Fast and Adaptive Online Training of Feature-Rich Translation Models

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ACL 2013

Feature-Rich Research	**Industry/Evaluations**
Liang et al. 2006	
Tillmann and Zhang 2006	
Arun and Koehn 2007	
Ittycheriah and Roukos 2007	
Watanabe et al. 2007	
Chiang et al. 2008; Chiang et al. 2009	*n*-best/lattice MERT
Haddow et al. 2011	
Hopkins and May 2011	MIRA (ISI)
Xiang and Ittycheriah 2011	
Cherry and Foster 2012	
Chiang 2012	
Gimpel 2012	
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Watanabe 2012	

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Feature-rich Shared Task Submissions

		# Feature-rich
2012	WMT	0
	IWSLT	1
2013	WMT	2 ?
	IWSLT	TBD

Speculation: Entrenchment Of MERT

Feature-rich on small tuning sets?

Implementation complexity

Open source availability

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Open source availability

Top-selling phone of 2003

Motivation: Why Feature-Rich MT?

Make MT more like other machine learning settings

Features for specific errors

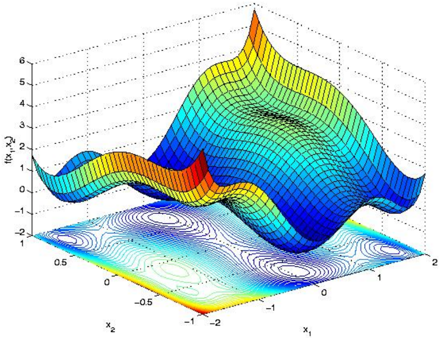
Domain adaptation

Motivation: Why Online MT Tuning?

Search: decode more often

Better solutions
   See: [Liang and Klein 2009]

Computer-aided translation:
incremental updating



Benefits Of Our Method

Fast and scalable

Adapts to dense/sparse feature mix

Not complicated

Online Algorithm Overview

Updating with an adaptive learning rate

Automatic feature selection via L_1 regularization

Loss function: Pairwise ranking

Notation

t time/update step

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t	time/update step
w_t	weight vector in $\mathbb{R}^n$

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$r(w)$	regularization function

Warm-up: Stochastic Gradient Descent

Per-instance update:

$$w_t = w_{t-1} - \eta z_{t-1}$$

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Issue #1: learning rate schedule

η / t ?

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$\eta \,/\, t$?

$\eta \,/\, \sqrt{t}$?

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$\eta \,/\, t$?

$\eta \,/\, \sqrt{t}$?

$\eta \,/\, (1 + \gamma t)$? Yuck.

Warm-up: Stochastic Gradient Descent

SGD update:

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Issue #2: same step size for every coordinate

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Issue #2: same step size for every coordinate

Intuitively, we might want:

- Frequent feature: small steps e.g. $\eta \,/\, t$
- Rare feature: large steps e.g. $\eta \,/\, \sqrt{t}$

SGD: Learning Rate Adaptation

SGD update:

$$w_t = w_{t-1} - \eta z_{t-1}$$

Scale learning rate with $A^{-1} \in \mathbb{R}^{n \times n}$:

$$w_t = w_{t-1} - \eta A^{-1} z_{t-1}$$

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Choices:

$A^{-1} = I$ (SGD)

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Choices:

$A^{-1} = I$ (SGD)

$A^{-1} = H^{-1}$ (Batch: Newton step)

AdaGrad

Duchi et al. 2011

Update:

$$w_t = w_{t-1} - \eta A^{-1} z_{t-1}$$

Set $A^{-1} = G_t^{-1/2}$:

$$G_t = G_{t-1} + z_{t-1} \cdot z_{t-1}^{\top}$$

AdaGrad: Approximations and Intuition

For high-dimensional w_t, use diagonal G_t

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$$w_t = w_{t-1} - \eta G_t^{-1/2} z_{t-1}$$

Intuition:

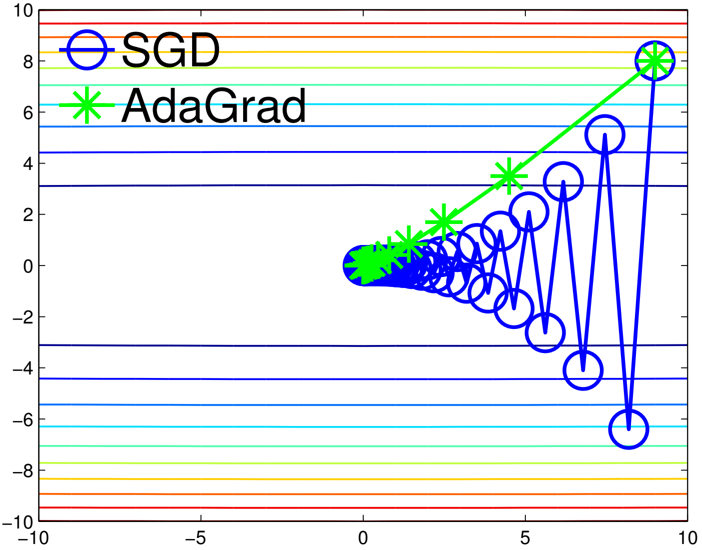
$1/\sqrt{t}$ schedule on constant gradient

Small steps for frequent features

Big steps for rare features

[Duchi et al. 2011]

AdaGrad vs. SGD: 2D Illustration



Feature Selection

Traditional approach: frequency cutoffs

Unattractive for large tuning sets (e.g. bitext)

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More principled: L_1 regularization

$$r(w) = \sum_i |w_i|$$

Feature Selection: FOBOS

Two-step update:

$$w_{t-\frac{1}{2}} = w_{t-1} - \eta z_{t-1} \tag{1}$$

$$w_t = \arg\min_w \left(\underbrace{\frac{1}{2}\left\| w - w_{t-\frac{1}{2}} \right\|^2}_{\text{proximal term}} + \underbrace{\lambda \cdot r(w)}_{\text{regularization}} \right) \tag{2}$$

[Duchi and Singer 2009]

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[Duchi and Singer 2009]

Extension: AdaGrad update in step (1)

Feature Selection: FOBOS

For L_1, FOBOS becomes soft thresholding:

$$w_t = \text{sign}(w_{t-\frac{1}{2}}) \left[\left| w_{t-\frac{1}{2}} \right| - \lambda \right]_+$$

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$$w_t = \text{sign}(w_{t-\frac{1}{2}})\left[\,\left|w_{t-\frac{1}{2}}\right| - \lambda\,\right]_+$$

Squared-L_2 also has a simple form

Feature Selection: Lazy Regularization

Lazy updating: only update active coordinates

Big speedup in MT setting

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Easy with FOBOS:

t'_j : last update of dimension j

Use $\lambda(t - t'_j)$

AdaGrad+FOBOS: Full Algorithm

1. Additive update: G_t

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1. Additive update: G_t
2. Additive update: $w_{t-\frac{1}{2}}$
3. Closed-form regularization: w_t

Not complicated

Very fast

Recap: Pairwise Ranking

For derivation d, feature map $\phi(d)$, references $e^{1:k}$

Metric: $B(d, e^{1:k})$ (e.g. BLEU+1)

Model score: $M(d) = w \cdot \phi(d)$

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Model score: $M(d) = w \cdot \phi(d)$

Pairwise consistency:

$$M(d_+) > M(d_-) \iff B\left(d_+, e^{1:k}\right) > B\left(d_-, e^{1:k}\right)$$

[Hopkins and May 2011]

Loss Function: Pairwise Ranking

$$M(d_+) > M(d_-) \iff w \cdot (\phi(d_+) - \phi(d_-)) > 0$$

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Loss formulation:

Difference vector: $v = \phi(d_+) - \phi(d_-)$

Find w so that $w \cdot v > 0$

Binary classification problem between v and $-v$

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Binary classification problem between v and $-v$

Logistic loss: convex, differentiable

[Hopkins and May 2011]

Parallelization

Online algorithms are inherently sequential

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Out-of-order updating:

$$w_7 = w_6 - \eta z_4$$
$$w_8 = w_7 - \eta z_6$$
$$w_9 = w_8 - \eta z_5$$

Parallelization

Online algorithms are inherently sequential

Out-of-order updating:

$$
\begin{aligned}
w_7 &= w_6 - \eta z_4 \\
w_8 &= w_7 - \eta z_6 \\
w_9 &= w_8 - \eta z_5
\end{aligned}
$$

Low-latency regret bound: $O(\sqrt{T})$ [Langford et al. 2009]

Translation Quality Experiments

Arabic-English (Ar–En) and Chinese-English (Zh–En)

Newswire and mixed-genre experiments

BOLT bitexts: data up to 2012

	Bilingual		Monolingual
	Sentences	*Tokens*	*Tokens*
Ar–En	6.6M	375M	990M
Zh–En	9.3M	538M	

MT System

Phrase-based MT: Phrasal

[Cer et al. 2010]

Dense baseline: MERT

Cer et al. 2008 line search

Accumulates *n*-best lists

Random starting points, etc.

Feature-Rich Baseline: PRO

Pairwise Ranking Optimization (PRO)

- Batch log loss minimization

Phrasal implementation:

- L-BFGS with L_2 regularization

[Hopkins and May 2011]

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[Hopkins and May 2011]

Sanity check: Moses PRO and kb-MIRA (batch) implementations

Dense Features

8	Hierarchical lex. reordering

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5	Moses phrase table features
1	Rule bitext count
1	Unique rule indicator

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5	Moses phrase table features
1	Rule bitext count
1	Unique rule indicator
1	Word penalty
1	Linear distortion
1	LM
1	Unknown word
19	

Sparse Feature Templates

Discriminative Phrase Table (PT)

Rule indicator: $\mathbb{1}\left(\text{برنامج الفضاء} \Rightarrow \text{space program}\right)$

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Discriminative Alignments (AL)

Source word deletion: $\mathbb{1}\left(\text{الفضاء} \Rightarrow\right)$

Word alignments: $\mathbb{1}\left(\text{الفضاء} \Rightarrow \text{space}\right)$

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Source word deletion: $\mathbb{1}\left(\text{الفضاء} \Rightarrow\right)$

Word alignments: $\mathbb{1}\left(\text{الفضاء} \Rightarrow \text{space}\right)$

Discriminative Lex. Reordering (LO)

Phrase orientation: $\mathbb{1}\left(\text{swap}(\text{الفضاء} \Rightarrow \text{space})\right)$

Evaluation: NIST OpenMT

Small tuning set: MT06

“Large” tuning set: MT0568 (≈4200 segments)

BLEU-4 uncased, Four references

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Small tuning set: MT06

“Large” tuning set: MT0568 (≈4200 segments)

BLEU-4 uncased, Four references

Paper: mixed genre (bitext) experiments

Results: Small Tuning Set (Dense)

	Ar–En		Zh–En	
	Tune	**Test Avg.**	Tune	**Test Avg.**
MERT	45.08	50.51	33.73	34.49
This paper	43.16	50.11	32.20	35.25

Results: Add More Features

	Ar–En		Zh–En	
	Tune	**Test Avg.**	Tune	**Test Avg.**
MERT—Dense	45.08	50.51	33.73	34.49
This paper +PT	50.61	50.52	34.92	35.12

Results: Add More Features

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	Tune	**Test Avg.**	Tune	**Test Avg.**
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This paper +PT	50.61	50.52	34.92	35.12
This paper +All	60.85	50.97	39.43	35.31

(MT06 tuning set)

Results: Add More Data

	Ar–En	Zh–En
	Test Avg.	**Test Avg.**
MERT—mt06	50.51	34.49
MERT—mt0568	50.74	34.55

Results: Add More Data

	Ar–En	Zh–En
	Test Avg.	**Test Avg.**
MERT—mt06	50.51	34.49
MERT—mt0568	50.74	34.55
This paper		
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	Test Avg.		**Test Avg.**	
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+All—mt06	50.97		35.31	
+All—mt0568	**52.34**	+1.60	**36.61**	+2.06

Results: Add More Data

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+All—mt0568	**52.34**	+1.60	**36.61**	+2.06

PRO+All worse than MERT—mt0568

Analysis: Zh–En MT06 Tuning

(16 threads)		Epochs	Min/epoch
MERT	Dense	22	180

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This paper	+PT	10	10

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This paper	+PT	10	10
PRO	+All	13	100
This paper	+All	5	15

Analysis: Zh–En MT06 Tuning

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MERT—mt0568 tuning takes about 5 days

Analysis: Runtime

Online regret bounds depend on # updates

- Large datasets: more updates per epoch
- Fewer epochs to converge

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Online regret bounds depend on # updates

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Lazy updating helps:

- $w_t \approx 100k$ features
- $z_{t-1} \approx 500$ features

Analysis: Reordering

Arabic matrix clauses often verb-initial

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Arabic matrix clauses often verb-initial

Manually selected 208 verb-initial segments (MT09)

Analysis: Reordering

Arabic matrix clauses often verb-initial

Manually selected 208 verb-initial segments (MT09)

32 differed for MERT–Dense vs. +All

Analysis: Reordering

+All correct	18	56.3%
MERT–Dense correct	4	12.5%
Both wrong	10	31.3%
	32	

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	32	

ref: `the newspaper and television reported`

MERT she said the newspaper and television

+All television and newspaper said

Analysis: Domain Adaptation

برنامج ⇒ *program, programme*

Analysis: Domain Adaptation

برنامج ⇒ *program, programme*

	# bitext–5k	# MT0568
programme	185	0
program	19	449

Analysis: Domain Adaptation

برنامج ⇒ *program, programme*

	# bitext–5k	# MT0568
programme	185	0
program	19	449
+PT rules: *programme*	353	79
+PT rules: *program*	9	31

Caveats and Next Steps

- Single-reference setting
  - BLEU+1 is unreliable
  - Lexicalized features cause overfitting

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- Single-reference setting
  - BLEU+1 is unreliable
  - Lexicalized features cause overfitting
- Current work
  - Bitext tuning
  - Different loss function

Conclusion

Fast, adaptive, online tuning for MT

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Sane feature engineering

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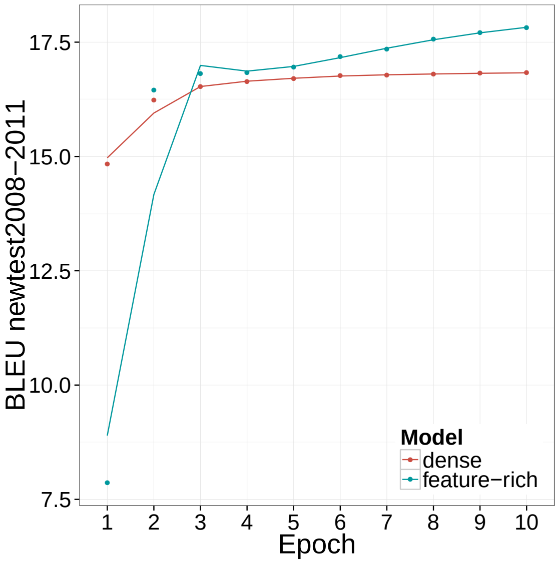
Daniel Cer **Christopher D. Manning**

Stanford University

Try the code in Phrasal:

nlp.stanford.edu/software/phrasal/

En–De Learning Curve



Sparse Features: Negative Results

Discriminative LM	Jane **called Sally**
Phrase boundary features	**Jane** || **called** Sally
Alignment constellation	**1-0 0-1**
Target word insertion	Jane called **the** Sally