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Integrating an Unsupervised Transliteration Model into Statistical Machine Translation

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Transliteration

- Languages are written in different scripts
  - Russian, Bulgarian and Serbian – written in Cyrillic Script
  - Urdu, Farsi and Pashto – written in Arabic Script
  - Hindi, Marathi and Nepalese – written in Devanagri

- Transliteration is converting text in one script into another
  - Pronunciation of words remain roughly the same
  - талботу (tælbət) → Talbot
  - مورغان (morghan) → Morgan
  - सीमा (sima) → Seema

Utility

- Transliteration can benefit major NLP applications
  - Cross language information retrieval
  - Terminology extraction
  - Machine translation
    - Translation of OOV words
    - Learning when to transliterate (Hermjakob 2008; Azab 2013)
      - E.g. “Dudley North visits North London”
    - Translating closely related languages (Nakov and Tiedeman 2012)
      - E.g. Bulgarian/Macedonian, Thai/Lao, Hindi/Urdu

Building a Transliteration System

- Rule-based approach
  - Manually built transliteration rules ح/ہ/ھ → h, ک/ق → q,k,c
  - Use edit-distance based techniques to score variants
  - Problem: Linguistic knowledge + effort required

- Data-driven approach
  - Learns transliteration rules automatically from the data
  - Problem: Requires a list of transliteration pairs

Transliteration Mining

- Solution: Mine transliteration pairs from parallel data

دوکان	Shop
طاقت	Power
نعمت	Blessing
ایڈنبرگ	Edinburgh
یونیورسٹی	University
ضرورت	Need
…	…
…	…
ریسرچ	Research

Transliteration Corpus

ایڈنبرگ	Edinburgh
یونیورسٹی	University
ریسرچ	Research

Approaches to Transliteration Mining

- Supervised and Semi-Supervised Approach
  - Sherif and Kondrak, 2007; Kahki et. al., 2011; Jiampojamarn et al., 2010; Noeman and Madkour, 2010
- Unsupervised Approach
  - Sajjad et al., 2012 (Fully unsupervised)
    - Based on EM algorithm

Unsupervised Transliteration Mining

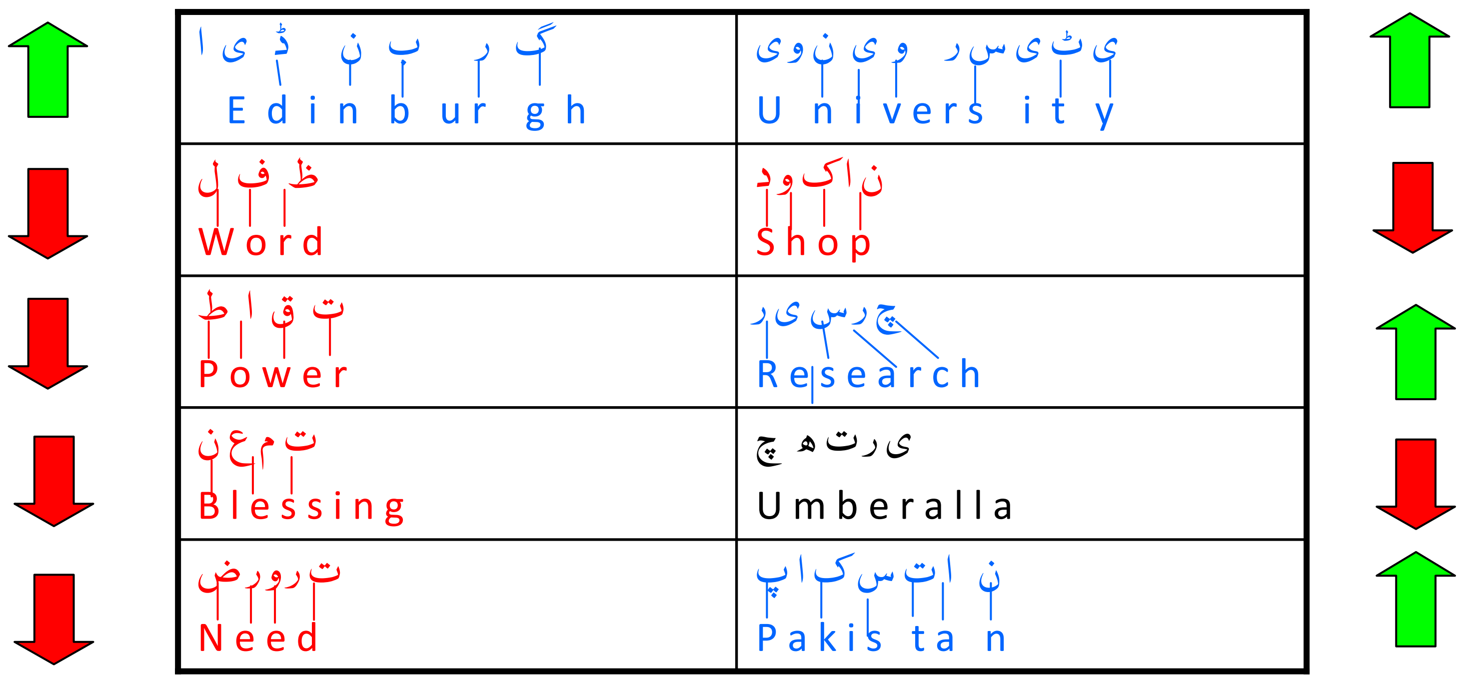
- Basic Idea
  - If we have a transliteration model, we can score the training data to extract transliteration corpus

а н а л о г a n a l o g	0.83
с и с т е м а a n a l o g	0.05
э н т о н и a n t h o n y	0.71
я з ы к о в о l i n g u i s t i c	0.001

a | a	0.78
э | a	0.45
a | e	0.07
г | g	0.75
и | y	0.88
л | l	0.82
…	…
…	…

Unsupervised Transliteration Mining

- Basic Idea
  - If we have a transliteration model, we can score the training data to extract transliteration corpus
  - If we knew which pairs in the training data are transliterations we can build transliteration model from these/boast these pairs



Unsupervised Transliteration Mining

- Transliteration Model
  - Joint sequence model
  - Only 1-1/1- ε / ε -1 mappings
  - No reoredering
  - Independence assumption
  - Sums over all character alignment sequences “a” of a word pair

$$p_1(e,f) = \sum_{a \in Align(e,f)} \prod_{j=1}^{|a|} p(q_j)$$

ا ی ڈ ε ن ب ε ر گ ε ε E d i n b u r g h	q_1: ا- ε q_2: ی-E q_3: ڈ-d q_4: ε -i ……q_9: گ-g q_{10}: ε - h
ا ی ڈ ε ن ب ε ر ε گ E ε d i n b u r g h	q_1: ا-E q_2: ی- ε q_3: ڈ-d q_4: ε -i ……q_9: ε - g q_{10} گ- h

Two different alignment sequences of a word pair

Unsupervised Transliteration Mining

- Overall model
  - We want EM to maximize the likelihood the entire training data
  - Transliteration model should only model the transliteration sub-data

$$p_1(e,f) = \sum_{a \in Align(e,f)} \prod_{j=1}^{|a|} p(q_j) \qquad p_2(e,f) = \prod_{i=1}^{|e|} p_E(e_i) \prod_{i=1}^{|f|} p_F(f_i)$$

Transliteration Model — Non-Transliteration Model

  - A mixture of transliteration and non-transliteration model

$$p(e,f) = (1-\lambda)p_1(e,f) + \lambda p_2(e,f)$$

  - Posterior Probability

$$\frac{(1-\lambda)p_1(e,f)}{p(e,f)} \qquad \frac{\lambda p_2(e_i,f_i)}{p(e_i,f_i)}$$

Transliteration Model — Non-Transliteration Model

Unsupervised Transliteration Mining

- Expectation Step
  - Compute expected counts for all bilingual character pairs “q”

$$c(q) = \sum_{i=1}^{N} \sum_{a \in Align(e_i, f_i)} \frac{(1-\lambda) p_1(a, e_i, f_i)}{p(e_i, f_i)} n_q(a)$$

$$c_{ntr} = \sum_{i=1}^{N} \frac{\lambda p_2(e_i, f_i)}{p(e_i, f_i)}$$

λ = prior probability of non-transliteration
$p_1(a,e_i,f_i)$ = probability of an alignment sequence “a”
$n_q(a)$ = number of times “q” occurs in “a”
c_{ntr} = sum of non-transliteration posterior probabilties

Unsupervised Transliteration Mining

- Maximization Steps

$$p(q) = \frac{c(q)}{\sum_{q'} c(q')} \qquad \lambda = \frac{c_{ntr}}{N}$$

λ = prior probability of non-transliteration
c_{ntr} = sum of non-transliteration posterior probabilities
p(q) = probability of a bilingual unit “q”

Intrinsic Evaluation

- Shared Task of Transliteration Mining (Kumaran et al. 2010)
  - Mine transliterations from a list of word pairs
  - Comparing F-Measures against best submitted system

Language	Unsupervised Mining	Best System
Arabic	P: 89.2 R: 95.7 F: 92.4	F:91.5
Hindi	P: 92.6 R: 99 F: 95.7	F:94.4
Russian	P: 67.2 R: 97.1 F: 79.4	F:87.5

Integration into Machine Translation

- Run unsupervised transliteration over word-alignments
  - 7 Language pairs:
    - Arabic, Bengali, Farsi, Hindi, Russian, Telegu and Urdu
  - Only 1-1 alignments are used as N-1/M-N alignments are less likely to be transliterations
  - Output: List of transliteration pairs

- Build transliteration model
  - We use phrase-based Moses
    - Segment training data into characters
    - 4-translation features
    - Monotonic decoding
  - Use 10% training data for tuning parameters

Evaluation

Lang	Data	$Train_{tm}$	$Train_{tr}$	Dev	$Test_1$	$Test_2$
		Sent	Types			
Arabic	IWSLT-13	152K	6795	887	1434	1704
Bengali	JHU	24K	1916	775	1000	
Farsi	IWSLT-13	79K	4039	852	1185	1116
Hindi	JHU	39K	4719	1000	1000	
Russian	WMT-13	2M	302K	1501	1502	3000
Telugu	JHU	45K	4924	1000	1000	
Urdu	JHU	87K	9131	980	883	

Integration into Machine Translation

- Run unsupervised transliteration over word-alignments
  - Only 1-1 alignments are used as N-1/M-N alignments are less likely to be transliterations
  - Output: List of transliteration pairs
- Build transliteration model
  - We use phrase-based Moses
    - Segment training data into characters
    - 4-translation features
    - Language model trained on target-side
    - Monotonic decoding
  - Use 10% training data for tuning parameters

Intrinsic Evaluation

Accuracy	AR	HI	RU
Test Size	1799	2394	1859
1-best	20.0%	25.3%	46.1%
100-best	80.2%	79.3%	87.5%

- Test Data = Seed Data + Reference Data provided for Transliteration Mining Shared Task (Kumaran et al. 2010)
- 1-best accuracy is quite low
- But 100-best accuracy is reasonable
- Hopefully MT system will bring out MT system at the top

Integration into Machine Translation

- Three methods for integration
  - Method 1: Replace OOV words with 1-best transliteration
  - Method 2: Selects transliteration from n-best list in post-decoding
  - Method 3: Integrates transliteration phrase-table inside decoder

Integration into Machine Translation

- Three methods for integration
  - Method 1: Replace OOV words with 1-best transliteration
    - Does not consider contextual information,
    - بيل → "Bell" in "Alexander Graham Bell"
    - بيل → "Bill" in "Bill Clinton"

SMT Evaluation

Lang	Test	B_0	M_1	M_2	M_3	OOV
AR	$iwslt_{11}$	26.75	+0.12	+0.36	+0.25	587
	$iwslt_{12}$	29.03	+0.10	+0.30	+0.27	682
BN	jhu	16.29	+0.12	+0.42	+0.46	1239
FA	$iwslt_{11}$	20.85	+0.10	+0.40	+0.31	559
	$iwslt_{12}$	16.26	+0.04	+0.20	+0.26	400
HI	jhu	15.64	+0.21	+0.35	+0.47	1629
RU	wmt_{12}	33.95	+0.24	+0.55	+0.49	434
	wmt_{13}	25.98	+0.25	+0.40	+0.23	799
TE	jhu	11.04	-0.09	+0.40	+0.75	2343
UR	jhu	23.25	+0.24	+0.54	+0.60	827
Avg		21.9	+0.13	+0.39	+0.41	950

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Integration into Machine Translation

- Three methods for integration
  - Method 1: Replace OOV words with 1-best transliteration
    - Does not consider contextual information,
    - بيل → "Bell" in "Alexander Graham Bell"
    - بيل → "Bill" in "Bill Clinton"
  - Method 2: Selecting the best transliteration from a list of n-best transliteration in a post-decoding step
    - Pipe the output of decoder into monotonic decoder
    - Features: Language Model, LM-OOV feature, Transliteration Phrase Table
    - 4 translation features to form a transliteration phrase-table

	Bill	
Alexander Graham	Bell	is credited with the invention of telephone
	Ball	
	Pill	

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Integration into Machine Translation

- Three methods for integration
  - Method 2: can not reorder unknown words
    - بحيره عرب

      (Arabian Sea) instead translates to Sea Arabian
  - Method 3 is also useful when translating words that can also be transliterated
    - आशा (Asha) translates into "hope" but transliterates to "Asha" in "Asha Bhosle" (the famous Indian singer)
    - Learning what to transliterate all previous work is language dependent
  - Method 3: Passes transliteration phrase-table into the decoder
    - Transliteration phrase-table
    - All features + LM-OOV feature

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SMT Evaluation

- Can we improve these results by improving 1-best accuracy?
  - Replace mined transliteration system (MTS) with gold-standard transliteration system (GST)

	AR		HI	RU	
Test	$iwslt_{11}$	$iwslt_{12}$	jhu	wmt_{12}	wmt_{13}
B_0	26.75	29.03	15.64	33.95	25.98
MTS	27.11	29.33	16.11	34.50	26.38
GST	26.99	29.20	16.11	34.33	26.22
$\triangle$	-0.12	-0.13	0.0	-0.17	-0.16
	Transliteration Pairs Used				
MTS	6795		4719	302K	
GST	1799		2394	1859	

Error Analysis

- MTS has better rule coverage – GST suffers from data sparsity

Source	MTS/Ref	GST
الغيغابكسل	Gigapixel	algegapixel
ال (al) → ε		
سبرلوك	Spurlock	Sbrlok
ب (b) → p		
талботу	Talbot	Talboty
y → ε		

Summary

- Integrated unsupervised mining in Moses
  - 3 Methods of integration
  - Achieved average gain of 0.41 ranging from (0.23 — 0.75) across 7 language pairs
  - Mined transliterations provide better rule coverage than gold-standard transliterations
  - All code is available for use in Moses git-repository
- Possible future work:
  - We have already spotted what words in parallel data are transliterations/Named Entities
    - May be this information can be handy to build an automatic NE recognizer/or for learning what to transliterate
  - Make this work for Chinese

Questions?