Discriminative Training

MT Marathon lecture

Miloš Stanojević

ILLC, University of Amsterdam

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Going from Generative to Discriminative models

Start with generative noisy channel model:

$$t^* = \operatorname*{argmax}_{t \in T(s)} p(t|s)$$

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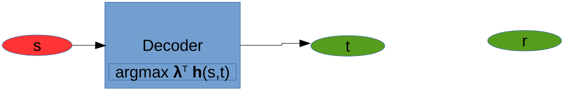
Disadvantage? Losing probabilistic interpretation

Optimize for BLEU directly



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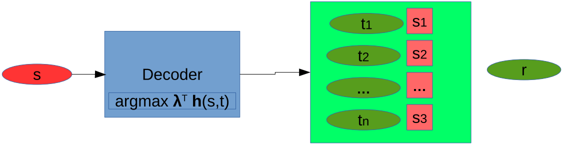

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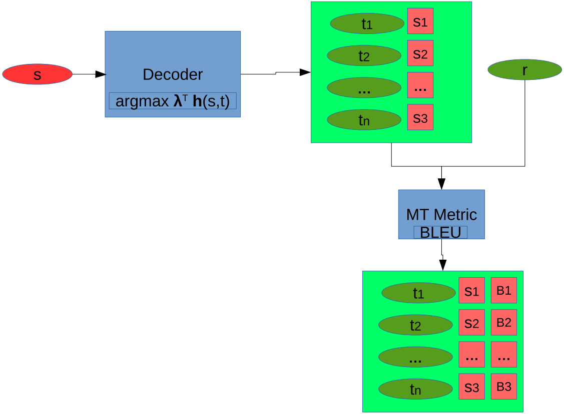

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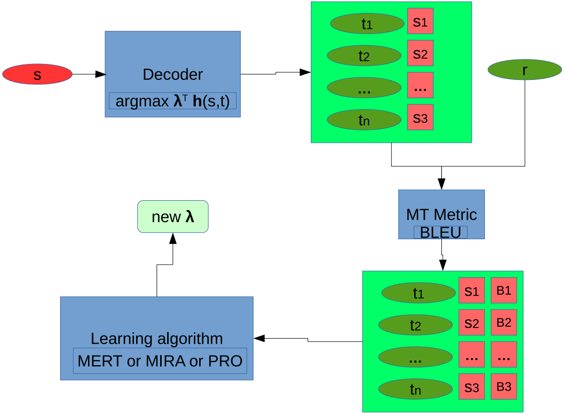

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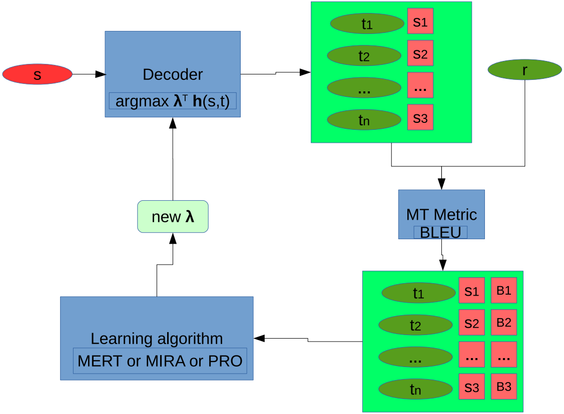

MERT[Och, 2003]

- MERT is the most often used algorithm for this task
- Optimizes parameters one by one
- Directly optimizes objective
- Works well with systems with small number of features

MERT[Och, 2003]

MERT optimizes only one parameter while keeping others fixed.

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\begin{aligned}
score(s, t) &= \lambda^T \mathbf{h}(s, t) \\
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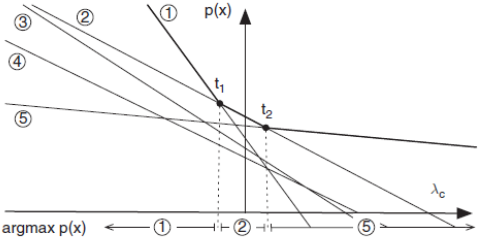

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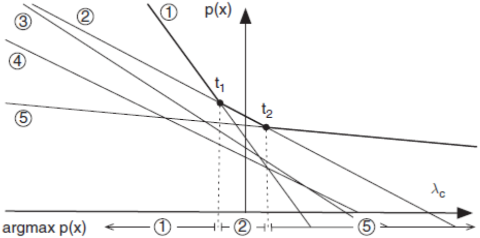

- Extract all **threshold points** where argmax changes

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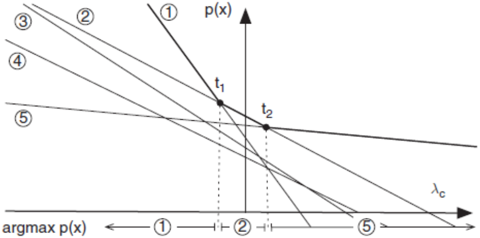

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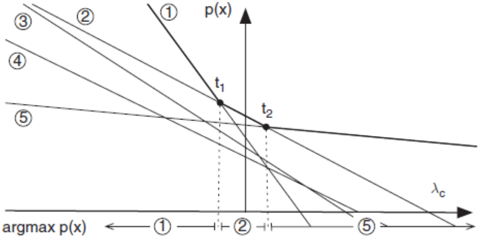

- Extract all **threshold points** where argmax changes
- Evaluate each set of threshold points with BLEU score
- Take the best one and then go again trough the decoding loop

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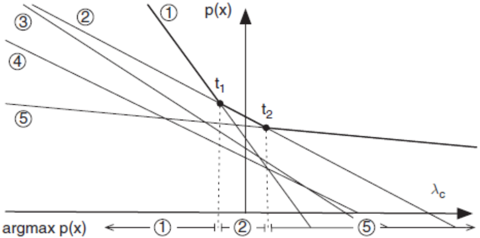

$$score(s, t_1) = score(s, t_2)$$

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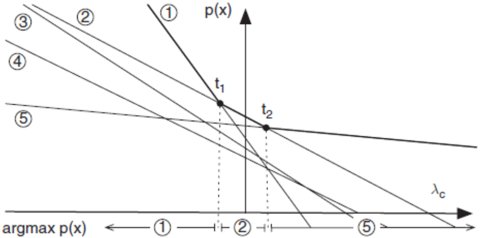

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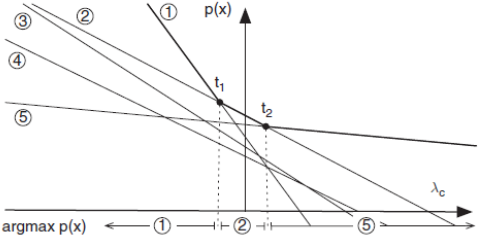

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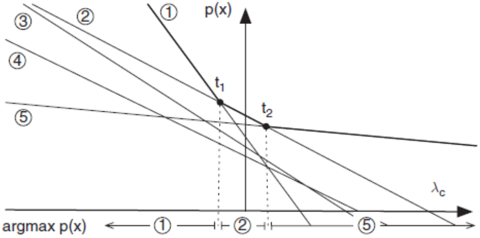

Few more tricks:

- We can speed up this by looking for top threshold points start with the steepest line (smallest $h_c(s, t_1)$)
  $score(x) = \lambda_c \, h_c(s, t_1) + u_c(s, t_1)$
  and find the most negative threshold point for that line

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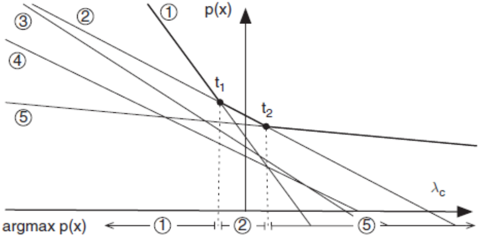

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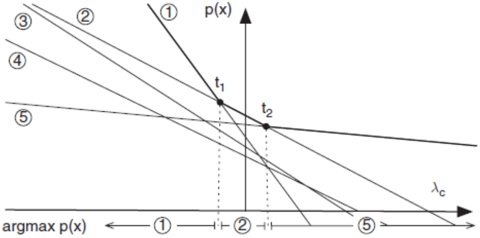

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- Accumulate n-best lists over different decoder runs
- Average the weights of 3 MERT runs

MERT – good and bad sides

Good sides:

- Optimizes corpus level metrics directly.

Bad sides:

- Gets stuck in local minima
  example of finding the highest point in San Francisco
  [Koehn, 2010]
- Instable: BLEU varies a lot
  requires at least 3 runs to make it significant
  [Clark et al., 2011]
- Cannot handle more than a dozen of features

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$$score(s, t_{better}) > score(s, t_{worse})$$
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\lambda^T (\mathbf{h}(s, t_{better}) - \mathbf{h}(s, t_{worse})) &> 0
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Train linear classifier with these as positive and negative training instance.

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Repeat this with the loop trough the decoder

MIRA

- MIRA is a **large-margin** online learning algorithm similar to perceptron [Watanabe et al., 2007].
- Large margin is enforced between between hope and fear translations [Chiang et al., 2008]

$$t_{hope} = \operatorname*{argmax}_t \ score(s, t) + eval(t, r)$$
$$t_{fear} = \operatorname*{argmax}_t \ score(s, t) - eval(t, r)$$

- Batch version [Cherry and Foster, 2012] present in Moses.

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\delta &= min\left(C, \frac{margin + cost}{||h(s, t_{hope}) - h(s, t_{fear})||^2}\right)
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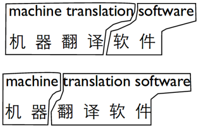
  - latent variables (towards which derivation to optimize?)



Tuning task

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- Organised Tuning Task on WMT15 to explore these options in proper way

Tuning task - system for tuning

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- any tuning algorithm or metric tuning was allowed (even manually setting weights)

Czech-English results

System Name	TrueSkill Score		BLEU
	Tuning-Only	All	
BLEU-MIRA-DENSE	0.153	-0.182	12.28
ILLC-UvA	0.108	-0.189	12.05
BLEU-MERT-DENSE	0.087	-0.196	12.11
AFRL	0.070	-0.210	12.20
USAAR-Tuna	0.011	-0.220	12.16
DCU	-0.027	-0.263	11.44
METEOR-CMU	-0.101	-0.297	10.88
BLEU-MIRA-SPARSE	-0.150	-0.320	10.84
HKUST	-0.150	-0.320	10.99
HKUST-LATE	—	—	12.20

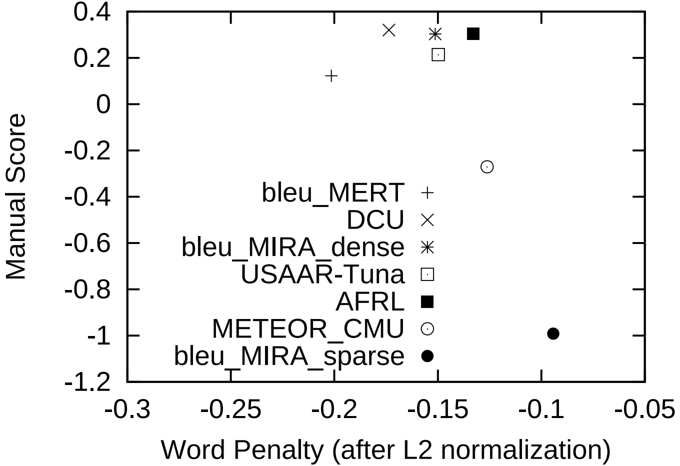
Table: Results on Czech-English tuning

English-Czech results

System Name	TrueSkill Score Tuning-Only	TrueSkill Score All	BLEU
DCU	0.320	-0.342	4.96
BLEU-MIRA-DENSE	0.303	-0.346	5.31
AFRL	0.303	-0.342	5.34
USAAR-TUNA	0.214	-0.373	5.26
BLEU-MERT-DENSE	0.123	-0.406	5.24
METEOR-CMU	-0.271	-0.563	4.37
BLEU-MIRA-SPARSE	-0.992	-0.808	3.79
USAAR-BASELINE-MIRA	—	—	5.31
USAAR-BASELINE-MERT	—	—	5.25

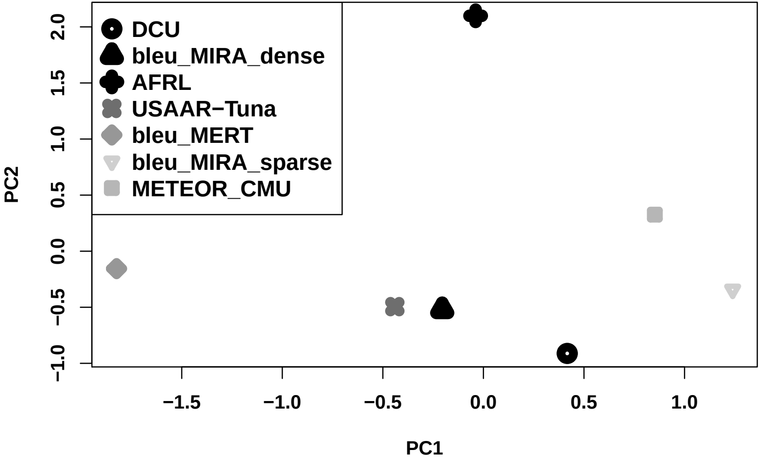
Table: Results on English-Czech tuning

Word Penalty weights for English-Czech



- Difficult to analyse individual weights but if we have to...
- All non-sparse systems find similar weights for WP

English-Czech PCA



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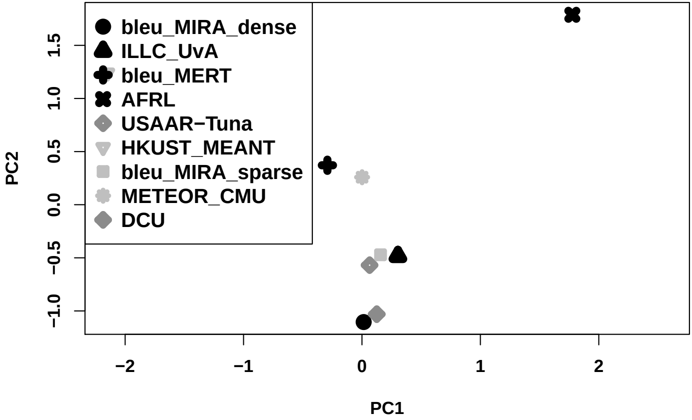
	PC1	PC2
LM0	**-0.69**	0.44
PhrasePenalty0	0.15	**-0.63**
TranslationModel0_0	**-0.91**	-0.13
TranslationModel0_1	**0.91**	-0.03
TranslationModel0_2	-0.55	**0.72**
TranslationModel0_3	0.36	**0.75**
TranslationModel1	0.42	**0.84**
WordPenalty0	**0.84**	0.27

Table: Loadings (correlations) of each component with each feature function for English-Czech

Czech-English PCA



- No obvious pattern
- Very similar systems perform complitely differently
- Very different systems perform similarly

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- **Tuning Task** will happen on again WMT16
- Questions?

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