Workpackage 4: Adaptive Translation Models
2nd Review Meeting

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Introduction

- Main objective of this WP: adaptation in ITP

  1. Develop algorithms for efficient model adaptation
  2. Develop techniques for efficient sentence selection
  3. Explore approaches for domain and user adaptation

- Tasks:

  T4.1: On-line learning for ITP (months 1-24)
  T4.2: Active learning for ITP (months 13-24)
  T4.3: Domain and user adaptation (months 13-30)

Task 1: Online Learning in ITP

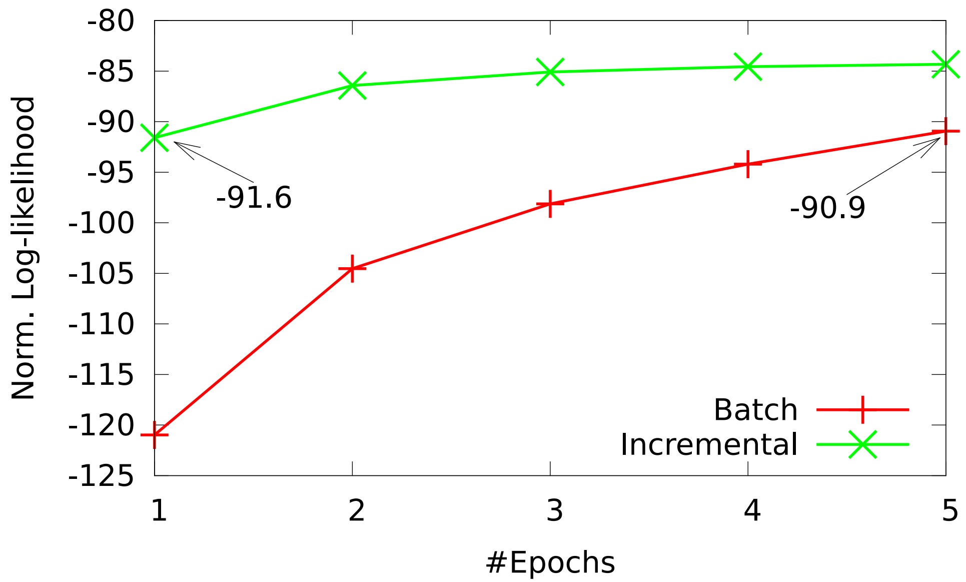
- First year: preliminary work with some restrictions (corpora or application)
- This year: extension to CasMaCat corpora and ITP experiments
- Three research directions:
  - Extended online learning experimentation
  - Distributed implementation of phrase-based model estimation
  - Online learning of log-linear weights

Online Learning Experiments

- First year experiments: online learning feasible in real time scenarios
- However, some crucial aspects were not studied:
  - Performance of incremental EM algorithm
  - Impact of update frequency in system performance
  - Batch versus online learning performance
- Integration within the CasMaCat Workbench
- Experiments conducted with official CasMaCat corpora
- Results reported in KSMR: $|\text{key-strokes}| + |\text{mouse-actions}| \ / \ |\text{reference characters}|$

Online Learning Experiments: EM Convergence

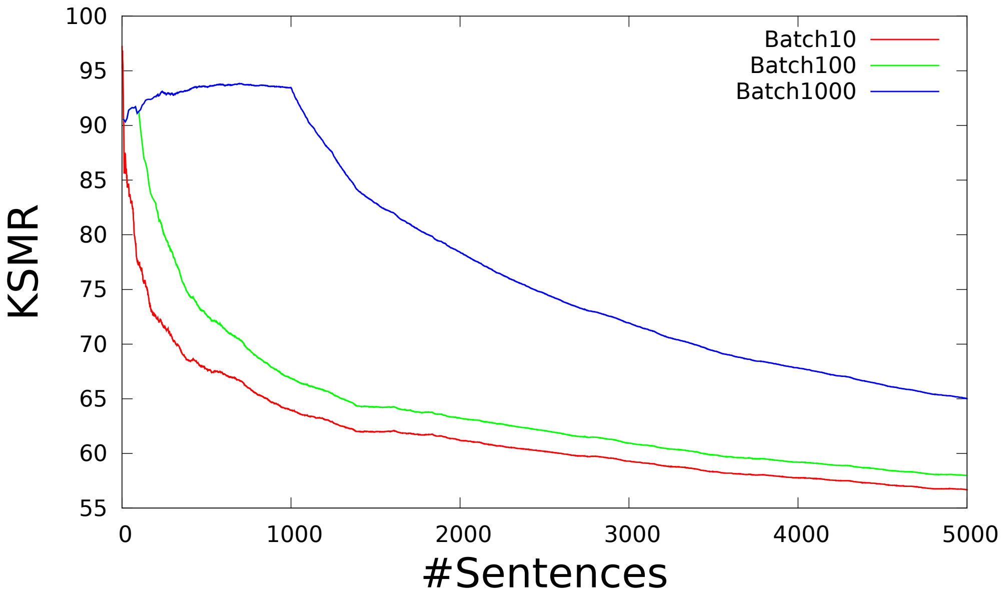
- Word alignments crucial in phrase-based models
- Online estimation requires the incremental EM
- Each training sample is discarded after being processed



Online Learning Experiments: Update Frequency

- The first $5\,000$ sentences of the Europarl training corpus were interactively translated

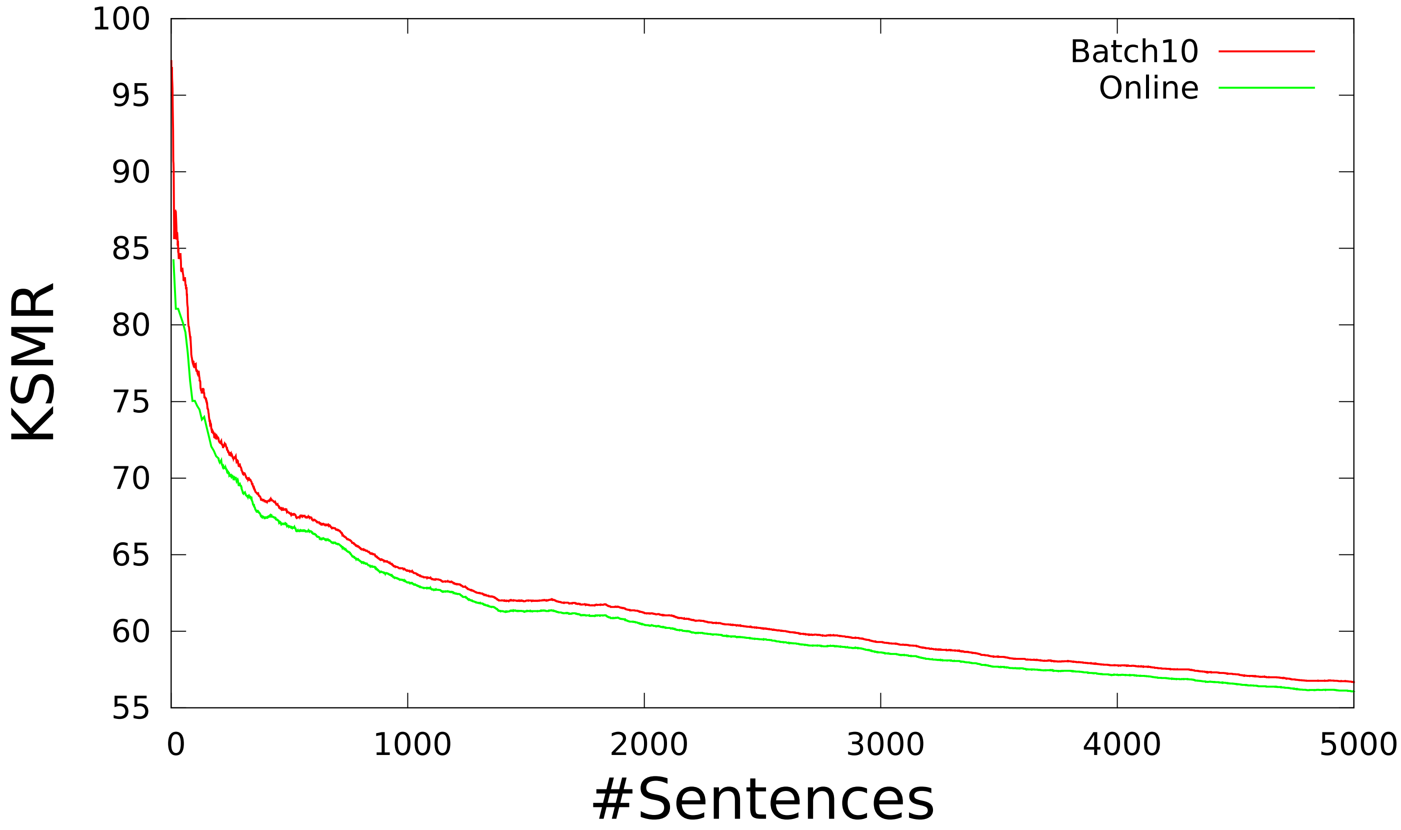
- Different update frequencies were tested (every 10, 100 or $1\,000$ sentences)



- Results clearly show that performance is better as we increase the update frequency

Online Learning Experiments: Batch vs Online

- Impact of frequent updates suggests to replace batch learning by online learning



Online Learning Experiments: Conclusions

- Incremental EM algorithm is competitive with batch EM
- Update frequency has a strong impact in system performance
- Ideally, models should be updated in a sentence-wise manner
- Batch learning is not appropriate for its use in online learning scenarios
- Online learning obtains the same or even better quality results than batch learning

Distributed Implementation of PB Model Estimation

- Initially implemented online learning techniques cannot be executed on large corpora
- First releases of Thot: no online estimation of word alignment models
- New functionality is being added to Thot, including:
  - Estimation of HMM-based alignment models using incremental EM
  - Map-Reduce implementation of PB estimation software
- The new software has been successfully applied in different tasks:
  - Experiments carried out during the second field trial
  - Extended online learning experiments presented above
- A new version of the Thot toolkit has been released

The Thot toolkit

- Open source toolkit for SMT (LGPL License)
- Hosted on github: https://github.com/daormar/thot
- Main features:
  - Fully-automatic SMT and ITP capabilities
  - Incremental learning
  - Scalable training
- Still under development but applied during second field trial

Online learning of log-linear weights

- During first year, promising results achieved in SMT
- Results did not carry over to ITP
  - Wordgraphs as compact representation of ITP search space pose problems:
  - Metric to be optimized does not depend on a single hypothesis
  - No single feature set for each weight set
- Approach adopted: weight sampling for building different quality wordgraphs
  - Gaussian sampling
  - Simplex sampling
- Experimentation with official CasMaCat corpora

Online learning of log-linear weights: results

Table 1: Results in KSMR of the different online learning strategies studied

Method	$\|$weights$\|$	KSMR
baseline	—	40.6
original	—	42.8
gaussian	201	40.9
simplex	70	40.4

- Algorithms applied very positive in SMT, not so in ITP
- Mixed results point towards the need of further research

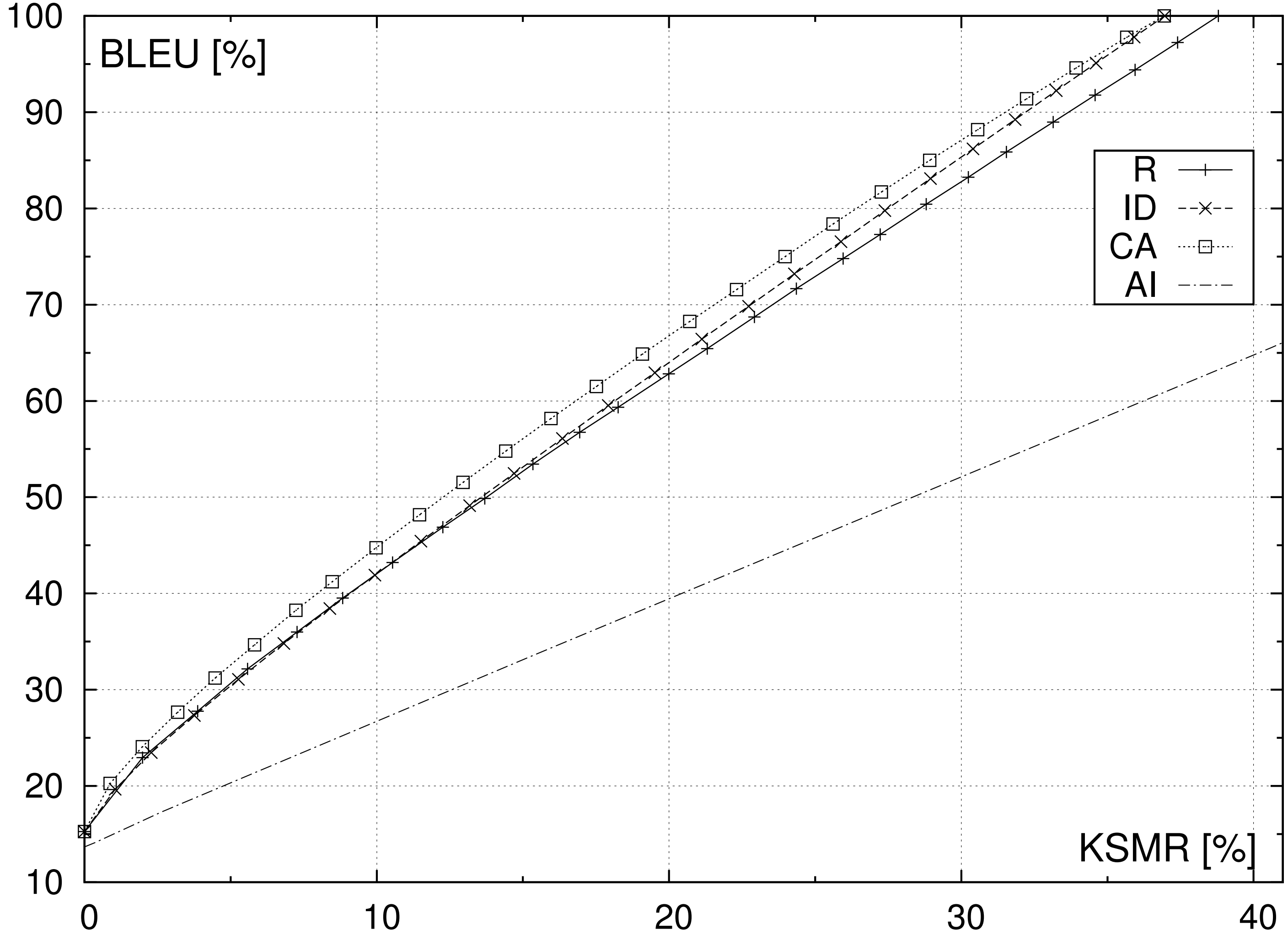
Task 2: Active Learning for ITP

- In ITP, the user is required to supervise all translations
- A more efficient approach can be implemented by:
  - Selectively supervising only a subset of the translations
  - Using an incremental SMT model to incorporate such subset
  - Maximizes the utility of each user interaction
- Related to the Active Interaction protocol in WP2 ,WP3

Implementation: Selective Supervision

- We decide which translations to supervise based on a translation-utility function
- The user supervises a given percentage of the higher-scoring translations
- Compute such score as:
  - **Uncertainty (U)**: Uncertainty of the SMT model on the translation
  - **Information Density (ID)**: Weights **U** by representativeness of future translations
  - **Coverage Augmentation (CA)**: Nr. of unknown n-grams in future translations
  - As a baseline we consider a **Random (R)** utility function

Results



Conclusions

- Active learning has the potential to further improve the efficiency of ITP
- Active learning halves the user effort required to obtain quality translations
- Best performing strategy: coverage augmentation (though small differences)

Task 3: Domain and User Adaptation

- Adaptation critical when train and test domains mismatch
- Log-linear weights typically estimated on dev set
  - → Relies on having sufficient matching (w.r.t. test) data
  - → Else, estimates might be inaccurate
- Work conducted so far focused on Bayesian adaptation of log-linear weights
  - → Formal framework for adaptation
  - → Adaptation data is considered when computing system hypothesis
  - → Gaussian prior over model parameters accounts for reliable predictions

Bayesian predictive adaptation

- Consider the integral over all the parametric space
- Consider a prior over parameters

$$
\begin{aligned}
p(y|x;T,A) &= \int p(y,\boldsymbol{\lambda}|x;T,A)d\boldsymbol{\lambda} \\
&\propto \mathcal{Z}' \int p(\mathcal{A} \mid \boldsymbol{\lambda};\mathcal{T})p(\boldsymbol{\lambda} \mid \mathcal{T})p(y \mid x,\boldsymbol{\lambda})\ d\boldsymbol{\lambda}
\end{aligned}
$$

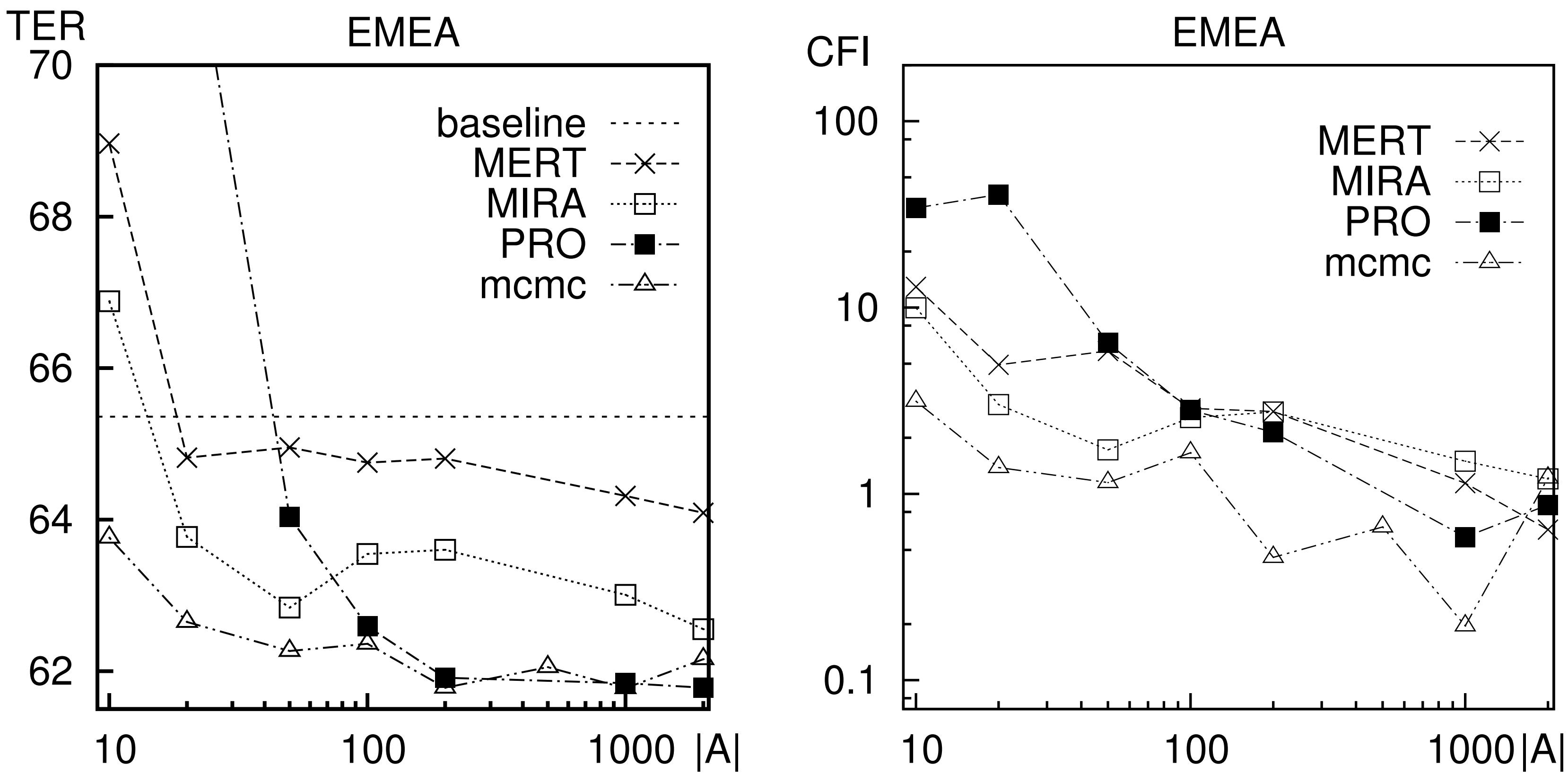
- Integral unfeasible $\Rightarrow$ sampling with Markov chain Monte-Carlo
- Once an adequate sample $\mathcal{S}(\boldsymbol{\lambda}_{\mathcal{T}})$ is obtained

$$
p(y \mid x;\mathcal{T},\mathcal{A}) \approx \mathcal{Z}' \sum_{\boldsymbol{\lambda}\in\mathcal{S}(\boldsymbol{\lambda}_{\mathcal{T}})} p(y \mid x,\boldsymbol{\lambda})
$$

Experiments with BPA: setup

- Conducted with standard Moses ($|\boldsymbol{\lambda}| = 14$)
- Baseline: Phrase-pairs from Hansards, $\boldsymbol{\lambda}$ estimated on Hansards dev.
- MCMC: $\mathcal{A}$ randomly extracted from new-domain training corpora, $\boldsymbol{\lambda}_{\mathcal{T}}$ as previous
- MERT: $\boldsymbol{\lambda}$ re-estimated on $\mathcal{A}$ with MERT
- MIRA: $\boldsymbol{\lambda}$ re-estimated on $\mathcal{A}$ with MIRA
- PRO: $\boldsymbol{\lambda}$ re-estimated on $\mathcal{A}$ with pairwise optimization
- Such strategies not really fair: more costly, several translation steps are performed

Experiments with BPA: TER



Conclusions

- Formal and experimental results regarding log-linear weights
- Re-estimation unstable with low amounts of data, BPA stable
- Future work: log-linear feature adaptation
- Future work: other adaptation approaches:
  - Sentence selection
  - Language model adaptation
  - Translation model adaptation

Related publications

- Jesús González-Rubio and Francisco Casacuberta. Cost-Sensitive Active Learning for Computer-Assisted Translation *Pattern Recognition Letters*, 2013. In press.

- Germán Sanchis-Trilles and Francisco Casacuberta. Improving Translation Quality Stability using Bayesian Predictive Adaptation *IEEE Transactions on Audio, Speech and Language Processing*, under review.

- Daniel Ortiz-Martínez, Ismael García-Varea and Francisco Casacuberta. Online Learning for Statistical Machine Translation. *Computational Linguistics*, in preparation.