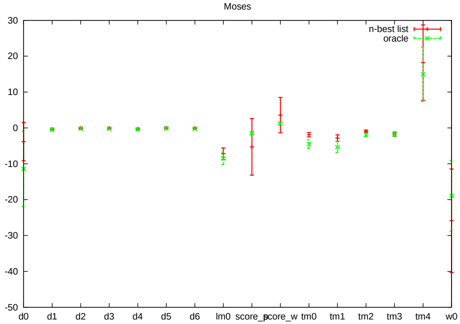
1. search spaces contain excellent oracles:
   - ∼80 BLEU, unrestricted [Wisniewski 10]
   - ∼50 BLEU, restricted to lattices [Sokolov 12]
2. oracles not reachable even with advanced learning:
   - lattice MERT [Macherey 08, Kumar 09, Sokolov 11b]
   - exact MERT [Galley 11]
   - MIRA [Chiang 08]
   - tuning as ranking [Hopkins 11]
3. **is scoring function main bottleneck?**
   - poor and few features?
   - wrong models? ←**this presentation**

Motivation question

Can conventional SMT systems benefit from non-linear scoring?

Why aren't linear functions sufficient?

1. convenient, but too simple
   - linear combination of 15-20 loosely related features
   - non-trivial measures' approximation
2. **theory:** motivated by max-entropy principle
   - maximize entropy + known means of observables ⇔
   - ⇔ optimize likelihood + log-linear prob. distribution
3. **practice:** we optimize BLEU, not likelihood
4. features means not saved:



Related work

Ranking in SMT

- tuning as ranking (PRO) [Hopkins 11]
- sampling (SampleRank) [Haddow 11]

Boosting for better scoring functions

- attractive learning algorithm
- applied several times for SMT
- all attempts used boosting for classification (like AdaBoost)
    - whole MERT procedure as a weak learner [Duh 08, Xiao 10]
    - reweighting a separate feature in the log-linear model [Lagarda 08]

Non-linear scoring

N-best lists vs. Lattice

- dynamic programming doesn't work in non-linear case
- cannot discard hypotheses early based on the partial score
  - partially fixable with monotone functions
- $\Rightarrow$ **use n-best lists**

Which function family to use?

- $\bar{g}(\mathbf{e}, \mathbf{f})$ – feature vector
- α_t – coefficients
- h_t – 'simple' non-linear functions
- **total score**:

$$H(\bar{g}(\mathbf{e}, \mathbf{f})) = \sum_{t=1}^{T} \alpha_t \cdot h_t(\bar{g}(\mathbf{e}, \mathbf{f}))$$

Tuning with Ranking

Why ranking?

- hypotheses naturally ordered under sentence-level BLEU
- deduce parameters comparing even mediocre or bad hypothesis
- earlier ranking approaches redefined losses, not scoring functions

Pair-Wise Loss

$$\mathcal{L}(H) = \sum_{\mathbf{f}} \sum_{\substack{\mathbf{e}_i, \mathbf{e}_j \in n\text{-best}(\mathbf{f}) \\ b(\mathbf{e}_i, \mathbf{r}_\mathbf{f}) < b(\mathbf{e}_j, \mathbf{r}_\mathbf{f})}} D(i,j) [\![H(\bar{g}(\mathbf{e}_i, \mathbf{f})) \geq H(\bar{g}(\mathbf{e}_j, \mathbf{f}))]\!]$$

- $b(\mathbf{e}, \mathbf{r})$ – sentence level BLEU wrt. $\mathbf{r}$
- $[\![A]\!] = 1$ if the $A =$ true and 0 otherwise
- the higher is $D(i,j)$, the more important is pair $(\mathbf{e}_i, \mathbf{e}_j)$

RankBoost

Given $(\bar{g}_1, y_1), \ldots, (\bar{g}_m, y_m) : g_i \in \mathcal{G}, y_i \in \mathcal{Y}$

Algorithm

- Initialize D on $\mathcal{G} \times \mathcal{G}$, to reflect "importance" of pairs.
- For $t = 1, \ldots, T$:
  - Find weak learner $h_t : \mathcal{G} \rightarrow \mathbb{R}$ using D_t ←chosen to minimize Z_t
  - Choose $\alpha_t \in \mathbb{R}$ ←chosen to minimize Z_t
  - Update

$$D_{t+1}(\bar{g}_0, \bar{g}_1) = \frac{D_t(\bar{g}_0, \bar{g}_1) exp(\alpha_t(h_t(\bar{g}_0) - h_t(\bar{g}_1))}{Z_t},$$

  where Z_t is chosen to make D_t a distribution.
- Output the final ranking: $\boxed{H(\bar{g}) = \sum_{t=1}^{T} \alpha_t h_t(\bar{g})}$.

Ranking loss

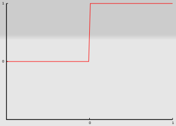
$$\mathcal{L}(H) \leq \prod_{t=1}^{T} Z_t.$$

Weak Functions

One-dimensional learners

- decision stumps
  - simplest nonlinear
  - approximates complex curves

$$h(\bar{g}(\mathbf{e},\mathbf{f});\theta,k) = [\![g_k > \theta]\!]$$

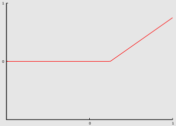


- linear weak learners to discriminate:
  - learning with ranking
  - non-linearity

$$h(\bar{g}(\mathbf{e},\mathbf{f});k) = g_k$$

- piece-wise linear learners:
  - non-linear, but captures linear dependencies easily
  - important, as beam-search pruning is linear

$$h(\bar{g}(\mathbf{e},\mathbf{f});\theta,k) = g_k \cdot [\![g_k > \theta]\!]$$



Decoder configurations

N-code decoder configurations:

- N-code decoder (based on biling. n-grams)
- **basic: 11** features (found in any decoder), **100**-best
  - language model
  - distortion + 2 reordering models,
  - translation model + 4 lexical translation weights
  - 2 penalties for words and phrases
- **extended: 23** features (WMT'12 best system for fr↔en), **300**-best
  1. +2 translation models, +2 lexicalized reordering models
  2. reoptimize with MERT (15 features)
  3. add neural-network models' features:
     - +1 linear score (over 15 features)
     - +4 neural-network language models [Le 11]
     - +4 neural-network translation models [Le 12]

Feature Transformations

```
0 qid:0
1:  -108.63
2:  -108.09
3:  -116.04
4:  -118.12
...
# at the end of trading , the Prague bascula award in the negative
```

	configuration	feature sets	#features
linear	basic		11
	extended		23
non-linear	basic	scale	32
		scale & rank	44
	extended	scale	68
		scale & rank	92

Feature Transformations

```
0 qid:0
1:  -108.63 1N:-8.59 1P:-8.59
2:  -108.09 2N:-8.33 2P:-8.33
3:  -116.04 3N:-8.57 3P:-8.57
4:  -118.12 4N:-9.17 4P:-9.17
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Normalization

- prob. features incomparable for different sentence lengths (e.g., LM score)
- divide by number of words (N) /phrases (P)

Feature Transformations

```
0 qid:0
1:  -108.63 1N:-8.59 1P:-8.59 1S:0.17 1NS:0.07 1PS:0.29
2:  -108.09 2N:-8.33 2P:-8.33 2S:0.60 2NS:0.08 2PS:0.33
3:  -116.04 3N:-8.57 3P:-8.57 3S:0.82 3NS:0.17 3PS:0.37
4:  -118.12 4N:-9.17 4P:-9.17 4S:0.29 4NS:0.15 4PS:0.31
...
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- divide by number of words (N) /phrases (P)

Scale-features

- regularize range among different phrases
- rescale to $[0;1]$ (S)

Feature Transformations

```
0 qid:0
1:  -108.63 1N:-8.59 1P:-8.59 1S:0.17 1NS:0.07 1PS:0.29 1R:1
2:  -108.09 2N:-8.33 2P:-8.33 2S:0.60 2NS:0.08 2PS:0.33 2R:68
3:  -116.04 3N:-8.57 3P:-8.57 3S:0.82 3NS:0.17 3PS:0.37 3R:98
4:  -118.12 4N:-9.17 4P:-9.17 4S:0.29 4NS:0.15 4PS:0.31 4R:11
...
# at the end of trading , the Prague bascula award in the negative
```

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Scale-features

- regularize range among different phrases
- rescale to $[0;1]$ (S)

Rank-features

- sort according to feature
- take its rank (R)

used S, NS, PS & R features – the rest discarded

Datasets

- dev-set for MERT: WMT'09
- dev-set for RankBoost: WMT'09
  - training labels: sentence level BLEU
- test-sets:
  - WMT'10
  - WMT'11
  - WMT'12

MERT setup

- MERT is unstable ⇒ 8 independent (re)runs, each with:
  - 20 init. points restarts
  - 30 random direction (additional to axes)

Learning reranking

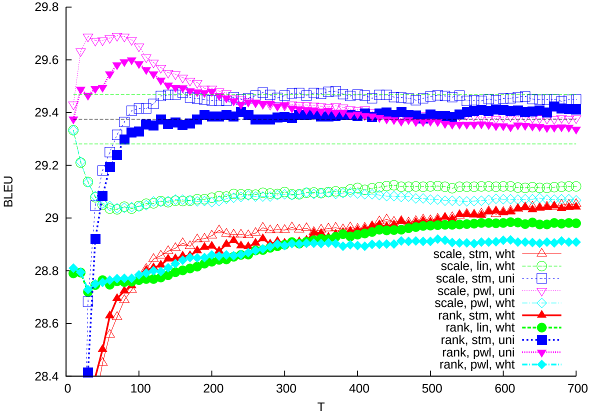
Process

- run full MERT
- take last iteration's n-best list
- transform features
- sample:
  - 2000 pairs
  - discard those less than 0.05 BLEU apart
- train RankBoost for some T

Tested variants

- 2 weighting schemes:
  - uniform $D(i,j) = 1$
  - difference $D(i,j) = BLEU(\mathbf{e}_i, \mathbf{r}) - BLEU(\mathbf{e}_j, \mathbf{r})$
- 3 weak learners:
  - stumps
  - linear
  - piece-wise linear

Weak learner selection



Weak learners, weighting schemes and features sets on WMT'10.
Weighting: uniform (`uni`), weighted with sentence-BLEU (`wht`).
Learners: stumps (`stm`/`stm`), linear (`lin`), piece-wise linear (`pwl`/`pwl`).
Features sets: scale- and **scale-+rank-**.

piece-wise linear + uniform weighting performs the best

Weak learner analysis

- piece-wise linear functions include linear as subclass
- possible that RankBoost still uses linear models

Selection phases of models/features

1. $T \lesssim 10$: `score` feature is selected (reusing MERT linear model)
2. $10 \lesssim T \lesssim 50$: more features, still linear model (but better BLEU)
3. $50 \lesssim T$: piece-wise linear models start to appear (improving BLEU)
4. $T \gtrsim M$: over-fitting

Per dataset performance peak analysis

- WMT'10 – "ranking" (2) phase
- WMT'11 – "linear" (1) or "non-linear" (3) phases
- WMT'12 – "non-linear" (3) phase

Maximum relative gains

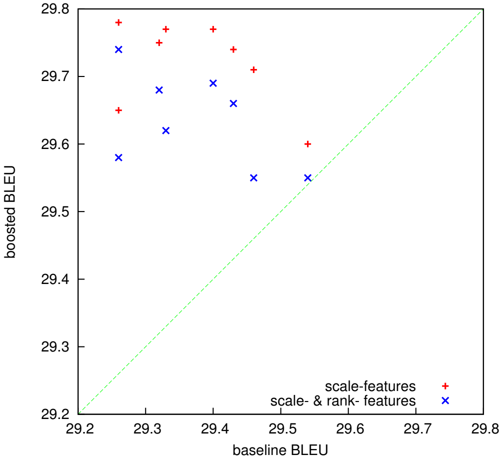
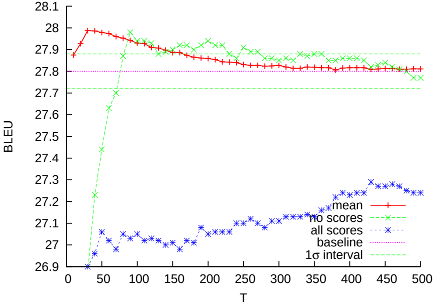
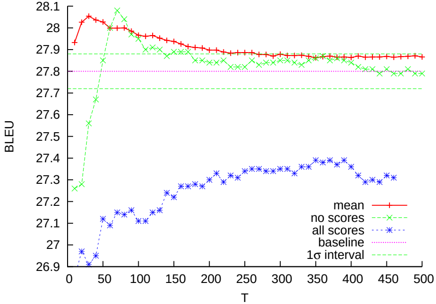


Figure: Maximum relative gains in BLEU on WMT'10.

WMT'10 Basic

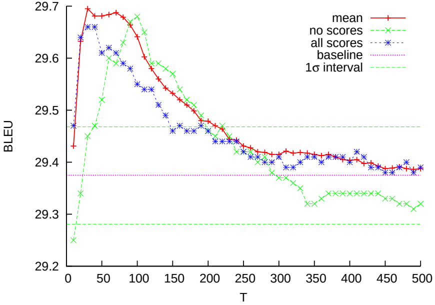


(a) Basic conf., WMT'10, scale-features

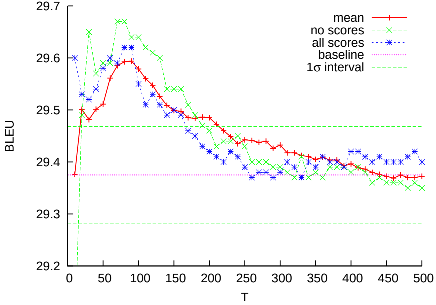


(b) Basic conf., WMT'10, scale- & rank-features

WMT'10 Extended

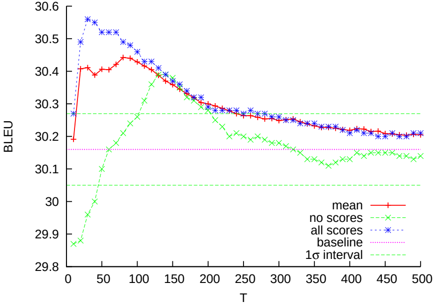


(c) Ext. conf., WMT'10, scale-features

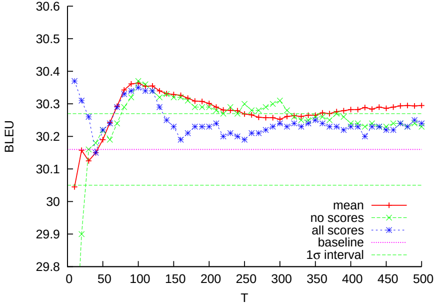


(d) Ext. conf., WMT'10, scale- & rank-features

WMT'11 Extended

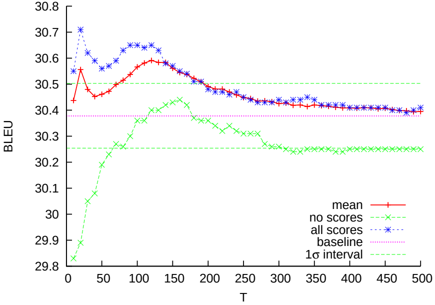


(e) Ext. conf., WMT'11, scale-features

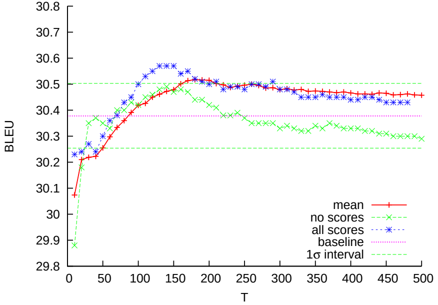


(f) Ext. conf., WMT'11, scale- & rank-features

WMT'12 Extended

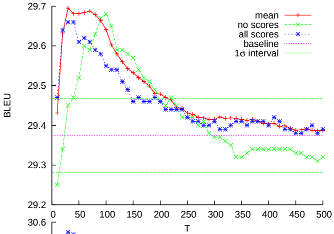


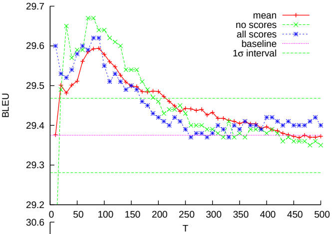
(g) Ext. conf., WMT'12, scale-features



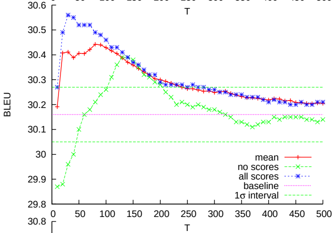
(h) Ext. conf., WMT'12, scale- & rank-features

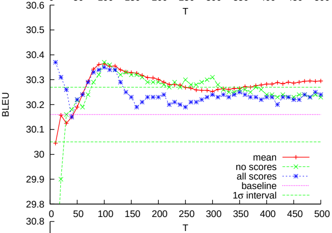
WMT'10



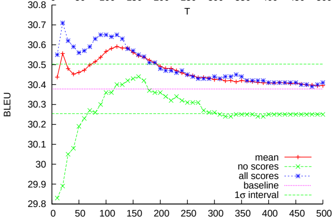


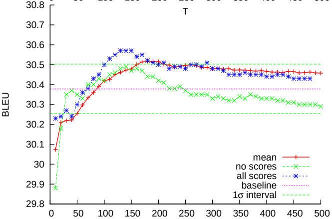
WMT'11





WMT'12





Cross-results

test \ valid		WMT'10	WMT'11	WMT'12	MERT mean	MERT interval	300-best oracle
WMT'10	mean	-	29.68±0.07	29.58±0.09	29.38±0.09	[29.26,29.54]	39.72
	all scores	-	29.66	29.55			
	no scores	-	29.58	29.54			
WMT'11	mean	30.42±0.07	-	30.41±0.05	30.16±0.11	[29.97,30.34]	41.11
	all scores	30.55	-	30.46			
	no scores	30.26	-	30.35			
WMT'12	mean	30.50±0.08	30.52±0.06	-	30.38±0.12	[30.19,30.62]	40.64
	all scores	30.59	30.62	-			
	no scores	30.36	30.42	-			

Conclusion

Conclusion

- non-linear approach to reranking n-best lists
- approach potentially boosts performance by **+0.4** BLEU-points
- heterogenous validation/test corpora lessen gains
- stable gains on homogeneous corpora

Gains obtained attributable to:

- appropriateness of the ranking loss
- flexibility of non-linear modeling

Future Work

Learning non-linear functions on lattices

- MERT on n-best lists is ∼optimal [Duh 08, Galley 11]
- n-best lists rescoring was
  - proof-of-concept to avoid tight decoder integration
  - limited, as influence pruning and scoring partial hyps
  - restricted to forms like $h_t(\sum_i g_k)$ ⇒ triggers feature design problems
- lattice non-linear learning
  - boosting = functional gradient descend
  - large-margin framework
  - can derive non-linear functions in forms $\sum_i h_t(g_k)$ (less normalizing/scaling problems)