Cross-Lingual Information Extraction 601.764

2/2/23

Note that many of the examples come Bikel and Zitouni 2012

Information Extraction (IE)

♦ Identifying

♦ Extracting

♦ Useful *text information*

Useful?

- Ser/Task/Application specific
- Arbitrarily broad
- ♦ Even up to world knowledge

2 Main Subtasks

- Mention Detection
- ♦ Coreference Resolution

Mention Detection

- Detecting the boundary of a mention
- ♦ Possibly detecting semantic type (PERSON, ORGANIZATION, PLACE, etc)
- * Other attributes (Named, Nominal, Pronomial, etc.)

Coreference Resolution

* Cluster mentions referring to the same entity into equivalence classes

"I voted for Nader because he was most aligned with my values," she said.

Stanford NLP CoRef Project

Anaphora Resolution

- Related to Coreference Resolution
- ♦ Much of the literature is at odds and I would argue incorrect
- ✤ For simplicity, we will just say coreference in this lecture

President Ford said that he has no comments

Mention Detection

President Ford said that he has no comments

Nominal I President Ford said that he has no comments

Nominal Named I I President Ford said that he has no comments

Nominal Named Pronominal I I I Pronominal Pronominal

When asked about what Nixon had to say: **President Ford** said that he has no comments

Named Entity Resolution

♦ NER

- ♦ Historically, NER has been central
- ♦ Message Understanding Conference (MUC-6) in 1995:
 - ♦ Person
 - ♦ Organization
 - \diamond Location
 - ♦ Time
 - ♦ Percent
 - ♦ Money

spaCy English Entity List

PERSON:	People, including fictional.
NORP:	Nationalities or religious or political groups.
FAC:	Buildings, airports, highways, bridges, etc.
ORG:	Companies, agencies, institutions, etc.
GPE:	Countries, cities, states.
LOC:	Non-GPE locations, mountain ranges, bodies of water.
PRODUCT:	Objects, vehicles, foods, etc. (Not services.)
EVENT:	Named hurricanes, battles, wars, sports events, etc.
WORK_OF_ART:	Titles of books, songs, etc.
LAW:	Named documents made into laws.
LAW: LANGUAGE:	Named documents made into laws. Any named language.
LANGUAGE:	Any named language.
LANGUAGE: DATE:	Any named language. Absolute or relative dates or periods.
LANGUAGE: DATE: TIME:	Any named language. Absolute or relative dates or periods. Times smaller than a day.
LANGUAGE: DATE: TIME: PERCENT:	Any named language. Absolute or relative dates or periods. Times smaller than a day. Percentage, including "%".
LANGUAGE: DATE: TIME: PERCENT: MONEY:	Any named language. Absolute or relative dates or periods. Times smaller than a day. Percentage, including "%". Monetary values, including unit.

Feature Based Approaches

- ♦ Still Used ...
- ♦ … but more historical*

Feature Based Approaches

- ♦ Still Used ...
- ♦ … but more historical*
 - ♦ Lexical Features (n-Grams, 3)
 - ♦ Syntactic Features (POS)
 - ♦ Gazetteer-based (list of names)

Cross-Lingual

Cross-Lingual

"Instead, language-dependent phenomena are handled by either a preprocessing step
 Space-delimited words may not be a good unit for [entity detection and tracking], and a morph is often chosen to counter the data-sparseness problem."

Cross-Lingual

"Instead, language-dependent phenomena are handled by either a preprocessing step
 Space-delimited words may not be a good unit for [entity detection and tracking], and a morph is often chosen to counter the data-sparseness problem."

What's wrong with this?

Automatic Content Extraction (ACE)

- ♦ DARPA program for IE
- ♦ Evaluations in 2005, 2007, 2008
- ♦ Training data from 2004 and 2005

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Do we still use this?

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- ♦ DARPA program for IE
- ♦ Evaluations in 2005, 2007, 2008
- ♦ Training data from 2004 and 2005

Do we still use this?



ACE 2004

	English		Chines	e	Arabic		
Genre	Files	Words	Files	Words	Characters	Files	Words
Broadcast News	220	60,291	314	67,702	135,405	304	63,238
Newswire	128	59,840	226	60,251	120,502	253	63,122
Chinese Treebank	37	12,337	106	25,749	51,499		
Arabic Treebank	58	12,855				132	25,010
Fisher CTS	8	12,630					
Totals	451	157,953	646	153,703	307,406	689	151,360

Some of the Sources

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Everything Is All It Takes: A Multipronged Strategy for Zero-Shot Cross-Lingual Information Extraction

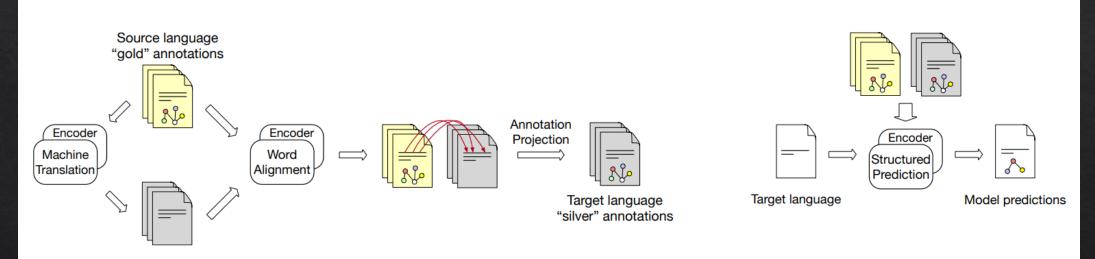


Figure 1: Process for creating projected "silver" data from source "gold" data (left). Downstream models are trained on a combination of gold and silver data (right). Components in boxes have learned parameters.

Yarmohammadi et al., 2021

Everything Is All It Takes: A Multipronged Strategy for Zero-Shot Cross-Lingual Information Extraction

	Base	Large
Multilingual	mBERT	XLM-R
Bilingual	(Devlin et al.) GBv4	(Conneau et al.) L64K & L128K
Diniguui	(Lan et al.)	(Ours)

Table 1: Encoders supporting English and Arabic.

Base models are 12-layer Transformers (d_model = 768), and large models are 24-layer Transformers (d_model = 1024)

Yarmohammadi et al., 2021

GigaBERT

Models	Training Data		,	Vocabulary		Configuration		
Widdels	source	#tokens (all/en/ar)	tokenization	size (all/en/ar)	cased	size	#parameters	
AraBERT	newswire	2.5B/ - /2.5B	SentencePiece	64k/ – / 58k	no	base	136M	
mBERT	Wiki	21.9B/2.5B/153M	WordPiece	110k/53k/5k	yes	base	172M	
XLM-R _{base}	CommonCrawl	295B/55.6B/2.9B	SentencePiece	250k/80k/14k	yes	base	270M	
XLM-R _{large}	CommonCrawl	295B/55.6B/2.9B	SentencePiece	250k/80k/14k	yes	large	550M	
GiagBERT-v0	Gigaword	4.7B/3.6B/1.1B	SentencePiece	50k/28k/19k	yes	base	125M	
GigaBERT-v1	Gigaword, Wiki	7.4B/6.1B/1.3B	WordPiece	50k/25k/23k	yes	base	125M	
GigaBERT-v2/3	Gigaword, Wiki, Oscar	10.4B/6.1B/4.3B	WordPiece	50k/21k/26k	no	base	125M	
GigaBERT-v4	Gigaword, Wiki, Oscar (+ code-switch)	10.4B/6.1B/4.3B	WordPiece	50k/21k/26k	no	base	125M	

Table 1: Configuration comparisons for AraBERT (Antoun et al., 2020), mBERT (Devlin et al., 2019), XLM-RoBERTa (Conneau et al., 2020a), and GigaBERT (this work).

Wan et al., 2020

Everything Is All It Takes: A Multipronged Strategy for Zero-Shot Cross-Lingual Information Extraction

Encoder	BLEU
Public	12.7
None	14.9
mBERT GBv4	15.7 15.7
XLM-R L64K L128K	16.0 16.2 15.8

Table 2: BLEU scores of MT systems with differentpre-trained encoders on English–Arabic IWSLT'17.

Yarmohammadi et al., 2021

Everything Is All It Takes: A Multipronged Strategy for Zero-Shot Cross-Lingual Information Extraction

Model	Layer†	AER	Р	R	F
fast-align*	n/a	47.4	53.9	51.4	52.6
Awesome-ali	ign w/o FT				
mBERT	8	35.6	78.5	54.5	64.4
GBv4	8	32.7	85.6	55.4	67.3
XLM-R	16	40.1	78.6	48.4	59.9
L64K	17	34.0	81.5	55.5	66.0
L128K	17	35.1	80.0	54.5	64.9
Awesome-ali	ign w/ FT				
mBERT _{ft}	8	30.0	81.9	61.2	70.0
GBv4 _{ft}	8	29.3	86.9	59.7	70.7
XLM-R _{ft}	18	27.8	90.3	60.2	72.2
L64K _{ft}	17	29.1	84.9	60.9	70.9
$L128K_{ft}$	16	32.2	80.3	58.7	67.8
Awesome-ali	ign w/ FT &	k supervi	sion		
XLM-R _{ft.s}	16	23.3	92.5	65.6	76.7
$L128K_{ft.s}$	17	23.5	93.7	64.6	76.5

Table 3: Alignment performance on GALE EN–AR. *Trained on MT bitext. †We report the best layer of each encoder based on dev alignment error rate (AER).

Yarmohammadi et al., 2021

	MT
(Z)	-
(A)	public
(B) (B)	public public
(C) (C) (C)	public public public
(D) (D) (D)	public public public
(E) (E) (E) (E)	GBv4 GBv4 L128K L128K
(S)	public
(Z)	-
(C) (C) (C)	public public public
(E) (E) (E) (E)	GBv4 GBv4 L128K L128K
(F) (F) (F) (F) (F)	GBv4 GBv4 L128K L128K L128K
(S)	public

	MT	Align	ACE	NER	POS	Parsing	вет. асе	NER	POS	Parsing	BET.
		_									
(Z)) –										
(A)) public	-									
(B) (B)											
(C) (C) (C)) public										
(D) (D) (D)) public	-									
(E) (E) (E) (E)) GBv4) L128K										
(S)											
(Z)) -	-									
(C) (C) (C)) public										
(E) (E)) GBv4										
(E) (E) (E)) L128K										
(F) (F)	GBv4 GBv4										
(F) (F) (F)	L128K										
(S)											

	MT	Align	ACE	NER	POS	Parsing	BET.	ACE	NER	POS	Parsing	BET.
(Z)	-	-										
(A)	public	FA										
(B) (B)	public public	mBERT XLM-R										
(C) (C) (C)	public public public	mBERT _{ft} XLM-R _{ft} XLM-R c										
(C) (D) (D) (D)	public public public	$\frac{\text{XLM-R}_{ft.s}}{\text{GBv4}_{ft}}$ $\frac{\text{GBv4}_{ft}}{\text{L128K}_{ft}}$ $\frac{\text{L128K}_{ft.s}}{\text{L128K}_{ft.s}}$										
(E) (E) (E)	GBv4 GBv4 L128K L128K	mBERT _{ft} XLM-R _{ft} mBERT _{ft}										
(E) (S)	public	XLM-R _{ft} ST										
(Z)	-	-										
(C) (C) (C)	public public public	mBERT _{ft} XLM-R _{ft} XLM-R _{ft.s}										
(E) (E) (E)	GBv4 GBv4 L128K	mBERT _{ft} XLM-R _{ft} mBERT _{ft}										
(E)	L128K	$XLM-R_{ft}$										
(F) (F) (F) (F) (F)	GBv4 GBv4 L128K L128K L128K	$\begin{array}{c} {\rm GBv4}_{ft} \\ {\rm L128K}_{ft} \\ {\rm GBv4}_{ft} \\ {\rm L128K}_{ft} \\ {\rm L128K}_{ft.s} \end{array}$										
(S)	public	ST										

	MT	Align	ACE	NER	POS	Parsing	BET.	ACE	NER	POS	Parsing	BET.
			mBERT	r (base, n	nultilingu	al)						
(Z)	-	-	27.0	41.6	59.7	29.2	39.9					
(A)	public	FA	+2.5	-3.8	+8.5	+7.3	+2.6					
(B) (B)	public public	mBERT XLM-R	+6.5 +0.9	+0.2 -2.9	+8.5 +9.5	+7.6 +9.0	+2.3 -1.2					
(C) (C) (C)	public public public	mBERT _{ft} XLM-R _{ft} XLM-R _{ft.s}	+7.8 +7.7 +7.3	+5.6 +4.9 +1.5	+7.7 +6.2 +10.1	+10.0 +9.3 +12.4	+4.1 +4.5 +4.8					
(D) (D) (D)	public public public	$\frac{\text{GBv4}_{ft}}{\text{L128K}_{ft}}$ $\text{L128K}_{ft.s}$	+8.5 +6.4 +7.0	+4.3 +3.1 +3.7	+5.9 +6.5 +10.3	+8.9 +8.2 +11.8	+5.0 +1.6 +5.4					
(E) (E) (E) (E)	GBv4 GBv4 L128K L128K	$\begin{array}{c} \text{mBERT}_{ft} \\ \text{XLM-R}_{ft} \\ \text{mBERT}_{ft} \\ \text{XLM-R}_{ft} \end{array}$	+8.4 +9.6 +12.1 +10.2	+3.2 +1.8 +3.3 -1.9	+7.7 +7.0 +7.9 +6.1	+9.9 +9.5 +9.9 +9.4	+4.7 +5.2 +4.7 +4.8					
(S)	public	ST JI	-	+5.5	+0.1	-20.3	+0.3					
			*									
(Z)	-	-										
(C) (C) (C)	public public public	mBERT _{ft} XLM-R _{ft} XLM-R _{ft.s}										
(E) (E) (E) (E)	GBv4 GBv4 L128K L128K	mBERT _{ft} XLM-R _{ft} mBERT _{ft} XLM-R _{ft}										
(F) (F) (F) (F) (F)	GBv4 GBv4 L128K L128K L128K	$\begin{array}{c} \mathrm{GBv4}_{ft} \\ \mathrm{L128K}_{ft} \\ \mathrm{GBv4}_{ft} \\ \mathrm{L128K}_{ft} \\ \mathrm{L128K}_{ft.s} \end{array}$										
(S)	public	ST										

	MT	Align	ACE	NER	POS	Parsing	BET.	ACE	NER	POS	Parsing	BET.	
			mBERT	'(base, n	ıultilingu	ual)	XLM-R (large, multilingual)						
(Z)	-	-	27.0	41.6	59.7	29.2	39.9	45.1	46.4	73.3	48.0	50.8	
(A)	public	FA	+2.5	-3.8	+8.5	+7.3	+2.6	-7.5	-0.1	-7.7	-9.5	-1.6	
(B) (B)	public public	mBERT XLM-R	+6.5 +0.9	+0.2 -2.9	+8.5 +9.5	+7.6 +9.0	+2.3	-4.4 -10.0	+6.9 +0.0	-6.1 -5.9	-8.4 -8.8	-2.6 -6.3	
(C) (C) (C)	public public public	mBERT _{ft} XLM-R _{ft} XLM-R _{ft.s}	+7.8 +7.7 +7.3	+5.6 +4.9 +1.5	+7.7 +6.2 +10.1	+10.0 +9.3 + 12.4	+4.1 +4.5 +4.8	-0.6 -2.6 -3.0	+7.4 +7.0 +9.1	-8.0 -9.0 -3.8	-6.8 -7.6 -3.7	+0.3 +1.0 +2.3	
(D) (D) (D)	public public public	${ m GBv4}_{ft}$ L128K $_{ft}$ L128K $_{ft.s}$	+8.5 +6.4 +7.0	+4.3 +3.1 +3.7	+5.9 +6.5 +10.3	+8.9 +8.2 +11.8	+5.0 +1.6 +5.4	-1.5 -1.6 -0.3	+7.7 +6.1 +5.2	-9.4 -9.0 -4.4	-9.1 -9.4 -4.6	-0.1 -3.6 +2.1	
(E) (E) (E) (E)	GBv4 GBv4 L128K L128K	$\begin{array}{c} \mathrm{mBERT}_{ft} \\ \mathrm{XLM-R}_{ft} \\ \mathrm{mBERT}_{ft} \\ \mathrm{XLM-R}_{ft} \end{array}$	+8.4 +9.6 +12.1 +10.2	+3.2 +1.8 +3.3 -1.9	+7.7 +7.0 +7.9 +6.1	+9.9 +9.5 +9.9 +9.4	+4.7 +5.2 +4.7 +4.8	-1.5 -0.4 -1.4 -0.5	+3.2 +1.4 +7.2 +4.6	-7.1 -8.3 -8.1 -9.8	-6.7 -7.7 -6.7 -7.5	+0.7 +1.4 +1.3 +2.0	
(S)	public	ST	-	+5.5	+0.1	-20.3	+0.3	-	+10.0	+1.8	-29.6	+1.2	
(Z)	-	-											
(C) (C) (C)	public public public	mBERT _{ft} XLM-R _{ft} XLM-R _{ft.s}											
(E) (E) (E) (E)	GBv4 GBv4 L128K L128K	mBERT _{ft} XLM-R _{ft} mBERT _{ft} XLM-R _{ft}											
(F) (F) (F) (F) (F)	GBv4 GBv4 L128K L128K L128K	$GBv4_{ft}$ $L128K_{ft}$ $GBv4_{ft}$ $L128K_{ft}$ $L128K_{ft}$ $L128K_{ft.s}$											
(S)	public	ST											

	MT	Align	ACE	NER	POS	Parsing	BET.	ACE	NER	POS	Parsing	BET.
			mBERT	<mark>r (base</mark> , n	nultilingu	ual)		XLM-F	R (large, 1	nultiling	ual)	
(Z)	-	-	27.0	41.6	59.7	29.2	39.9	45.1	46.4	73.3	48.0	50.8
(A)	public	FA	+2.5	-3.8	+8.5	+7.3	+2.6	-7.5	-0.1	-7.7	-9.5	-1.6
(B) (B)	public public	mBERT XLM-R	+6.5 +0.9	+0.2 -2.9	+8.5 +9.5	+7.6 +9.0	+2.3 -1.2	-4.4 -10.0	+6.9 +0.0	-6.1 -5.9	-8.4 -8.8	-2.6 -6.3
(C) (C) (C)	public public public	mBERT _{ft} XLM-R _{ft} XLM-R _{ft.s}	+7.8 +7.7 +7.3	+5.6 +4.9 +1.5	+7.7 +6.2 +10.1	+10.0 +9.3 + 12.4	+4.1 +4.5 +4.8	-0.6 -2.6 -3.0	+7.4 +7.0 +9.1	-8.0 -9.0 -3.8	-6.8 -7.6 -3.7	+0.3 +1.0 +2.3
(D) (D) (D)	public public public	${ m GBv4}_{ft}$ L128K $_{ft}$ L128K $_{ft.s}$	+8.5 +6.4 +7.0	+4.3 +3.1 +3.7	+5.9 +6.5 +10.3	+8.9 +8.2 +11.8	+5.0 +1.6 +5.4	-1.5 -1.6 -0.3	+7.7 +6.1 +5.2	-9.4 -9.0 -4.4	-9.1 -9.4 -4.6	-0.1 -3.6 +2.1
(E) (E) (E) (E)	GBv4 GBv4 L128K L128K	$\begin{array}{l} \mathrm{mBERT}_{ft} \\ \mathrm{XLM-R}_{ft} \\ \mathrm{mBERT}_{ft} \\ \mathrm{XLM-R}_{ft} \end{array}$	+8.4 +9.6 +12.1 +10.2	+3.2 +1.8 +3.3 -1.9	+7.7 +7.0 +7.9 +6.1	+9.9 +9.5 +9.9 +9.4	+4.7 +5.2 +4.7 +4.8	-1.5 -0.4 -1.4 -0.5	+3.2 +1.4 +7.2 +4.6	-7.1 -8.3 -8.1 -9.8	-6.7 -7.7 -6.7 -7.5	+0.7 +1.4 +1.3 +2.0
(S)	public	ST	-	+5.5	+0.1	-20.3	+0.3	-	+10.0	+1.8	-29.6	+1.2
			GBv4 (base, bili	ingual)							
(Z)	-	-	46.0	45.4	64.7	33.2	41.7	-				
(C) (C) (C)	public public public	mBERT _{ft} XLM-R _{ft} XLM-R _{ft.s}	+0.6 -1.4 -0.1	+3.7 + 4.5 +3.4	+2.6 +1.8 +5.1	+6.9 +6.0 +9.2	+7.5 +8.4 +8.0					
(E) (E) (E) (E)	GBv4 GBv4 L128K L128K	mBERT _{ft} XLM-R _{ft} mBERT _{ft} XLM-R _{ft}	-0.1 +0.1 -0.6 +0.9	+0.1 +0.4 +1.0 -2.1	+3.3 +1.5 +2.6 +1.1	+7.2 +6.0 +6.1 +5.5	+8.1 +9.7 +7.4 +7.8	-				
(F) (F) (F) (F) (F)	GBv4 GBv4 L128K L128K L128K	$GBv4_{ft}$ $L128K_{ft}$ $GBv4_{ft}$ $L128K_{ft}$ $L128K_{ft}$ $L128K_{ft.s}$	+0.0 -0.9 -4.3 -3.5 +1.9	-1.9 -1.4 -1.0 -1.1 +0.2	+1.6 +1.5 +0.4 +0.3 +3.3	+4.5 +4.1 +4.1 +3.8 +7.4	+9.1 +5.7 +7.4 + 4.5 +7.2					
(S)	public	ST	-	-2.5	-1.3	-18.6	+1.9					

	MT	Align	ACE	NER	POS	Parsing	BET.	ACE	NER	POS	Parsing	BET.		
		mBERT (base, multilingual)							XLM-R (large, multilingual)					
(Z)	-	-	27.0	41.6	59.7	29.2	39.9	45.1	46.4	73.3	48.0	50.8		
(A)	public	FA	+2.5	-3.8	+8.5	+7.3	+2.6	-7.5	-0.1	-7.7	-9.5	-1.6		
(B)	public	mBERT	+6.5	+0.2	+8.5	+7.6	+2.3	-4.4	+6.9	-6.1	-8.4	-2.6		
(B)	public	XLM-R	+0.9	-2.9	+9.5	+9.0	-1.2	-10.0	+0.0	-5.9	-8.8	-6.3		
(C)	public	$mBERT_{ft}$	+7.8	+5.6	+7.7	+10.0	+4.1	-0.6	+7.4	-8.0	-6.8	+0.3		
(C)	public	$XLM-R_{ft}$	+7.7	+4.9	+6.2	+9.3	+4.5	-2.6	+7.0	-9.0	-7.6	+1.0		
(C)	public	$XLM-R_{ft.s}^{ft}$	+7.3	+1.5	+10.1	+12.4	+4.8	-3.0	+9.1	-3.8	-3.7	+2.3		
(D)	public	GBv4 _{ft}	+8.5	+4.3	+5.9	+8.9	+5.0	-1.5	+7.7	-9.4	-9.1	-0.1		
(D)	public	L128Ř _{ft}	+6.4	+3.1	+6.5	+8.2	+1.6	-1.6	+6.1	-9.0	-9.4	-3.6		
(D)	public	$L128K_{ft.s}$	+7.0	+3.7	+10.3	+11.8	+5.4	-0.3	+5.2	-4.4	-4.6	+2.1		
(E)	GBv4	mBERT _{ft}	+8.4	+3.2	+7.7	+9.9	+4.7	-1.5	+3.2	-7.1	-6.7	+0.7		
(E)	GBv4	XLM-R _{ft}	+9.6	+1.8	+7.0	+9.5	+5.2	-0.4	+1.4	-8.3	-7.7	+1.4		
(E)	L128K	mBERŤ _{ft}	+12.1	+3.3	+7.9	+9.9	+4.7	-1.4	+7.2	-8.1	-6.7	+1.3		
(E)	L128K	$XLM-R_{ft}$	+10.2	-1.9	+6.1	+9.4	+4.8	-0.5	+4.6	-9.8	-7.5	+2.0		
(S)	public	ST	-	+5.5	+0.1	-20.3	+0.3	-	+10.0	+1.8	-29.6	+1.2		
			GBv4 (base, bili	ngual)			<i>L128K</i>	(large, b	oilingual)			
(Z)	-	-	46.0	45.4	64.7	33.2	41.7	42.7	46.3	67.9	36.7	40.9		
(C)	public	mBERT _{ft}	+0.6	+3.7	+2.6	+6.9	+7.5	+2.7	+8.2	-0.9	+4.9	+11.7		
(C)	public	$XLM-R_{ft}$	-1.4	+4.5	+1.8	+6.0	+8.4	+1.2	+9.0	-2.5	+3.9	+10.5		
(C)	public	$XLM-R_{ft.s}^{ft}$	-0.1	+3.4	+5.1	+9.2	+8.0	+2.7	+7.0	+1.2	+7.2	+12.1		
(E)	GBv4	mBERT _{ft}	-0.1	+0.1	+3.3	+7.2	+8.1	+4.2	-0.5	-0.1	+5.1	+11.2		
(E)	GBv4	XLM-R _{ft}	+0.1	+0.4	+1.5	+6.0	+9.7	+2.4	+0.0	-1.3	+4.2	+10.8		
(E)	L128K	$mBERT_{ft}$	-0.6	+1.0	+2.6	+6.1	+7.4	+5.5	+0.8	-0.7	+4.7	+10.6		
(E)	L128K	$XLM-R_{ft}$	+0.9	-2.1	+1.1	+5.5	+7.8	+4.4	-3.6	-2.2	+4.1	+11.3		
(F)	GBv4	GBv4 _{ft}	+0.0	-1.9	+1.6	+4.5	+9.1	+2.0	-0.3	-1.7	+3.2	+10.9		
(F)	GBv4	$L128K_{ft}$	-0.9	-1.4	+1.5	+4.1	+5.7	+2.3	-1.7	-2.4	+2.6	+8.3		
(F)	L128K	$GBv4_{ft}$	-4.3	-1.0	+0.4	+4.1	+7.4	+4.1	-3.6	-2.1	+2.3	+11.4		
(F)	L128K	L128K _{ft}	-3.5	-1.1	+0.3	+3.8	+ 4.5	+2.9	+0.1	-2.9	+2.0	+6.7		
(F)	L128K	$L128K_{ft.s}$	+1.9	+0.2	+3.3	+7.4	+7.2	+2.8	-1.8	+0.8	+6.0	+11.8		
(S)	public	ST	-	-2.5	-1.3	-18.6	+1.9	-	+7.1	+1.5	-21.7	+8.1		

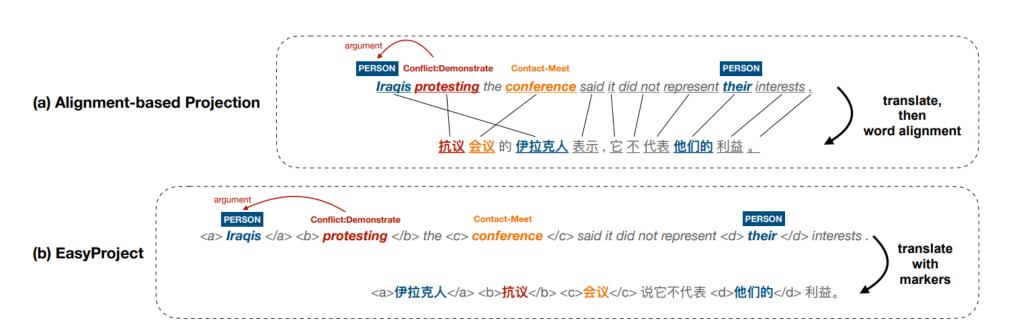


Figure 1: An example of translating and projecting English ACE event triggers and named entities to Chinese. (a) Label projection pipeline starts with machine translation of the English sentence to Chinese, followed by word-to-word alignment. Then, label spans are projected based on word alignments. (b) Markers are inserted around entity and event trigger spans in the text. The modified sentence with markers inserted is then fed as input to a machine translation system, projecting the label span markers to the target language as a byproduct of translation.

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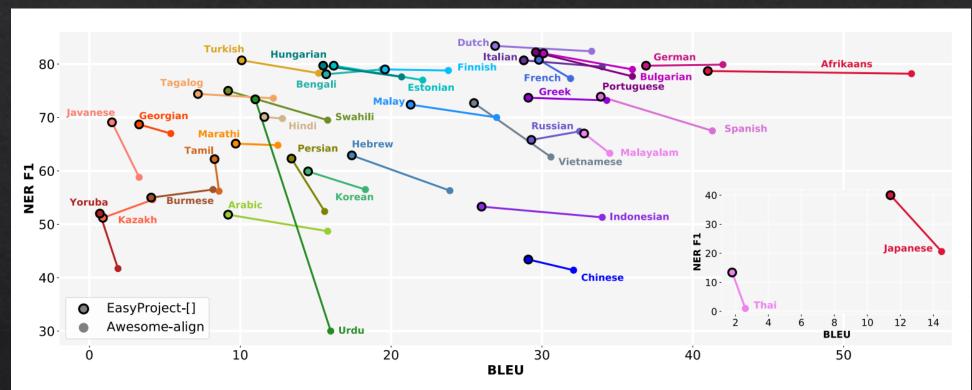


Figure 2: Comparison of translation quality and end-task performance for different label projection methods on the WikiANN dataset. EasyProject ($\S3.3$) outperforms the alignment-based approach on F₁ scores for most languages, although inserting span markers degrade translation quality. The detailed experimental setting is in \$4.1.

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$en \rightarrow Lang.$		Fine-tune		M2M+Word Aligner		M2M+Markers		GMT+Word Aligner			GMT+Markers		
		Ref	Ref XLM _R		QAalign awesome $awes_{ft}$		XML	L EProj. (Δ_{XLM_R})		QAalign awesome $awes_{ft}$			EProj. (Δ_{XLM_R})
	yo	41.3	37.1	-	46.8	48.3	56.0	58.3 (+21.2)	-	72.1	66.1	71.8	73.8 (+36.7)
	ja	18.3	18.0	19.3	21.1	24.9	40.2	40.8 (+22.8)	19.3	23.0	22.6	42.0	43.5 (+25.5)
	zh	25.8	27.1	43.1	40.5	39.5	42.4	44.4 (+17.3)	45.2	43.3	39.6	43.8	45.9 (+18.8)
	th	1.5	0.7	-	2.4	1.0	12.3	13.0 (+12.3)	-	1.2	1.3	14.7	15.1 (+14.4)
	ur	54.2	63.6	-	37.0	58.7	77.4	76.1 (+12.5)	-	70.2	72.3	76.3	74.7 (+11.1)
	he	54.1	56.0	-	56.6	56.3	60.1	62.1 (+6.1)	-	59.6	60.2	63.7	67.1 (+11.1)
	ms	69.8	64.1	-	70.7	71.8	74.2	73.9 (+9.8)	-	73.0	73.8	73.2	74.1 (+10.0)
	my	51.3	53.5	-	61.0	60.4	53.8	57.0 (+3.5)	-	60.2	60.1	57.0	62.0 (+8.5)
	ar	43.7	48.5	49.7	46.6	49.3	43.0	48.9 (+0.4)	50.7	50.9	51.2	51.3	56.3 (+7.8)
	jv	58.4	62.3	-	60.4	56.6	64.4	65.9 (+3.6)	-	64.6	68.8	69.2	69.8 (+7.5)
	tl	72.2	73.0	-	73.3	73.9	78.1	76.5 (+3.5)	-	80.4	80.4	79.9	80.0 (+7.0)
	hi	71.0	69.5	-	72.1	71.3	73.2	72.3 (+2.8)	-	75.6	76.0	75.9	75.7 (+6.2)
	ka	68.9	68.8	-	66.6	67.1	68.4	71.1 (+2.3)	-	73.5	73.2	72.7	74.7 (+5.9)
	bn	76.3	75.1	-	79.7	79.5	80.7	79.1 (+4.0)	-	82.0	81.7	80.6	80.9 (+5.8)
	ta	56.9	58.8	-	56.1	56.3	59.0	62.1 (+3.3)	-	62.4	63.2	63.9	64.3 (+5.5)
	eu	62.1	63.6	-	-	-	-	-	-	69.8	66.5	67.5	69.0 (+5.4)
	ko	58.0	57.9	-	57.5	58.1	57.4	60.9 (+3.0)	-	62.9	62.4	61.7	61.9 (+4.0)
NER	mr	64.1	63.9	-	64.9	62.9	66.9	64.3 (+0.4)	-	62.6	61.2	64.0	67.1 (+3.2)
NEK	SW	70.0	68.5	-	70.2	70.1	74.1	71.8 (+3.3)	-	70.2	71.5	72.2	70.7 (+2.2)
	te	52.3	55.6	-	-	-	-	-	-	57.4	56.8	57.6	57.4 (+1.8)
	vi	77.2	74.2	-	64.1	62.7	75.4	74.9 (+0.7)	-	70.4	67.2	77.5	76.0 (+1.8)
	id	52.3	52.4	-	53.0	53.2	53.4	53.9 (+1.5)	-	52.7	55.0	57.3	53.9 (+1.5)
	ml	65.8	63.5	-	66.7	66.1	65.6	68.9 (+5.4)	-	61.9	63.0	68.1	64.3 (+0.8)
	es	68.8	74.8	-	69.8	68.2	71.8	73.5 (-1.3)	-	71.3	72.6	73.5	75.6 (+0.8)
	de	77.9	79.4	79.5	79.9	80.0	80.2	80.7 (+1.3)	79.5	80.0	79.4	79.8	80.2 (+0.8)
	kk	49.8	53.5	-	54.2	51.6	50.5	51.1 (-2.4)	-	53.2	55.1	51.3	54.2 (+0.7)
	fr	79.0	80.1	79.1	78.5	79.8	80.7	81.7 (+1.6)	79.6	80.7	79.4	81.5	80.8 (+0.7)
	af	77.6	78.6	-	77.5	78.4	78.9	79.1 (+0.5)	-	79.1	78.9	79.0	79.2 (+0.6)
	et	78.0	79.6	-	78.6	78.4	78.2	80.9 (+1.3)	-	80.2	79.6	78.6	80.1 (+0.5)
	hu	79.3	81.0	-	77.1	77.1	79.0	80.8 (-0.2)	-	79.9	79.7	80.6	80.7 (-0.3)
	fi	78.6	80.6	-	79.2	78.8	78.3	80.1 (-0.5)	-	80.7	79.7	78.8	80.3 (-0.3)
	ĭt	81.1	81.3	-	80.2	80.5	80.7	81.1 (-0.2)	-	80.3	80.4	81.1	80.9 (-0.4)
	tr	78.9	80.3	-	78.4	77.8	82.7	82.0 (+1.7)	-	80.1	80.2	81.5	79.6 (-0.7)
	nl	84.3	84.1	-	82.1	82.3	83.1	84.2 (+0.1)	-	83.5	82.9	83.0	83.1 (-1.0)
	bg	81.2	82.1	-	80.3	79.9	82.1	81.3 (-0.8)	-	80.9	79.7	82.5	80.6 (-1.5)
	pt	79.6	82.0	-	76.8	78.0	81.9	82.3 (+0.3)	-	79.0	80.2	80.6	80.1 (-1.9)
	ru	71.5	71.1	-	67.4	67.9	67.6	67.8 (-3.3)	-	67.4	66.8	67.4	68.2 (-2.9)
	el	77.2	79.3	-	73.3	74.5	75.6	75.6 (-3.7)	-	73.1	75.2	76.2	75.0 (-4.3)
	fa	61.1	64.3	-	59.0	51.7	56.0	62.4 (-1.9)	-	52.9	52.4	45.5	52.0 (-12.3)
AVG(-e	eu/te)	63.6	64.6	-	63.8	64.1	67.1	68.1 (+3.6)	-	66.9	66.8	68.6	69.3 (+4.7)

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Event Extraction		Fine-tune	M2M+Word Aligner	M2M+Markers	GMT+Word Aligner	GMT+Markers	
		XLM _R	QAalignawesome $awes_{ft}$	$\overline{\text{XML} \text{EProj.} (\Delta_{\text{XLM}_R})}$	QAalignawesome $awes_{ft}$	$\overline{\text{XML} \text{EProj.} (\Delta_{\text{XLM}_R})}$	
Arabic	Entity Relation Trig-I Trig-C Arg-I Arg-C	69.2 28.1 42.7 40.0 33.5 30.8	74.373.774.135.032.933.943.944.044.042.242.042.337.936.337.834.933.634.7	73.773.4 (+4.2)30.331.3 (+3.2)44.544.1 (+1.4)42.742.3 (+2.3)37.838.1 (+4.6)35.135.1 (+4.3)	74.474.374.034.833.134.243.644.243.741.842.642.037.737.937.634.635.234.5	73.774.0 (+4.8)31.833.7 (+5.6)43.844.0 (+1.3)41.542.0 (+2.0)36.937.8 (+4.3)34.135.2 (+4.4)	
	AVG	40.7	44.7 43.7 44.5	44.0 44.1 (+3.4)	44.5 44.5 44.3	43.6 44.4 (+3.7)	
Chinese	Entity Relation Trig-I Trig-C Arg-I Arg-C	59.1 20.4 25.0 23.9 28.6 28.1	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	69.070.5 (+11.4)25.635.0 (+14.6)41.946.8 (+21.8)37.643.4 (+19.5)37.641.7 (+13.1)34.840.0 (+11.9)	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccc} 70.2 & 71.0 \ (+11.9) \\ 35.6 & 28.4 \ (+8.0) \\ 50.7 & 52.6 \ (+27.6) \\ 47.4 & 49.3 \ (+25.4) \\ 39.8 & 40.1 \ (+11.5) \\ 38.2 & 38.2 \ (+10.1) \end{array}$	
	AVG	30.8	43.9 46.8 45.0	41.1 46.2 (+15.4)	43.0 46.4 45.8	47.0 46.6 (+15.8)	

Other Major Programs

- ✤ DARPA LORELEI
- ♦ IARPA BETTER
- ✤ DARPA TIDES

What am I missing from this lecture?

What am I missing from this lecture?

♦ Modeling!

What am I missing from this lecture?

- ♦ Modeling!
- ♦ CRFs
- ♦ Seq2Seq
- ♦ Encoders