QCRI's Machine Translation Systems for IWSLT'16

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Motivation

- Can NMT beat current state-of-the-art?
  - for Arabic-English language pairs

Teams

Phrase-based vs. Neural MT

Road Map

- Data Preparation
- Systems
  - Phrase-based
  - Neural
- Conclusion

Domain Adaptation

- How to best utilize large out-domain data?

Parallel Corpus	Tokens (en)	Helps TED tests?
TED	4.7M	
UN	489M	Harmful
QED	1.6M	No affect
OPUS	184M	?

- QED Test Sets
  - One combined system or separate systems?

Data Preparation

- Preprocessing
  - –All arabic data segmented and normalized using MADAMIRA (Rambow et al. 2009)
  - –English data tokenized using moses tokenizer
  - –English→Arabic target data detokenized using Mada detokenizer (Kholy et al. 2010)
- Evaluation
  - – avg. BLEU score on IWSLT test11-14

Phrase based Machine Translation

Phrase based System

Base Setup

- Framework: Moses (Koehn et al. 2007)
- Fast Aligner (Dyer et al. 2013)
- Default Moses parameters
- Lexicalized Reordering Model (Galley and Manning. 2008)
- Operation Sequence Model (Durrani et al. 2013)
- Neural Network Joint Model (Devlin et al. 2014)
- Kneser-Ney Smoothing Interpolated LM
- K-batch Mira (Cherry and Foster 2012)

Phrase based System

Key Experiments

- Data selection
  - Large out-of-domain data
    - not entirely relevant to the in-domain data
      - e.g. complete UN data hurts
  - Select a subset of the out-of-domain data
    - cross entropy difference (Axelrod et al. 2011)
    - +0.5 using MML (3.75% ~680K sentences)
    - +0.4 using Back-off Phrase-table
    - Opus was very helpful (+1.2)

Δ:+1.7

Phrase based System

Key Experiments

- Neural Network Joint Model (Devlin et al. 2014)
  - Baseline trained on TED corpus only (+0.7)
- NNJM Adaptation
  - Trained for 25 epochs on UN and OPUS data
  - Finetuned for 25 epochs on in-domain data (+0.2)

Δ:+0.9

Phrase based System

Key Experiments

- Baseline Operation Sequence Model
  - trained from concatenated parallel corpus
- Interpolated OSM (+0.6)
  - Train OSM models from each parallel corpus
  - Interpolate to minimize perplexity on tuning
- Class-based OSM (+0.1)

Δ:+0.7

Phrase based System

Results

Train	Avg. BLEU	Description
TED (baseline)	28.6	
TED + QED + UN	27.3 (-1.3)	Concatenation
TED + Back-off PT(QED,UN)	29.1 (+0.5)	
TED + MML (QED,UN)	29.2 (+0.6)	
TED + MML (QED,UN) + OPUS	30.4 (+1.8)	
Interpolated LM	30.9 (+2.3)	
Interpolated OSM	31.5 (+2.9)	
NNJM	32.1 (+3.5)	Train on concatenation
NNJM-Opus	32.3 (+3.7)	Train on OPUS, fine tune on TED
Class-based OSM	32.4 (+3.8)	
Drop-OOV	**32.6 (+4.0)**	

Phrase based System

Key Experiments

- QED Test-set
  - Phrase-table trained on concatenation
  - Use TED weights but replace TED with QED to be in-domain
    - for Language Model
    - for Interpolated OSM
  - NNJM: Fine-tuning with QED instead of TED

- English-to-Arabic Systems
  - Replicated what worked in Ar->En direction

Neural Machine Translation

Neural System
Base Setup

- Framework: Nematus (Sennrich et al. 2016)
- Bidirectional encoder model with attention
- BPE to avoid unknown words problem
- 1024 LSTM units in the encoder
- Batch size of 80
- Maximum sentence length of 80
- Dropout for only in-domain data

Neural System
Baseline

- Baseline system trained only on TED data

System	Avg. BLEU	Description
Phrase based	28.6	-

32.6
Phrase
Based
Best

Neural System
Baseline

- Baseline system trained only on TED data

System	Avg. BLEU	Description
Phrase based	28.6	-
Neural	**25.2**	-

32.6
Phrase
Based
Best

Neural System

Replicate best data selection

- Best MML settings that worked for the phrase-based system: 3.75% selected UN data

System	Avg. BLEU	Description
Phrase based MML 3.75%	29.2	**Data:** Selected UN + TED

32.6
Phrase Based Best

Neural System

Replicate best data selection

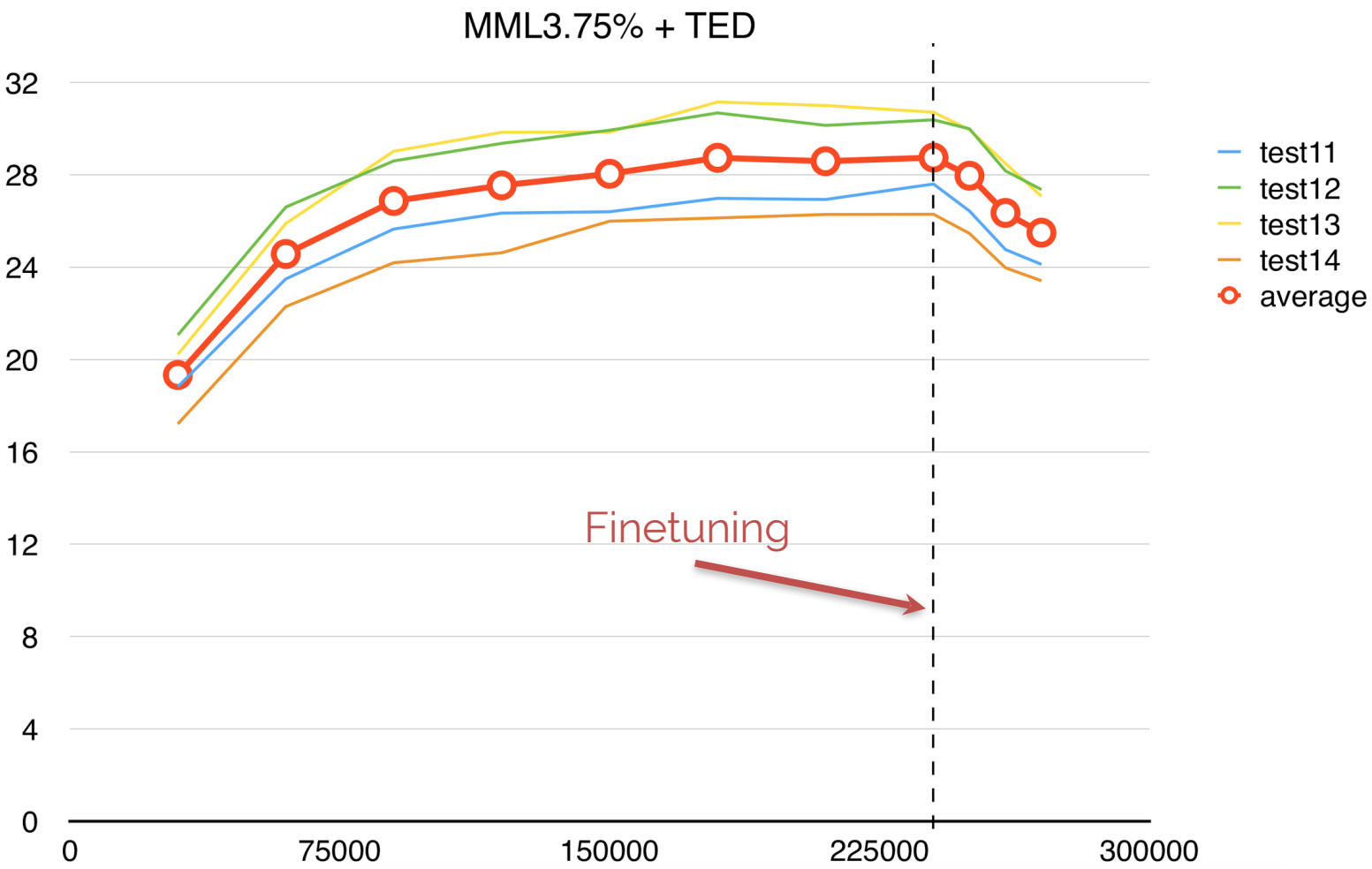
- Best MML settings that worked for the phrase-based system: 3.75% selected UN data

System	Avg. BLEU	Description
Phrase based MML 3.75%	29.2	**Data:** Selected UN + TED
Neural MML 3.75%	28.8	**Data:** Selected UN + TED

32.6
Phrase Based Best

Neural System

Why more data?



Neural System
Use more data

- Take the second best MML settings
  - UN10% (hurts in phrase-based by 0.4 points)

Train	Avg. BLEU	Description
Phrase based Baseline	28.6	**Data:** TED only
Phrase based MML 3.75%	29.2	**Data:** Selected UN + TED
Phrase based MML 10%	28.2	**Data:** Selected UN + TED
Neural MML 3.75%	28.8	**Data:** Selected UN + TED
Neural MML 10%	29.1	**Data:** Selected UN + TED

  - beats 3% but takes more time
  - be patient

32.6
Phrase Based Best

Neural System
Use all UN data

- Forget about selection, use all of the UN data

System	Avg. BLEU	Description
Phrase based best	32.6	**Data:** TED + QED + UN-MML + OPUS
Phrase based all UN	27.3	**Data:** UN + TED
Neural all UN	30.3	**Data:** UN + TED

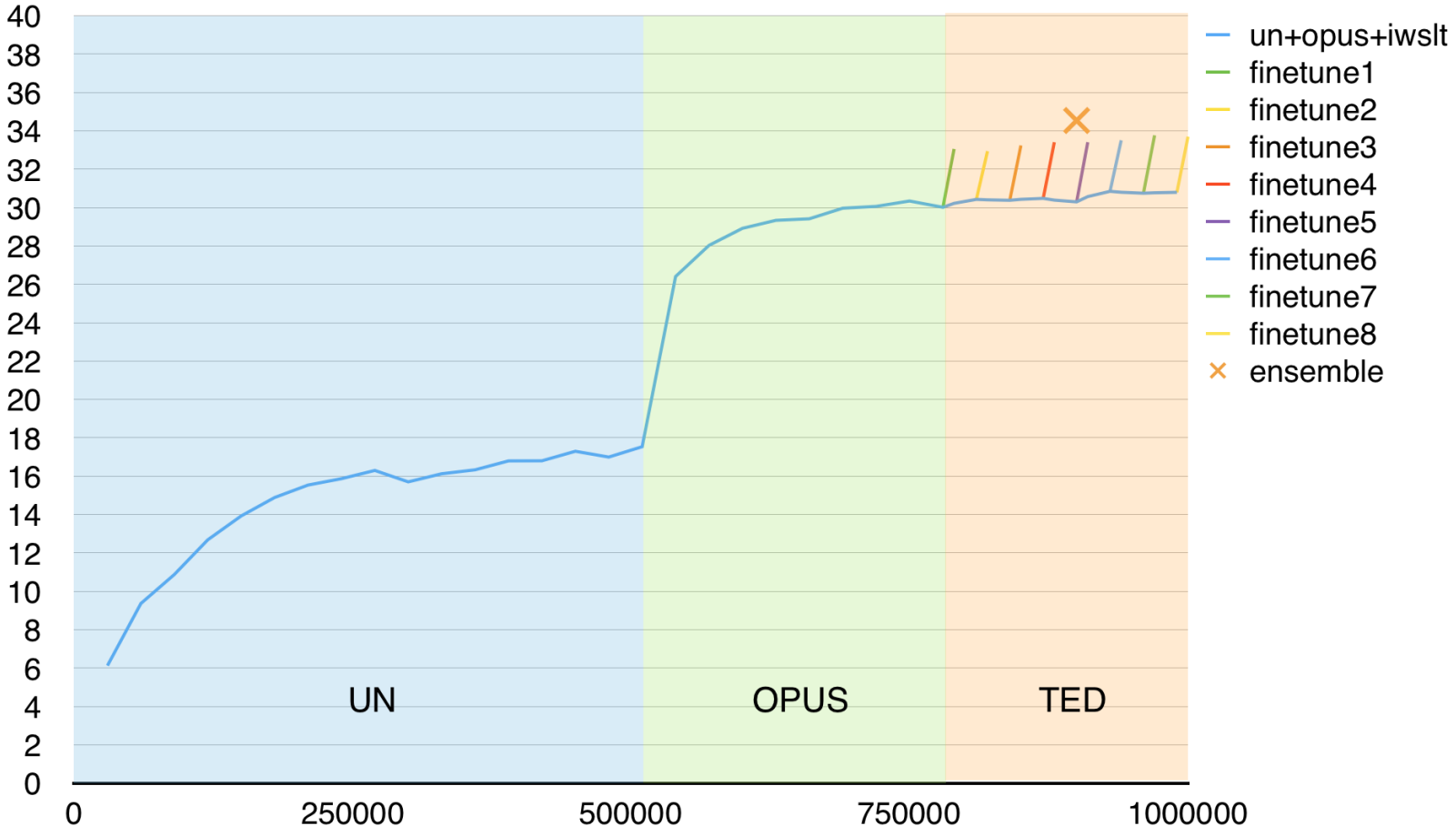
Neural System
Final system

- Add subtitle (OPUS) data

System	Avg. BLEU	Description
Phrase based best	32.6	**Data:** TED + QED + UN-MML + OPUS
Neural individual	33.7	**Data:** UN -> OPUS -> TED
Neural ensemble	**34.6**	Ensemble of eight models

Neural System

NMT improvement lifetime



Neural System

English to Arabic direction

- Spent considerably less time on this direction because of computational limitations
- Replicated most of the training process from the other direction
- QED Systems: Finetune with QED data as in-domain

Neural System
Other Experiments

- Finetuning variants
  - Layer Freezing
- Dropout
- Data concatenation in base model
- BPE model training data selection

Conclusions

Other Experiments

- NMT is SOTA for Arabic-English language pair
  - have not utilized monolingual data yet (+3.0 BLEU, Sennrich et al. 2016)
- More data is better for NMT
  - as long as you have time
  - our best NMT system is trained on around 42M parallel sentences
- Adaptation is very cumbersome in Phrase Based systems
- Human effort involved in Neural MT is considerable less

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