# **Optimized Online Rank Learning for Machine Translation**

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#### **Tuning for MT**

$$\hat{e} = \underset{e}{\operatorname{arg max}} p(e|f;\theta)$$

$$= \underset{e}{\operatorname{arg max}} \mathbf{w}^{\top} \mathbf{h}(f,e)$$

• MERT(Minimum Error Rate Training) by Och (2003)

$$\hat{\mathbf{w}} = \operatorname*{arg\,min}_{\mathbf{w}} \ell(\left\{\operatorname*{arg\,max}_{e} \mathbf{w}^{\top} \mathbf{h}(f^{i}, e)\right\}_{i=1}^{N}, \left\{\mathbf{e}^{i}\right\}_{i=1}^{N})$$

 PRO(Pair-wise Rank Optimization) by Hopkins and May (2010)

$$\underset{\mathbf{w}}{\operatorname{arg\,min}} \frac{\lambda}{2} \|\mathbf{w}\|_{2}^{2} + \ell(\mathbf{w}; D)$$

with hinge-loss:

$$\frac{1}{M(\mathbf{w}; D)} \sum_{\substack{(f, \mathbf{e}) \in D \\ e^*, e'}} \max \left\{ 0, 1 - \mathbf{w}^{\top} \Phi(f, e^*, e') \right\}$$

$$e' \in \text{NBEST}(\mathbf{w}; f) \setminus \text{ORACLE}(\mathbf{w}; f, \mathbf{e})$$

$$e^* \in \text{ORACLE}(\mathbf{w}; f, \mathbf{e})$$

$$\Phi(f, e^*, e') = \mathbf{h}(f, e^*) - \mathbf{h}(f, e').$$

• Batch algorithm: an iterative k-best merging approximation

# **Online Learning (SGD)**

1: 
$$k = 1, \mathbf{w}_1 \leftarrow \mathbf{0}$$
2: **for**  $t = 1, ..., T$  **do**
3: Choose  $B_t = \{b_1^t, ..., b_K^t\}$  from  $D$ 
4: **for**  $b \in B_t$  **do**
5: Compute  $n$ -bests and oracles of  $b$ 
6: Set learning rate  $\eta_k$ 
7:  $\mathbf{w}_{k+\frac{1}{2}} \leftarrow \mathbf{w}_k - \eta_k \nabla(\mathbf{w}_k; b)$ 
8:  $\mathbf{w}_{k+1} \leftarrow \min\left\{1, \frac{1/\sqrt{\lambda}}{\|\mathbf{w}_{k+\frac{1}{2}}\|_2}\right\} \mathbf{w}_{k+\frac{1}{2}}$ 
9:  $k \leftarrow k + 1$ 
10: **end for**
11: **end for**
12: **return**  $\mathbf{w}_k$ 

- Online approximation to the learning objective
- Optimization for sentence-BLEU ≠corpus BLEU!
- Larger sentence-batch for better corpus-BLEU approximation → slower convergence

### **Optimized Online Learning**

• First, suffer gradients from L2-regularizer

$$\mathbf{w}_{k+\frac{1}{4}} \leftarrow (1 - \lambda \eta_k) \mathbf{w}_k$$

• Second, solve:

$$\underset{\mathbf{w}}{\operatorname{arg\,min}} \frac{1}{2} \|\mathbf{w} - \mathbf{w}_{k+\frac{1}{4}}\|_{2}^{2} + \eta_{k} \sum_{(f,\mathbf{e}) \in b, e^{*}, e'} \xi_{f,e^{*},e'}$$
$$\mathbf{w}^{\top} \Phi(f, e^{*}, e') \geq 1 - \xi_{f,e^{*},e'}$$
$$\xi_{f,e^{*},e'} \geq 0.$$

• Third, Lagrangian dual:

$$\underset{\tau_{e^*,e'}}{\operatorname{arg\,min}} \frac{1}{2} \| \sum_{(f,\mathbf{e}) \in b, e^*, e'} \tau_{e^*,e'} \Phi(f, e^*, e') \|_{2}^{2}$$
$$- \sum_{(f,\mathbf{e}) \in b, e^*, e'} \tau_{e^*,e'} \left\{ 1 - \mathbf{w}_{k+\frac{1}{4}}^{\top} \Phi(f, e^*, e') \right\}$$

· Finally:

$$\mathbf{w}_{k+\frac{1}{2}} \leftarrow \mathbf{w}_{k+\frac{1}{4}} + \sum_{(f,\mathbf{e})\in b,e^*,e'} \tau_{e^*,e'} \Phi(f,e^*,e')$$

- Note:
  - Update by SGD

$$\mathbf{w}_{k+\frac{1}{2}} \leftarrow \mathbf{w}_{k+\frac{1}{4}} + \sum_{\substack{(f,\mathbf{e}) \in b, e^*, e'}} \frac{\eta_k}{M(\mathbf{w}_k; b)} \Phi(f, e^*, e')$$

• MIRA solve this:

$$\underset{\mathbf{w}}{\operatorname{arg\,min}} \frac{\lambda}{2} \|\mathbf{w} - \mathbf{w}_k\|_2^2 + \sum_{(f, \mathbf{e}) \in b, e^*, e'} \xi_{f, e^*, e'}$$

## **Optimized Parallel Learning**

1: 
$$\mathbf{w}^1 \leftarrow \mathbf{0}$$
  
2:  $\mathbf{for} \ t = 1, ..., T \ \mathbf{do}$   
3:  $\mathbf{w}^{t,s} \leftarrow \mathbf{w}^t$   
4: Each shard learns  $\mathbf{w}^{t+1,s}$  using  $D_s$   
5:  $\mathbf{w}^{t+\frac{1}{2}} \leftarrow 1/S \sum_s \mathbf{w}^{t+1,s}$   
6:  $\mathbf{w}^{t+1} \leftarrow (1-\rho)\mathbf{w}^t + \rho \mathbf{w}^{t+\frac{1}{2}}$   
7: end for  
8: return  $\mathbf{w}^{T+1}$ 

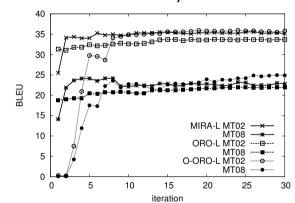
- Each shard learns locally + averaging in each round
- Line search to determine the optimal mixing  $\rho$

### **Experiments**

- NIST08 Chinese-to-English translation task
- MT02/MT06/MT08 for tuning/development testing/test
- SCFG / # of features = 14 / batch size = 16 / cores = 8
- MERT/PRO/MIRA and Online Rank Optimization(ORO) with hinge-loss/softmax-loss (1,000-best, 30-iterations)

	MT06	MT08
MERT	31.45†	24.13†
PRO	31.76†	$24.43^{\dagger}$
MIRA-L	31.42†	$24.15\dagger$
ORO-L <sub>hinge</sub>	29.76	21.96
$O$ - $ORO$ - $L_{\rm hinge}$	32.06	24.95
ORO-L <sub>softmax</sub>	30.77	23.07
$O$ - $ORO$ - $L_{softmax}$	31.16†	23.20

#### Main results by BLEU



#### Learning curve

	MT06	MT08
MIRA	30.95	23.06
MIRA-L	31.42†	$24.15\dagger$
$\overline{\mathrm{ORO}_{\mathrm{hinge}}}$	29.09	21.93
$ORO$ - $L_{hinge}$	29.76	21.96
ORO <sub>softmax</sub>	30.80	23.06
$ORO-L_{softmax}$	30.77	23.07
O-ORO <sub>hinge</sub>	31.15†	23.20
$O$ - $ORO$ - $L_{hinge}$	32.06	24.95
O-ORO <sub>softmax</sub>	31.40†	23.93†
O-ORO- $L$ <sub>softmax</sub>	31.16†	23.20

Mixing by line search