The MIT-LL/AFRL IWSLT-2009 MT System

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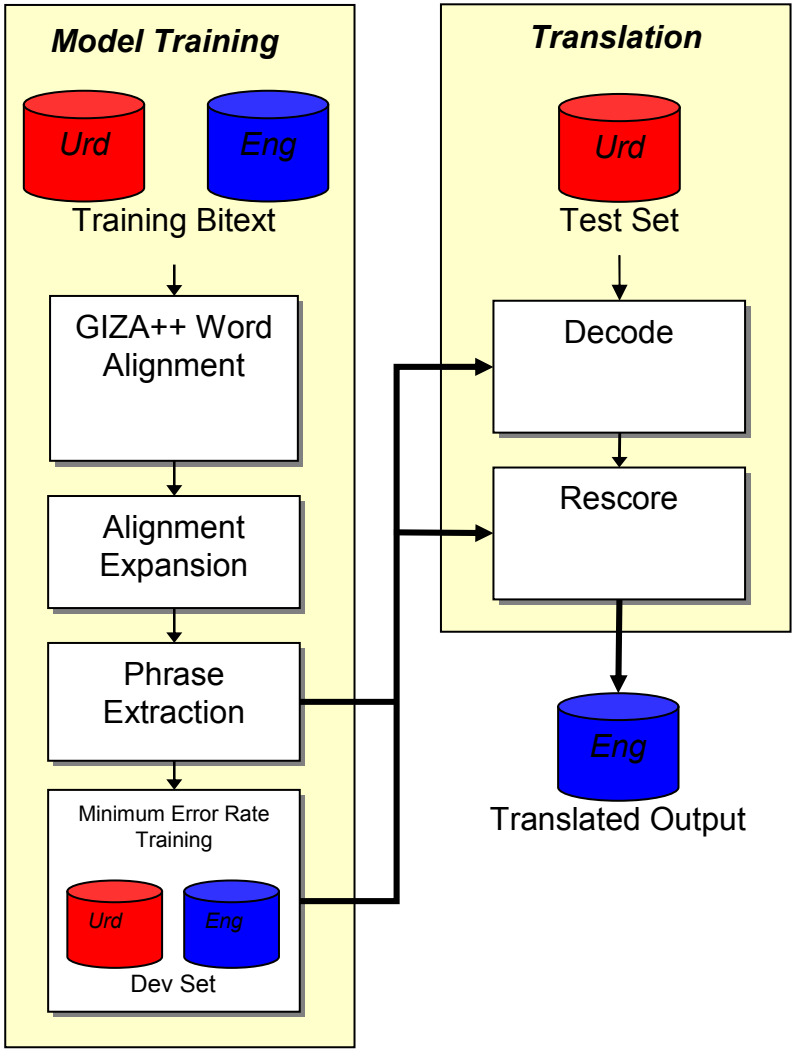
Outline

- **IWSLT-2009 System Architecture**
- Better Arabic Morphology Processing
  - CoMMA
- Domain Adaptation Overview
  - Unsupervised and Semi-supervised Adaptation
  - Human-in-the Loop Adaptation

Statistical Translation System

Experimental Architecture

- **Standard Statistical Architecture**
- **Developed in-house to support SMT experiments**
  - **Framework for experiments with low-resource languages**
  - **Test-bed for S2S MT system**
- **Most components are home-grown**
  - **Phrase Training/Minimum Error Rate Training**
  - **Moses and FST decoders used, comparable performance**
- **Participated in Arabic/Turkish ⇨ English BTEC Data track**



Phrase Based FST Decoder

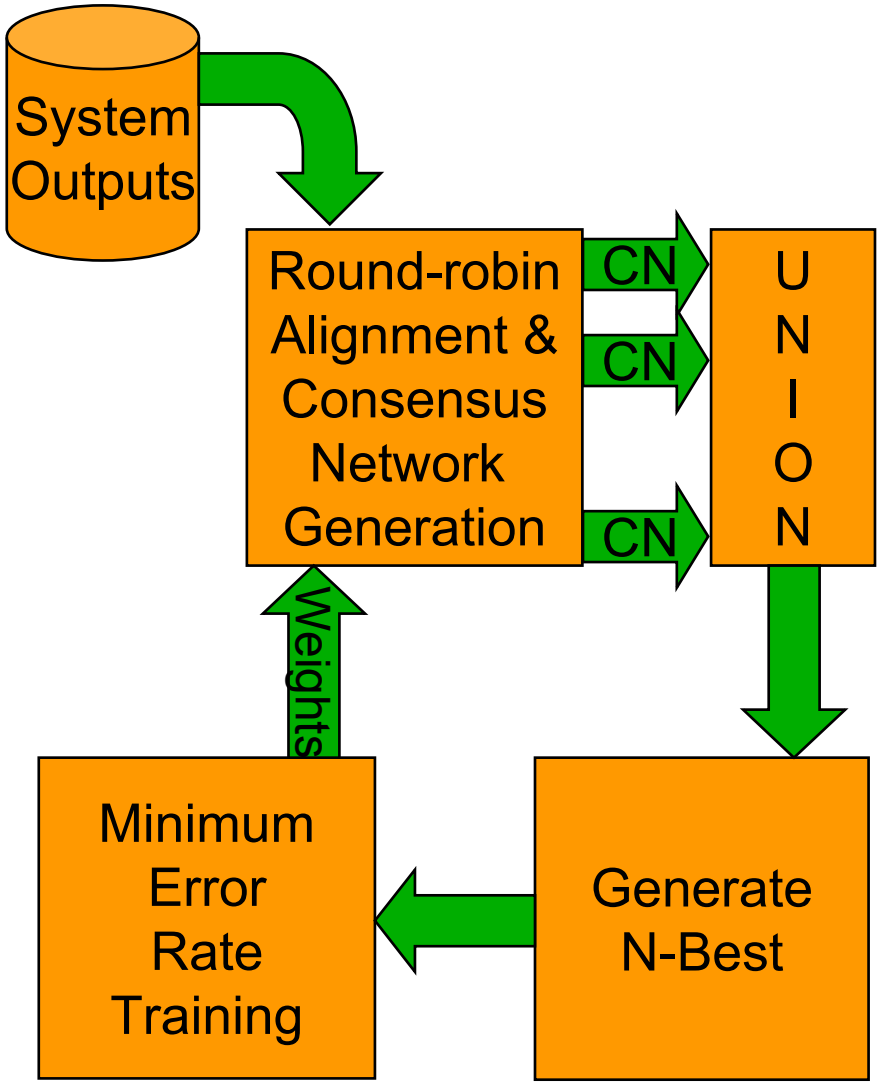
- Based on MIT FST toolkit: http://people.csail.mit.edu/ilh/fst/
- The target language hypothesis is the best path through the following transducer:

$$E = I \circ P \circ D \circ T \circ L$$

- where,
  - I = source language input acceptor
  - P = phrase segmentation transducer
  - D = weighted phrase swapping transducer
  - T = weighted phrase translation transducer (source phrases to target words)
  - L = weighted target language model acceptor
- Apply phrase swapping twice for long distance reordering
- OOV words are inserted during decoding as parallel links to P, D, T, and L models.
- Allows for direct decoding on pruned ASR lattices

System Combination

- Generate consensus networks using round-robin alignment, where each system gets to be the skeleton alignment
- Take union of all consensus networks and apply a language model
- Weight optimization on a development set using n-best lists
- Final combination on unseen data using optimized system weights



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Arabic Preprocessing

AP5 Review

Preprocessing Method	Mean BLEU on dev6
Baseline (No normalization or AP5)	**42.06**
Remove all diacritics except tanween, no AP5	**49.40**
Remove all diacritics, no AP5	**50.39**
Remove all diacritics, apply AP5	**53.55**

- "Diacritics" removed:
  - Short vowels
  - **Sukuun:** Marks absence of sort vowel
  - **Shadda:** Marks consonant gemination (i.e., doubling)
  - **Tanween:** Case markers for indefinite forms & other uses
  - **Tatweel:** Stretches letters in Arabic typography (not a true diacritic)
- AP5 segments the following from stems:
  - **Prefixes:** al-, bi-, fa-, ka-, li-, wa-
  - **Suffixes:** Attached pronouns

CoMMA Processing for Arabic

- **Observation:** *With limited training data more morphological processing seems to help, less with more training data*

- **Count Mediated Morphological Analysis**
  - **Modification to AP5: decide segmentation based on counts**

- **Given a count threshold t, and a vocabulary W**

- **Foreach w in |W|**
  - **Apply AP5 diacritic normalization procedure**
  - **If count(w) < t**

    Apply AP5 segmentation of clitics, etc.
  - **Else don't segment**

CoMMA Experiments

Baseline (No Tokenization)

COMMA Threshold	BLEU Score	
	Dev6	Dev7
0	50.00	51.94
20	53.92	54.29
200	53.14	54.64
2,000	54.02	54.57
10,000	53.33	54.48

CoMMa

AP5 (all tokens segmented)

- AP5 and CoMMa results in 7-8% relative improvement
- CoMMa only slightly better than AP5, +0.5–1.5 BLEU in system combination

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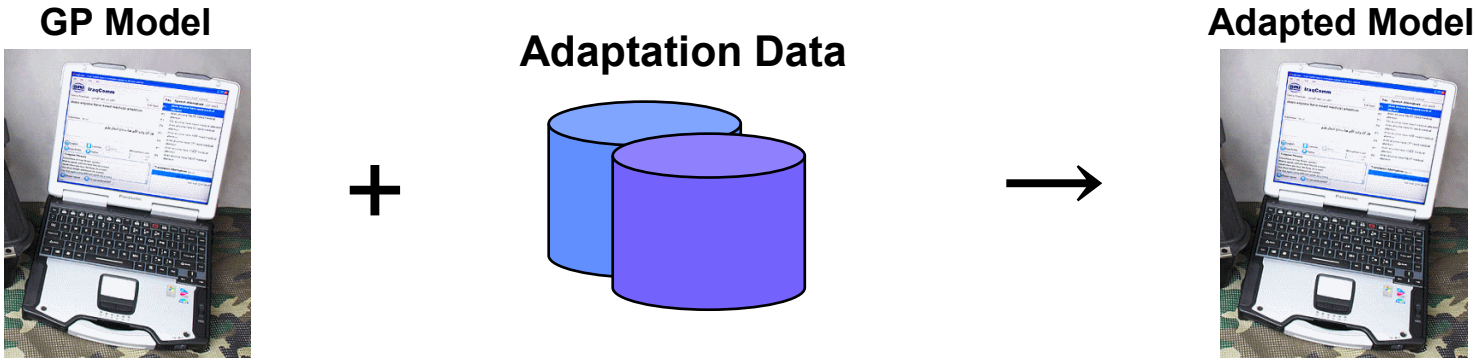
Cross Domain Adaptation Overview

- **Observations from past work**
  - **SMT performs best when training and test data are matched**
  - **Adding large volumes of out-of-domain data to training does not improve performance**

- **Adaptation**
  - **GOAL:** *Optimally port general purpose (out-of-domain) models to specific domain with limited in-domain data*



- **NOTE:** *Adapted Systems not used in IWSLT BTEC submissions*

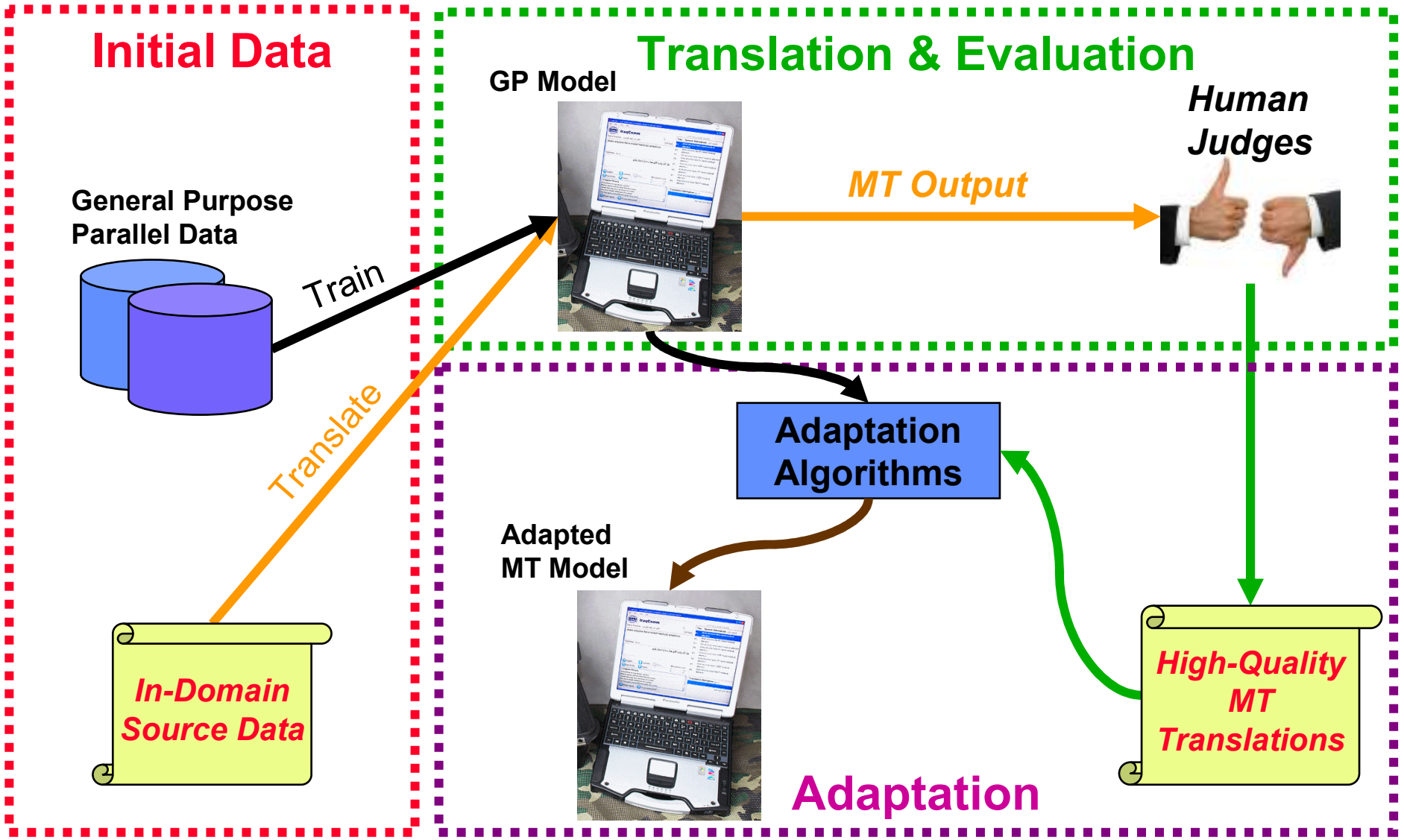
Data

- General purpose data:
  - 500k Arabic-English parallel data from ISI automatically extracted parallel corpus
  - Domain: newswire data

- In-domain (adaptation) data:
  - 20k IWSLT-2009 BTEC Arabic-English training set
  - Domain: travel

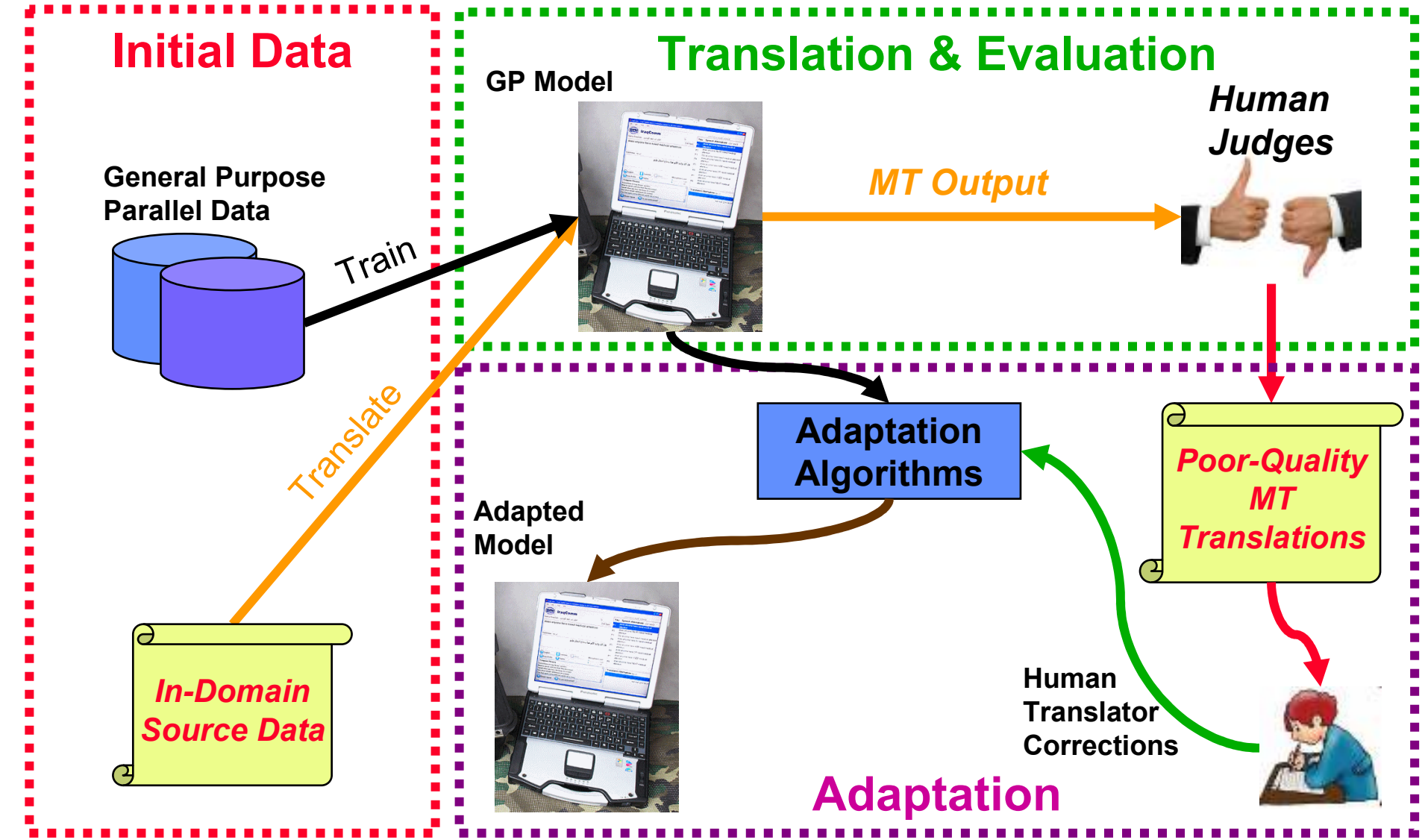
Adaptation of Phrase-based MT Models

Semi-supervised



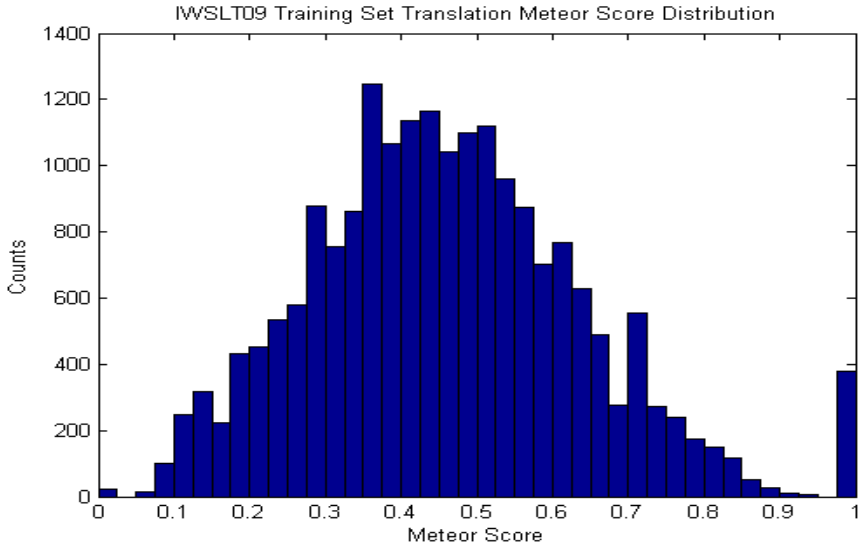
Adaptation of Phrase-based MT Models

Human-in-the-Loop



Selection of In-domain Adaptation Data

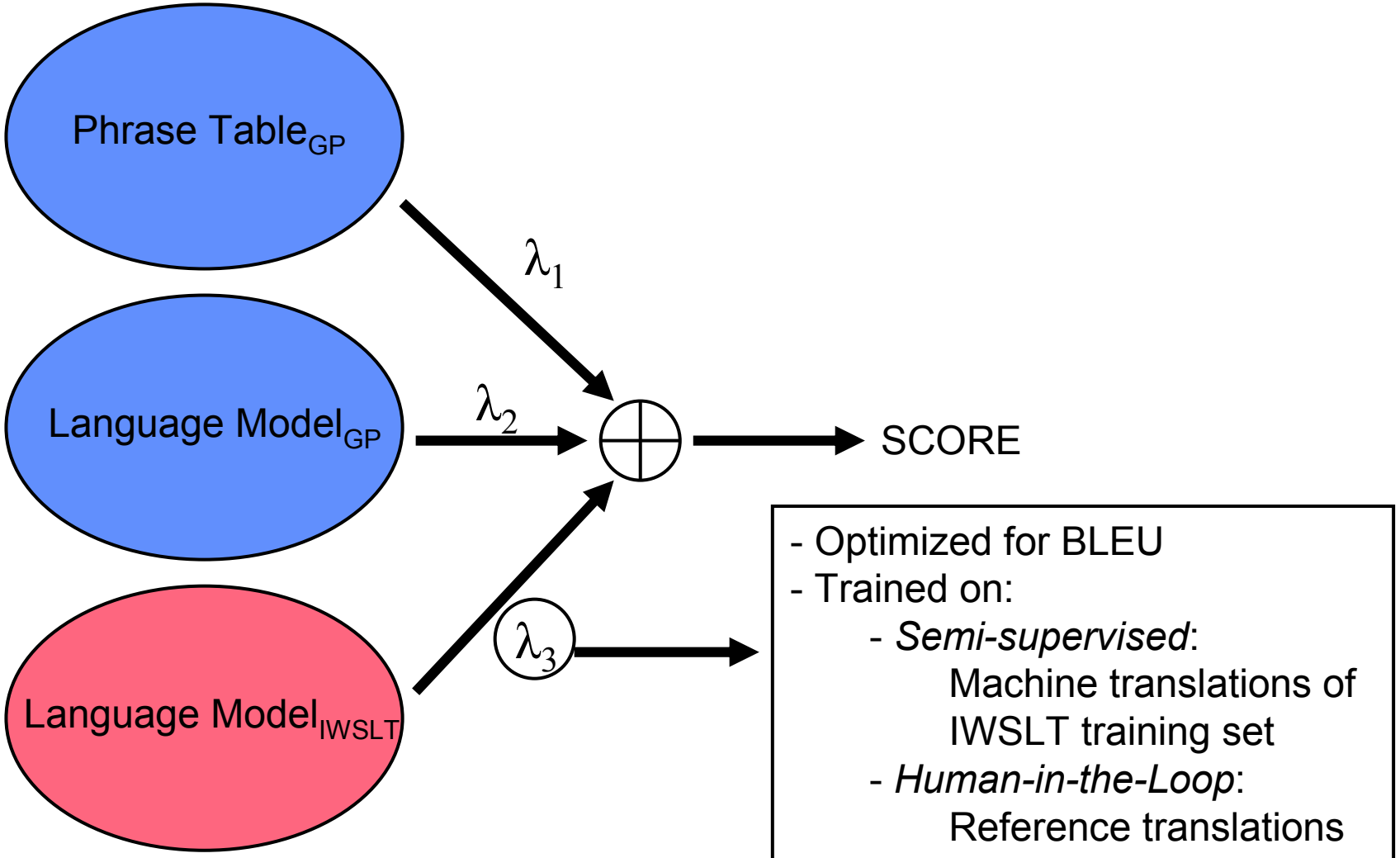
- **General purpose models used to translate the IWSLT '09 training set**
- **Translations ranked using METEOR as a proxy for a human judge**
- **Ranked sentences divided into octiles and used for experiments:**
  - **Semi-supervised adaptation:** *Use top scoring octiles for adaptation*
    Goal: is to use best in-domain target data
  - **Human-in-the-loop adaptation:** *Use bottom scoring octiles for adaptation*
    Goal: is to correct worst in-domain target data (active learning paradigm)



Octiles	1	2	3	4	5	6	7	8
METEOR	0.66	0.57	0.51	0.45	0.40	0.34	0.26	0.00

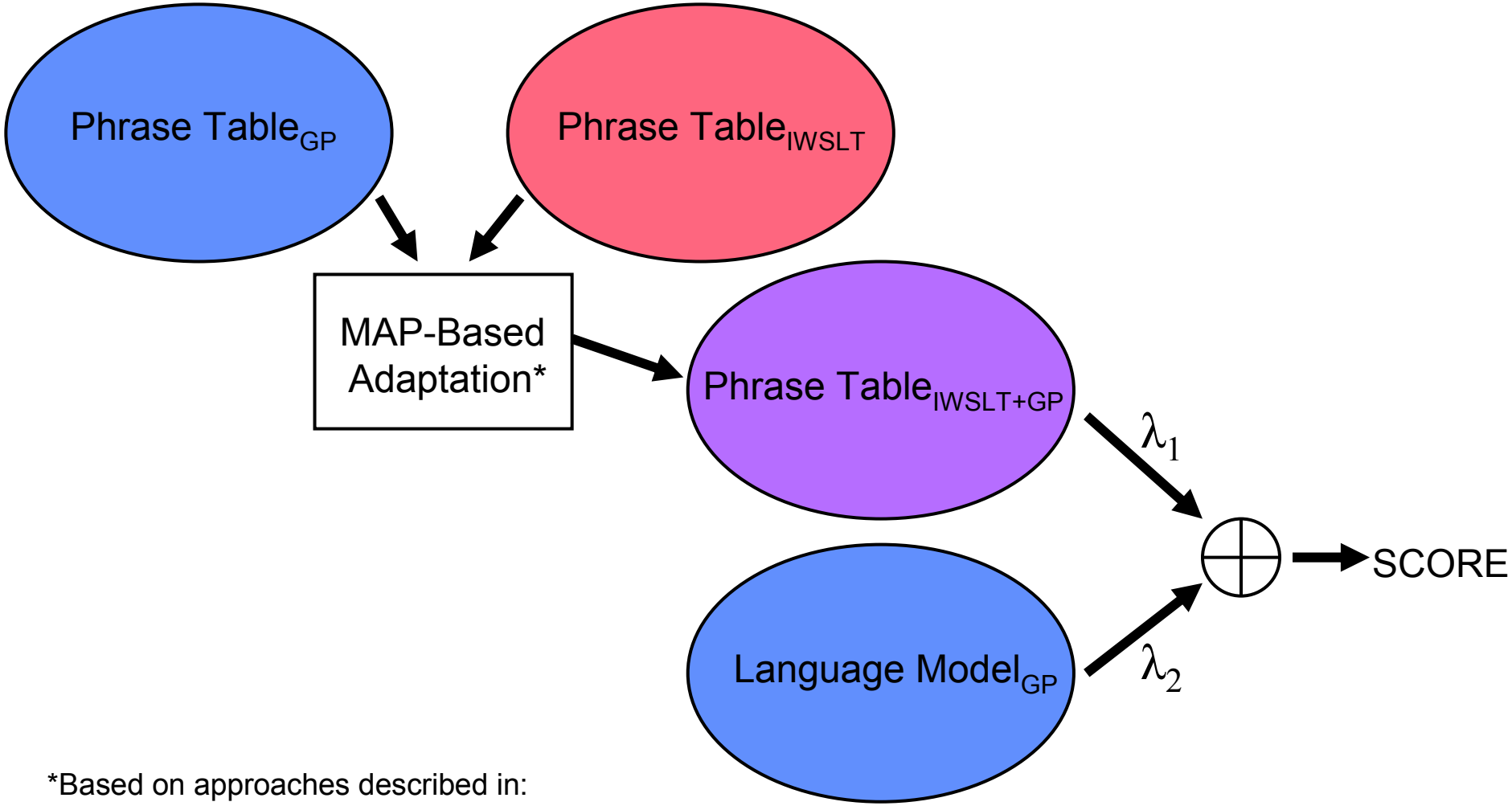
Adaptation Approaches

Language Model Adaptation



Adaptation Approaches

Phrase Table Adaptation



*Based on approaches described in:

[1] C. Lee & J. Gauvain, "*Speaker adaptation based on MAP estimation of HMM parameters*," ICASSP 1993.

[2] M. Federico, "Bayesian estimation methods for n-gram language model adaptation", ICSLP 1996.

[3] M. Bacchiani and B. Roark, "*Unsupervised Language Model Adaptation*," ICASSP 2003.

Phrase Table MAP Adaptation

- **Interpolated phrase table probabilities are computed using the following equation:**

$$\hat{p}(s \mid t) = \lambda p_{in-domain}(s \mid t) + (1-\lambda) p_{gp}(s \mid t)$$

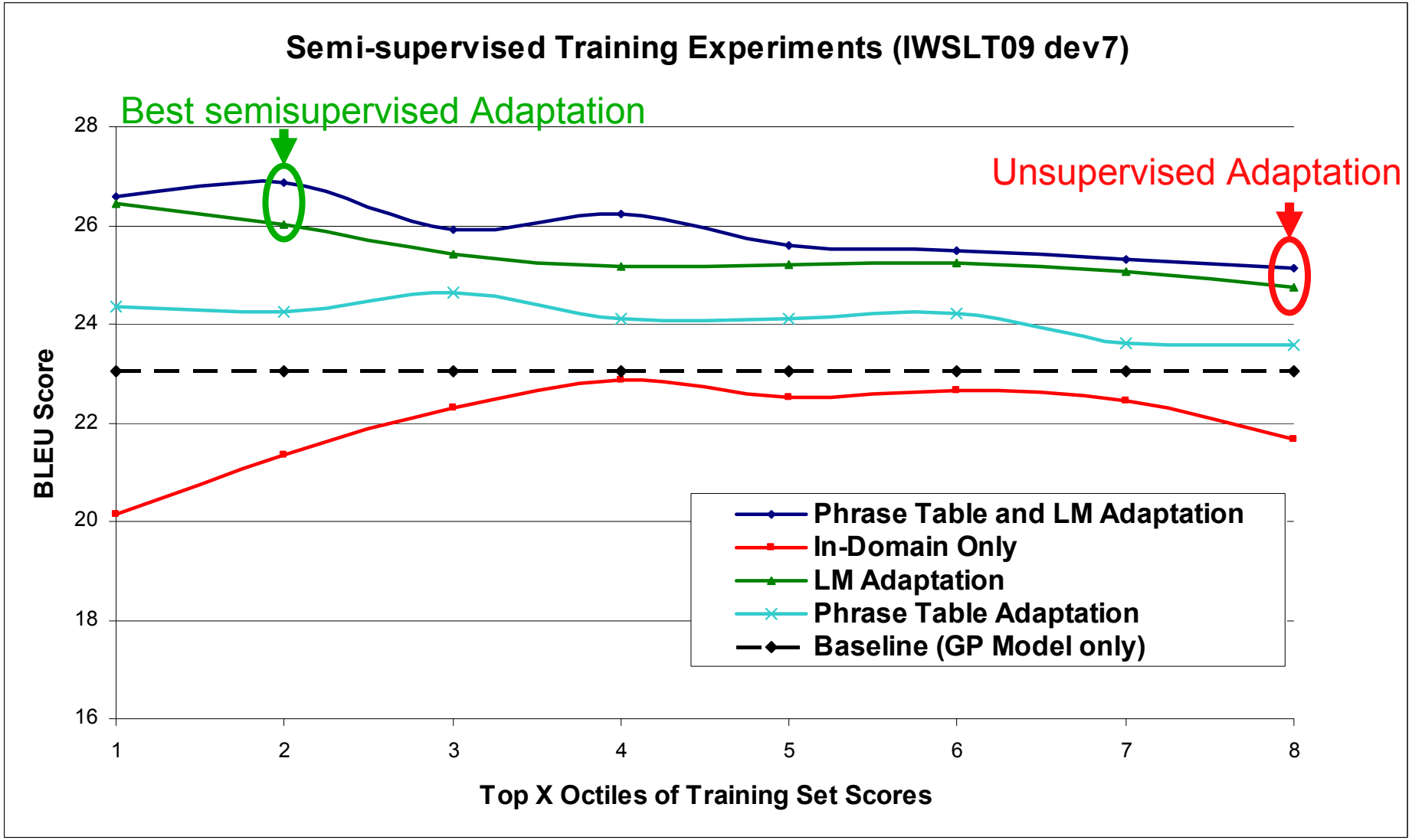
- $p_{in\text{-}domain}$: **probability estimate from in-domain models**
- p_{gp}: **probability estimate from general purpose models**
- λ: **interpolation coefficient computed using the following equation:**

$$\lambda = \frac{N_{in-domain}(s,t)}{N_{in-domain}(s,t) + \tau}$$

- τ: **Fixed-value MAP relevance factor**
- $N_{in\text{-}domain}$**(s,t): observed count of phrase pair (s,t)**

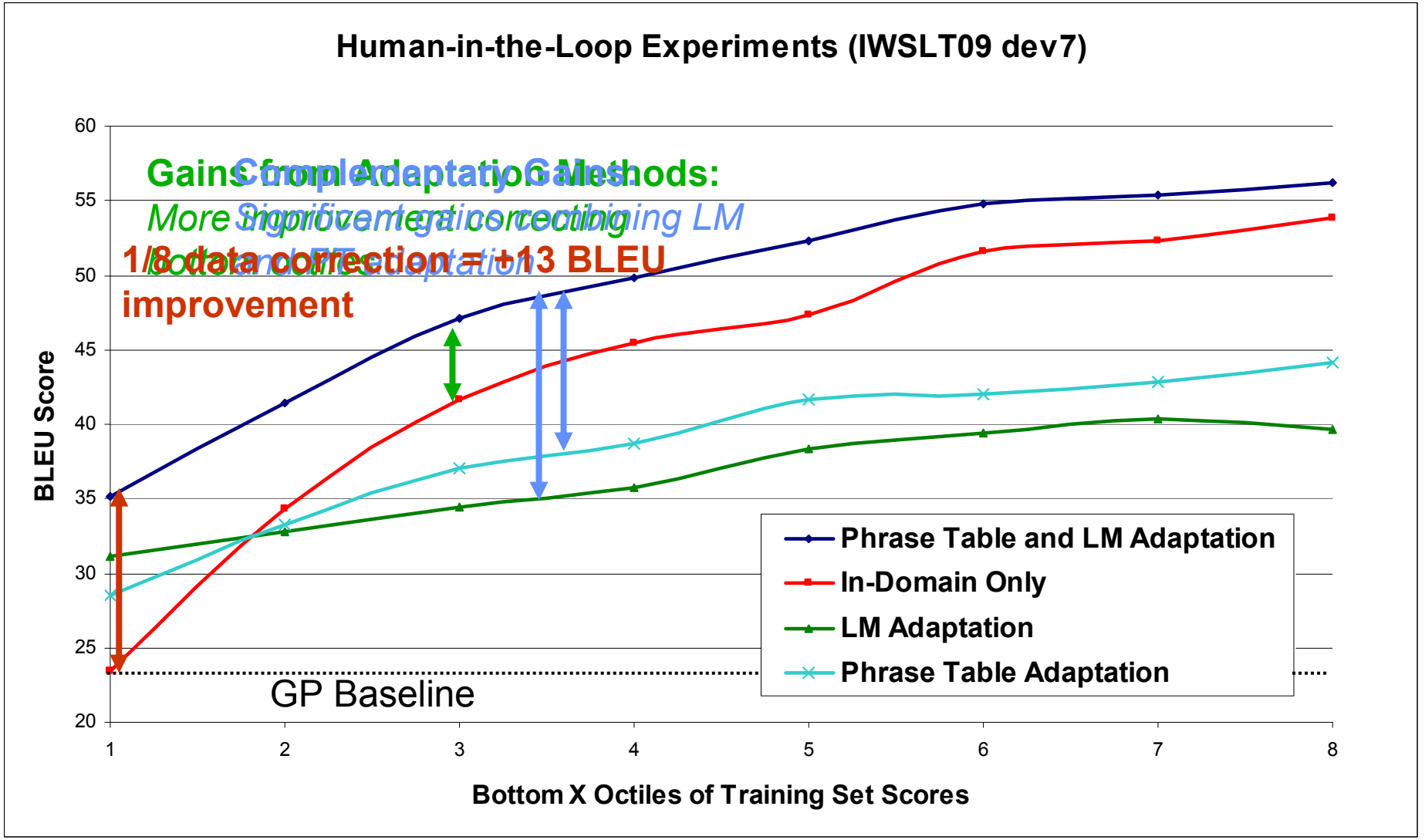
Experimental Results

Semi-supervised Adaptation



Experimental Results

Human-in-the-Loop Adaptation



Experimental Results

Best System Scores

System	dev7	eval
GP	23.06	21.35
GP + Unsupervised LM + PT Adaptation	25.74	23.86
GP + Semi-supervised LM + PT Adaptation (Top quartile)	27.19	25.89
IWSLT '09 Baseline	54.63	52.69
GP + Human-in-the-Loop LM + PT Adaptation	56.57	56.11

Conclusions

- Morphological processing is critical
  - +4 BLEU for Turkish using Bilkent Analyzer
  - +3.5-4 BLEU for Arabic using AP5
- CoMMa gains in system combination
  - Multiple CoMMa systems (20, 200, 2000): +0.5-1.5 BLEU over AP5
- Unsupervised Adaptation
  - LM: +1.5 BLEU, PT: +0.5 BLEU
  - Combined: +2.5-3.0 BLEU (15% relative) compared to GP only
- Semi-supervised Adaptation
  - Gains +1.5-2 BLEU over Unsupervised, only ¼ of total data
  - But requires human judgement
- Human-in-the-Loop Adaptation
  - +2-3.5 BLEU using all IWSLT data
  - +13 BLEU using 1/8th of total data
  - Gains from LM and PT are non-additive