UPPSALA UNIVERSITET

UNIVERSITÉ DE GENÈVE

Universal Dependencies

as a Resource for NLP

Joakim Nivre

UD for NLP

Parsing

- Monolingual, cross-lingual and universal parsing
- Multilingual parser evaluation
- Should we use UD for parsing at all?

Beyond parsing

- UD as a basis for semantic interpretation
- Other applications of UD

Parsing

Monolingual Parsing

Monolingual Parsing

Haverinen et al. (2015) Finnish

	POS	PM	FM	LAS	UAS
Baseline (Haverinen et al., 2013b)	94.3	90.5	89.0	81.4	85.2
Stanford Dependencies (SD)	96.3	93.4	90.3	80.1	84.1
Universal Dependencies (UD)	96.0	93.1	90.5	81.0	85.0
Pure Universal Dependencies (Pure UD)	96.0	93.1	90.5	81.5	84.7

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Silveira and Manning (2015) English

	full	*partial*	*simple*
auxhead	84.37%	84.84%	84.43%
casehead	84.13%*	84.91%	84.86%
cophead	84.28%*	84.53%	84.03%*
markhead	84.27%*	84.89%	85.00%
baseline		84.69%	

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Johannsen et al. (2015) Danish

	Mate			MST		
	LAS	UAS	LA	LAS	UAS	LA
CDT DEV	85.20	89.38	90.83	84.59	89.46	90.61
CDT TEST	84.38	88.70	90.17	84.11	89.44	90.69
UD-DANISH DEV	81.87	84.51	92.10	65.87	81.57	75.71
UD-DANISH TEST	81.56	84.64	92.00	63.87	80.91	74.54

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Attardi et al. (2015) Italian

Parser	LAS	UAS	Diff
DeSR	85.97	88.52	0.40
Turbo Parser	87.93	90.64	0.86
Mate	88.55	90.66	0.54

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auxhead	84.37%	84.84%	84.43%
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Øvrelid et al. (2016) Norwegian

		LAS		UAS	
Data	Tags	NDT	UD	NDT	UD
Dev	Gold	90.15%	88.50%	92.51%	91.13%
Dev	Auto	86.73%	83.91%	89.99%	87.16%
Test	Gold	90.55%	88.54%	92.76%	91.21%
Test	Auto	86.76%	83.86%	90.13%	87.16%

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Schuster and Manning (2016) English

Genre	LAS	UAS	Accuracy
Question-answers	92.0	95.4	93.7
Email	91.4	95.8	92.7
Newsgroups	93.1	96.8	94.0
Business reviews	92.5	95.9	93.9
Weblogs	94.5	97.1	95.7
Entire corpus	92.6	96.1	93.9

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Attardi e

Parser
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		LAS	
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Schuster a

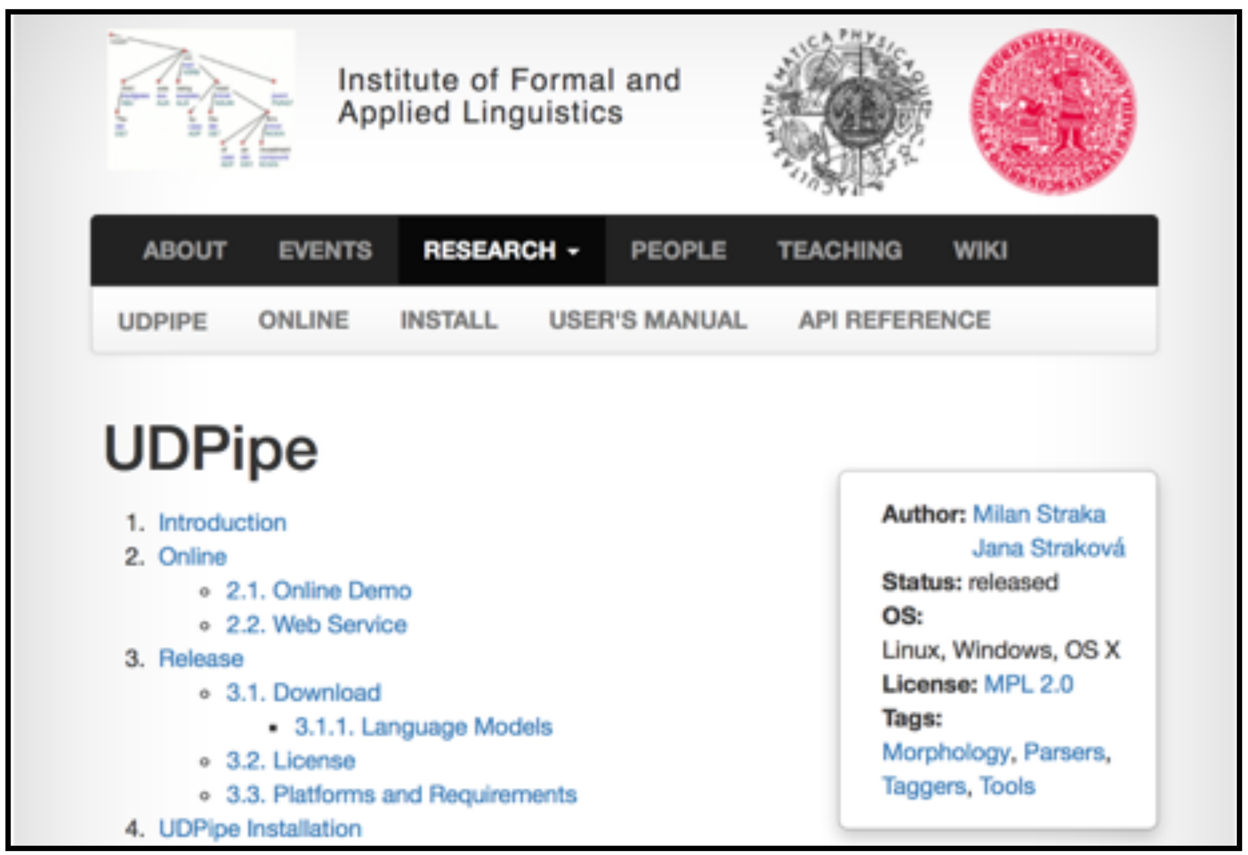
Genre
Question-answer
Email
Newsgroups
Business reviews
Weblogs
Entire corpus

Straka et al. (2015) All

Language	Size: Words / Sentences	Non-proj.: Non-proj. edges / Non-proj. sentences	Static oracle: Stack UAS / Stack LAS	Static oracle: Swap UAS / Swap LAS	Static oracle: Arc2 UAS / Arc2 LAS	Search-based oracle: Stack UAS / Stack LAS	Search-based oracle: Swap UAS / Swap LAS	Search-based oracle: Arc2 UAS / Arc2 LAS	DynO: Stack UAS / Stack LAS	SB+DO: Stack UAS / Stack LAS	MaltParser: Stack UAS / Stack LAS	MaltParser: Swap UAS / Swap LAS
Ancient Greek	244 993	9.78%	58.6	66.2	66.5	64.2	69.3	68.5	66.4	67.7	55.7	63.3
	16 221	63.22%	53.0	60.6	60.9	58.5	63.9	62.8	60.5	62.0	49.4	59.4
Ancient Greek-PROIEL	206 966	5.95%	72.3	75.7	74.8	74.4	76.1	75.5	75.8	75.9	69.7	73.4
	16 633	39.48%	67.0	70.6	69.6	69.2	71.3	70.5	70.7	71.0	64.5	68.7
Arabic	282 384	0.33%	79.9	79.8	80.2	80.4	80.6	80.7	78.2	79.4	80.1	79.7
	7 664	8.19%	74.6	74.7	75.3	75.5	75.8	75.7	73.4	74.7	74.6	74.3
Basque	121 443	4.95%	77.0	78.3	78.4	78.2	79.2	79.6	79.9	80.6	74.7	77.3
	8 993	33.74%	71.9	73.1	73.2	73.5	74.3	74.5	75.2	76.0	68.9	71.5
Bulgarian	156 319	0.21%	90.2	90.7	90.9	91.1	91.2	91.5	90.5	91.2	89.2	89.5
	11 138	2.83%	84.8	85.5	85.7	86.0	86.1	86.2	85.3	86.0	83.2	83.6
Croatian	87 765	0.46%	81.1	80.8	80.2	82.1	82.4	81.3	82.7	82.0	77.4	78.5
	3 957	7.48%	73.9	73.6	72.5	75.2	75.3	74.4	74.8	74.7	69.7	70.9
Czech	1 506 490	0.93%	86.7	87.9	87.8	87.7	88.0	88.2	87.2	87.5	85.2	86.5
	87 913	12.58%	83.2	84.3	84.4	84.3	84.7	84.8	83.8	84.1	81.3	82.4
Danish	100 733	1.97%	81.8	82.5	82.9	82.7	82.8	83.3	82.6	83.3	80.1	81.4
	5 512	22.84%	78.0	79.1	79.3	79.2	79.2	80.0	78.8	79.6	75.5	76.8
Dutch	200 654	4.10%	74.6	75.8	76.2	76.0	77.5	77.1	76.0	75.7	71.9	75.8
	13 735	30.87%	70.8	72.0	71.8	72.0	73.8	73.1	72.1	72.3	67.9	71.2
English	254 830	0.48%	86.7	86.5	86.9	87.4	87.2	87.3	87.3	87.7	86.3	86.5
	16 622	4.96%	84.2	83.8	84.2	84.7	84.5	84.5	84.5	84.7	82.9	83.2
Estonian	9 491	0.08%	85.0	85.3	86.0	87.4	86.5	86.3	86.4	86.2	86.4	88.1
	1 315	0.61%	81.7	81.9	83.0	83.2	82.8	83.1	83.1	83.0	83.8	85.7
Finnish	181 022	0.74%	80.4	81.2	81.1	81.5	81.7	81.6	82.7	83.5	81.0	80.8
	13 581	7.68%	77.0	77.9	77.6	78.2	78.3	78.6	79.2	80.2	76.9	77.0
Finnish-FTB	159 829	1.09%	80.3	80.1	80.0	81.3	81.0	80.4	81.6	82.3	79.6	80.1
	18 792	6.78%	77.2	76.9	76.6	78.1	78.0	77.3	78.0	79.1	75.8	76.3
French	401 491	0.83%	84.2	85.0	84.7	85.2	85.5	85.2	84.5	85.0	81.3	81.4
	16 446	12.45%	80.4	81.2	81.1	81.5	81.7	81.4	80.6	81.2	78.8	78.8
German	298 242	0.90%	82.3	82.6	83.0	83.3	83.3	83.1	83.2	84.4	81.3	82.2
	15 894	12.08%	76.9	77.1	77.6	78.0	78.0	77.6	77.6	78.8	75.2	75.8
Gothic	56 128	3.86%	76.2	76.1	76.2	78.3	77.4	77.9	78.0	78.5	73.2	76.2
	5 450	23.85%	70.5	70.4	70.7	72.2	71.4	72.4	72.1	73.0	69.1	70.5
Greek	59 156	1.95%	81.3	81.7	82.5	82.9	82.5	82.9	82.2	82.8	79.0	80.6
	2 411	27.87%	78.4	78.4	79.2	79.3	79.1	79.6	79.0	79.8	75.2	77.1
Hebrew	158 855	0.00%	85.1	86.0	85.9	86.0	86.2	86.1	85.6	85.8	83.2	83.1
	6 216	0.00%	80.6	81.1	81.3	81.6	81.9	81.4	81.2	81.8	78.5	78.4
Hindi	351 704	0.76%	92.5	93.3	93.0	93.3	93.7	93.6	93.8	93.9	89.4	89.5
	16 647	13.60%	89.5	90.0	89.7	90.1	90.5	90.3	90.6	90.6	84.5	84.6
Hungarian	26 538	2.09%	79.9	80.3	79.0	80.4	80.6	81.2	81.3	81.9	78.2	79.1
	1 299	25.17%	74.2	74.3	72.9	75.1	75.5	75.6	75.8	77.5	72.7	74.0
Indonesian	121 923	0.13%	83.1	83.1	83.3	83.3	83.3	83.3	82.1	82.4	81.7	81.8
	5 593	1.93%	77.8	77.6	78.0	77.9	78.2	77.9	76.7	77.0	75.8	75.9
Irish	23 686	0.81%	74.6	74.2	73.6	75.2	75.2	75.1	74.4	74.6	75.4	73.8
	1 020	12.84%	67.4	66.8	66.7	68.1	68.5	67.5	68.0	67.7	67.6	66.4
Italian	271 180	0.32%	90.1	90.0	90.3	90.6	90.6	90.8	89.8	90.6	89.0	88.8
	12 677	3.94%	87.7	87.5	87.8	88.0	88.1	88.4	87.3	88.2	85.4	86.2
Japanese-KTC	267 631	0.00%	85.1	85.2	84.9	85.5	85.7	85.7	85.1	85.3	84.2	84.1
	9 995	0.00%	75.1	75.0	74.8	75.5	75.3	75.3	75.1	75.2	72.9	73.3
Latin	47 303	7.13%	58.2	57.2	57.9	59.2	59.2	58.3	61.1	60.7	58.1	57.2
	3 269	46.22%	49.8	50.4	50.6	51.7	52.0	51.0	53.6	53.9	50.2	50.1
Latin-ITT	259 684	3.45%	77.2	80.5	79.0	77.8	80.8	79.3	79.8	79.5	72.4	76.3
	15 295	37.20%	73.8	77.5	75.7	74.6	77.9	76.2	76.5	76.6	68.3	72.3
Latin-PROIEL	165 201	5.22%	73.4	74.3	75.2	74.6	75.2	76.1	76.1	76.6	70.0	72.5
	14 982	30.09%	68.3	69.3	70.1	69.5	70.3	71.0	70.8	71.5	64.8	67.7
Norwegian	311 277	0.60%	89.2	89.2	89.7	89.8	90.0	90.1	89.7	90.1	88.9	88.9
	20 045	7.70%	86.8	86.8	87.4	87.7	87.7	87.8	87.3	87.8	85.8	86.0
Old Church Slavonic	57 507	3.71%	81.0	82.6	82.2	82.1	83.3	83.0	82.6	82.8	80.1	82.0
	6 346	21.37%	75.4	77.8	76.9	77.0	78.0	77.9	77.5	77.9	73.0	77.2
Persian	152 871	0.38%	83.8	83.1	83.5	84.5	84.2	84.6	84.8	85.0	80.8	80.8
	5 997	5.14%	80.2	79.8	80.0	81.1	80.8	81.2	81.3	81.5	77.2	77.2
Polish	83 571	0.04%	88.3	88.7	88.2	89.0	89.0	89.3	89.8	89.5	87.7	87.3
	8 227	0.32%	84.1	84.6	83.8	84.8	84.5	85.2	85.5	85.2	83.1	82.8
Portuguese	212 545	1.27%	85.8	87.6	87.5	87.5	88.4	88.1	86.9	87.5	84.5	85.5
	9 359	18.44%	82.7	84.6	83.9	84.5	85.4	85.0	83.8	84.3	80.5	81.5
Romanian	12 094	0.89%	75.4	74.5	76.3	76.7	76.9	77.4	75.5	76.3	72.8	73.1
	633	11.37%	61.9	60.9	62.1	62.7	63.2	63.2	62.2	62.2	59.5	59.6
Slovenian	140 418	1.11%	86.5	87.3	87.5	87.6	88.9	88.1	88.2	88.2	84.3	85.7
	7 996	13.61%	84.5	85.4	85.4	85.8	87.0	86.0	86.1	86.4	81.9	83.4
Spanish	431 587	0.30%	86.8	86.9	87.1	87.6	87.2	87.4	85.7	86.4	83.4	83.2
	16 013	6.05%	83.6	83.7	83.7	84.4	84.1	84.0	82.5	83.4	81.2	81.2
Swedish	96 819	0.19%	85.3	85.7	85.7	85.9	86.1	86.1	86.2	86.2	84.7	84.7
	6 026	2.77%	81.4	81.9	82.0	82.3	82.5	82.5	82.4	82.4	80.3	80.5
Tamil	9 581	0.29%	75.8	76.3	76.2	76.6	77.1	75.7	78.4	78.0	78.3	78.3
	600	2.17%	67.1	68.5	67.5	67.9	68.7	67.3	69.6	69.5	69.7	69.4

Off-the-shelf Models

UDPipe



SyntaxNet

Cross-Lingual Parsing

Cross-lingual learning:

- Using data from language X to create a model for language Y
- Usually motivated by a low-resource scenario

Three main approaches:

- Annotation projection (Hwa et al., 2002)
- Model transfer (Zeman and Resnik, 2008)
- Treebank translation (Tiedemann et al., 2014)

UD for Evaluation

McDonald et al. (2011)

Target Test Language	Source Training Language: da	de	el	en	es	it	nl	pt	sv
da	**79.2**	45.2	44.0	45.9	45.0	48.6	46.1	48.1	47.8
de	34.3	**83.9**	53.2	47.2	45.8	53.4	55.8	55.5	46.2
el	33.3	52.5	**77.5**	63.9	41.6	59.3	57.3	58.6	47.5
en	34.4	37.9	45.7	**82.5**	28.5	38.6	43.7	42.3	43.7
es	38.1	49.4	57.3	53.3	**79.7**	68.4	51.2	66.7	41.4
it	44.8	56.7	66.8	57.7	64.7	**79.3**	57.6	69.1	50.9
nl	38.7	43.7	62.1	60.8	40.9	50.4	**73.6**	58.5	44.2
pt	42.5	52.0	66.6	69.2	68.5	74.7	67.1	**84.6**	52.1
sv	44.5	57.0	57.8	58.3	46.3	53.4	54.5	66.8	**84.8**

UD for Evaluation

McDonald et al. (2011)

Target Test Language	Source Training Language: da	de	el	en	es	it	nl	pt	sv
da	**79.2**	45.2	44.0	45.9	45.0	48.6	46.1	48.1	47.8
de	34.3	**83.9**	53.2	47.2	45.8	53.4	55.8	55.5	46.2
el	33.3	52.5	**77.5**	63.9	41.6	59.3	57.3	58.6	47.5
en	34.4	37.9	45.7	**82.5**	28.5	38.6	43.7	42.3	43.7
es	38.1	49.4	57.3	53.3	**79.7**	68.4	51.2	66.7	41.4
it	44.8	56.7	66.8	57.7	64.7	**79.3**	57.6	69.1	50.9
nl	38.7	43.7	62.1	60.8	40.9	50.4	**73.6**	58.5	44.2
pt	42.5	52.0	66.6	69.2	68.5	74.7	67.1	**84.6**	52.1
sv	44.5	57.0	57.8	58.3	46.3	53.4	54.5	66.8	**84.8**

McDonald et al. (2013)

Source Training Language	Target Test Language											
	Unlabeled Attachment Score (UAS)						Labeled Attachment Score (LAS)					
	Germanic			Romance			Germanic			Romance		
	DE	EN	SV	ES	FR	KO	DE	EN	SV	ES	FR	KO
DE	74.86	55.05	65.89	60.65	62.18	40.59	64.84	47.09	53.57	48.14	49.59	**27.73**
EN	58.50	83.33	**70.56**	68.07	70.14	**42.37**	48.11	78.54	**57.04**	56.86	58.20	26.65
SV	**61.25**	**61.20**	80.01	67.50	67.69	36.95	**52.19**	**49.71**	70.90	54.72	54.96	19.64
ES	55.39	58.56	66.84	78.46	**75.12**	30.25	45.52	47.87	53.09	70.29	**63.65**	16.54
FR	55.05	59.02	65.05	**72.30**	81.44	35.79	45.96	47.41	52.25	**62.56**	73.37	20.84
KO	33.04	32.20	27.62	26.91	29.35	71.22	26.36	21.81	18.12	18.63	19.52	55.85

Cross-Lingual Dependency Parsing with Universal Dependencies and Predicted PoS Labels

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- Three methods for cross-lingual dependency parsing
- The impact of not having gold part-of-speech tags
- Reveals weaknesses of delexicalized model transfer

Proceedings of the Third International Conference on Dependency Linguistics (Depling 2015), pages 340–349,
Uppsala, Sweden, August 24–26 2015.

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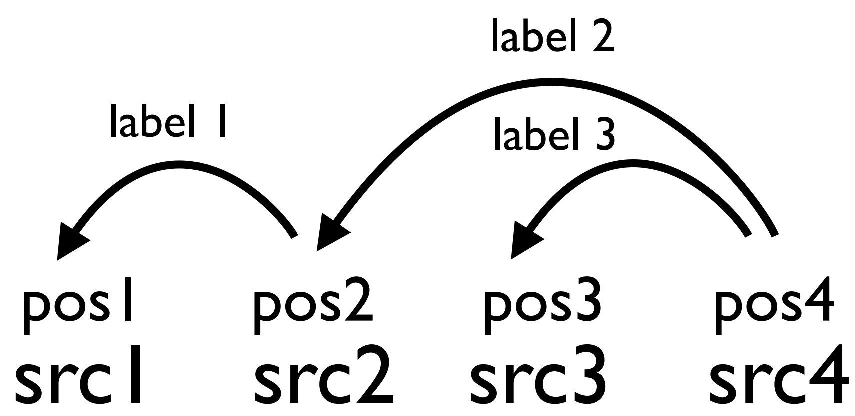
- The impact of not having gold part-of-speech tags
- Reveals weaknesses of delexicalized model transfer

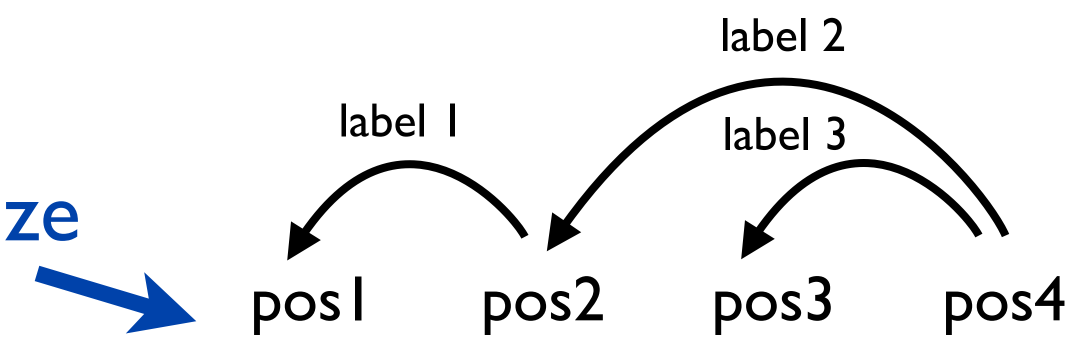
Thanks to Jörg for sharing slides!

Delexicalized Model Transfer

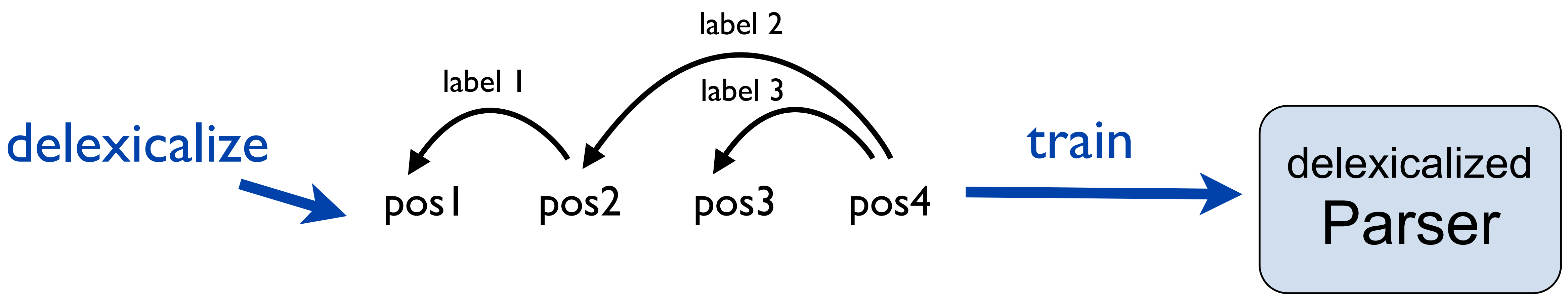


Delexicalized Model Transfer

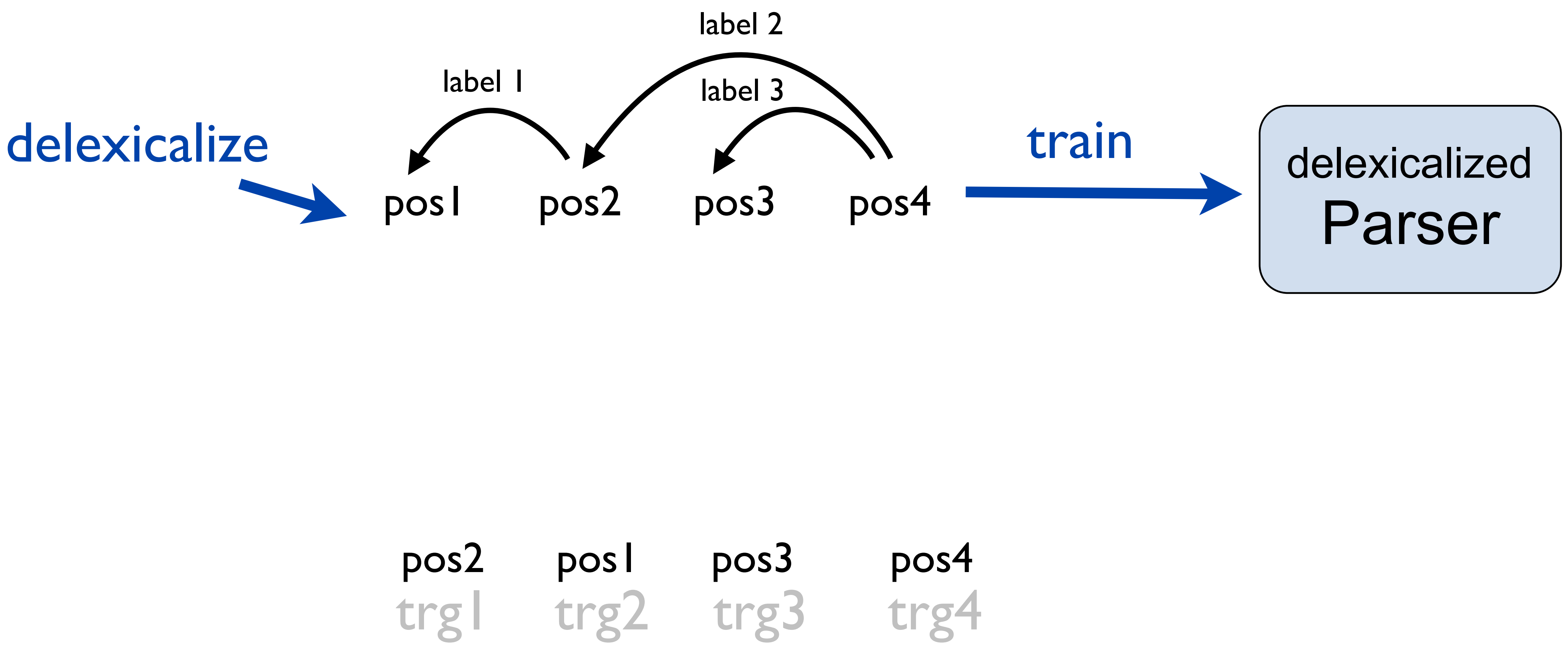
delexicalize



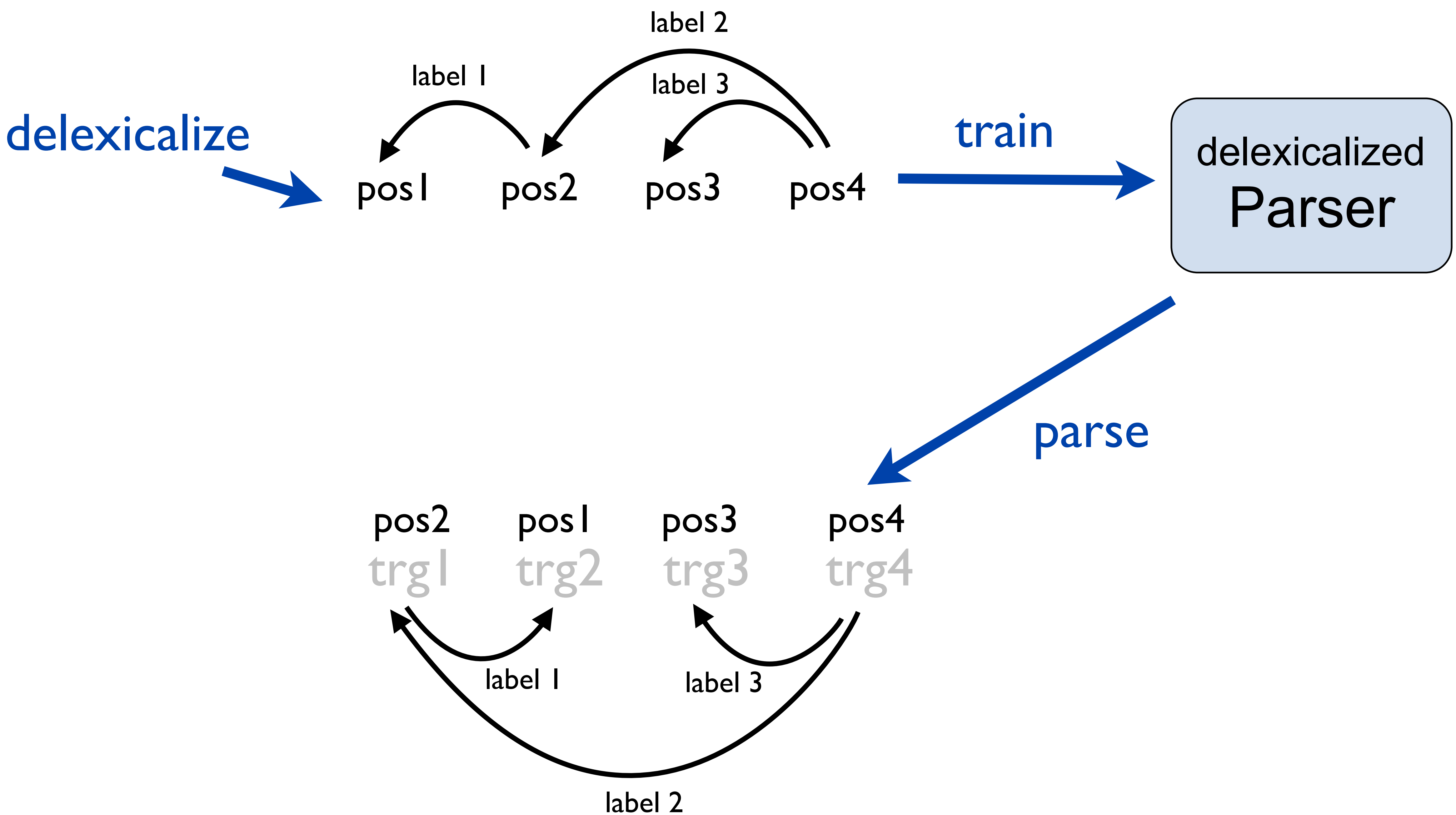
Delexicalized Model Transfer



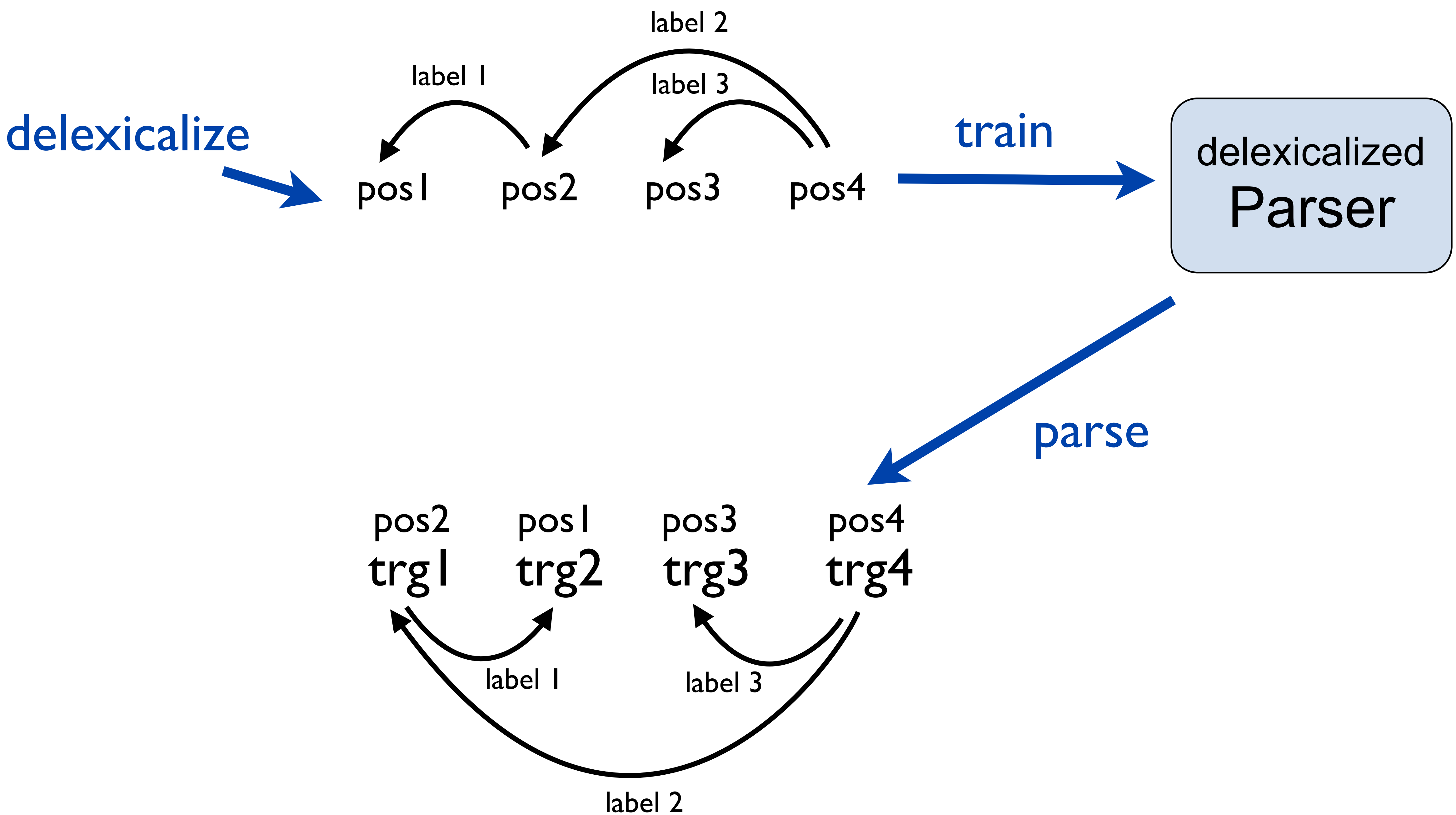
Delexicalized Model Transfer



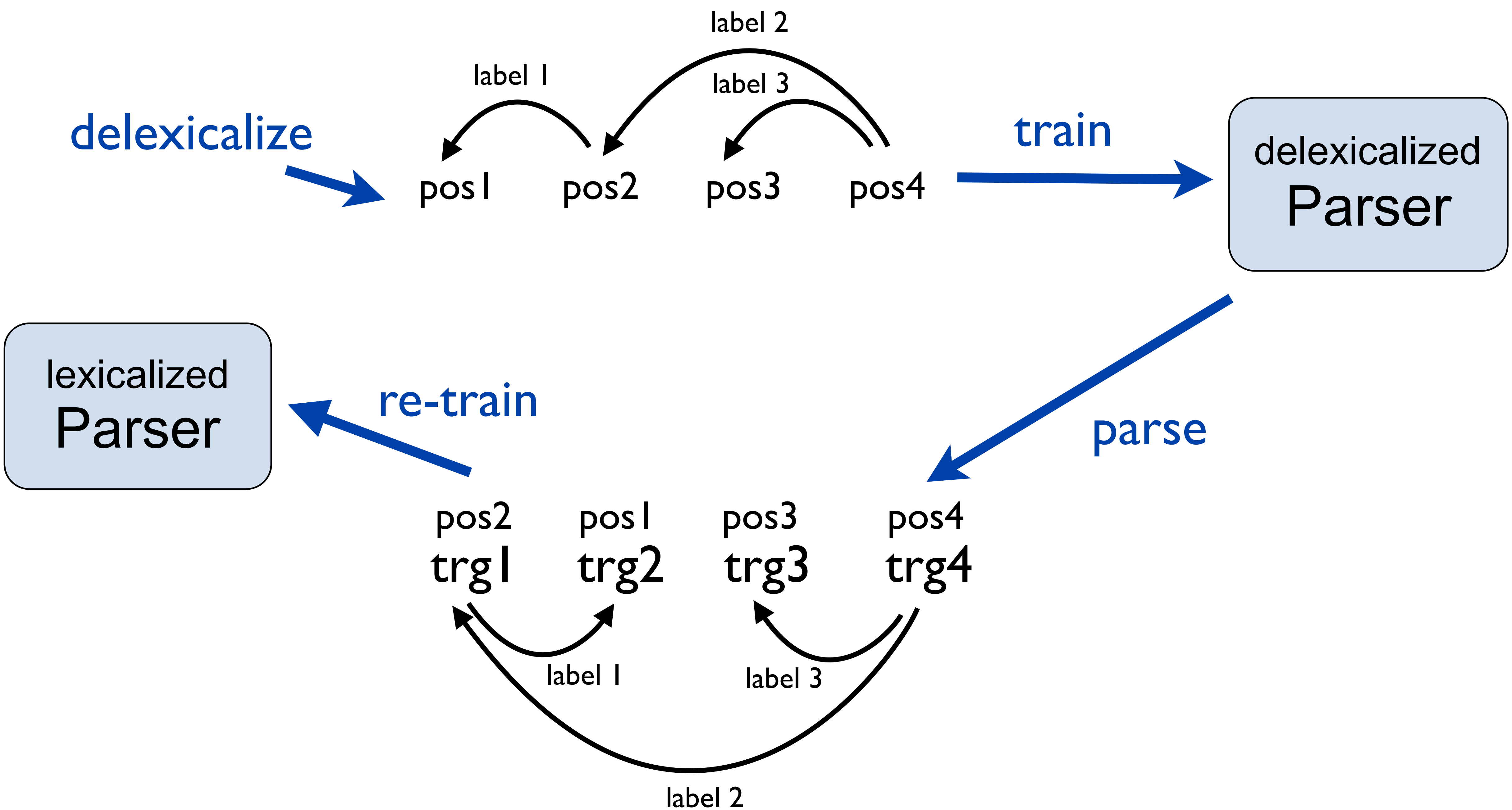
Delexicalized Model Transfer



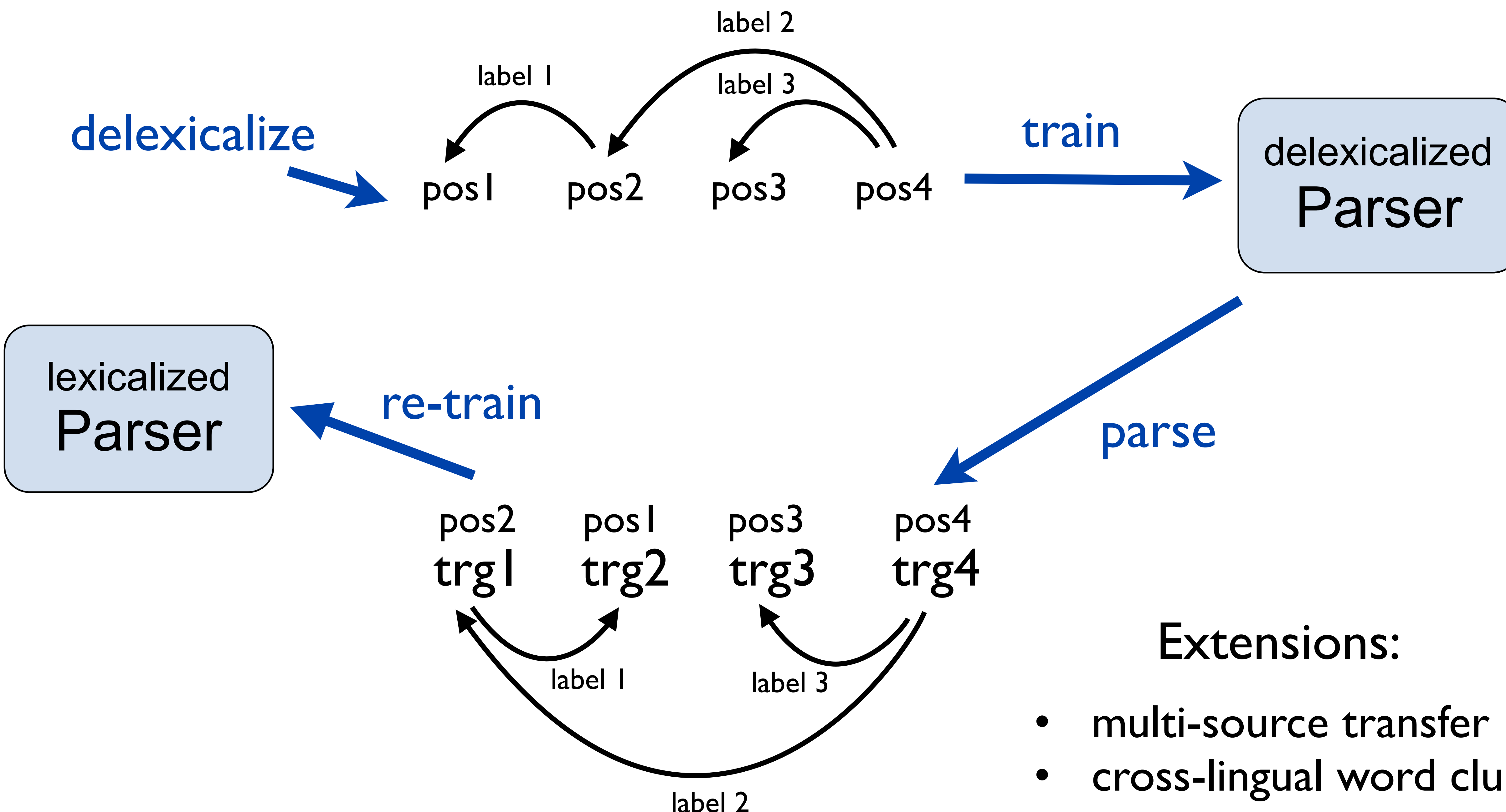
Delexicalized Model Transfer



Delexicalized Model Transfer



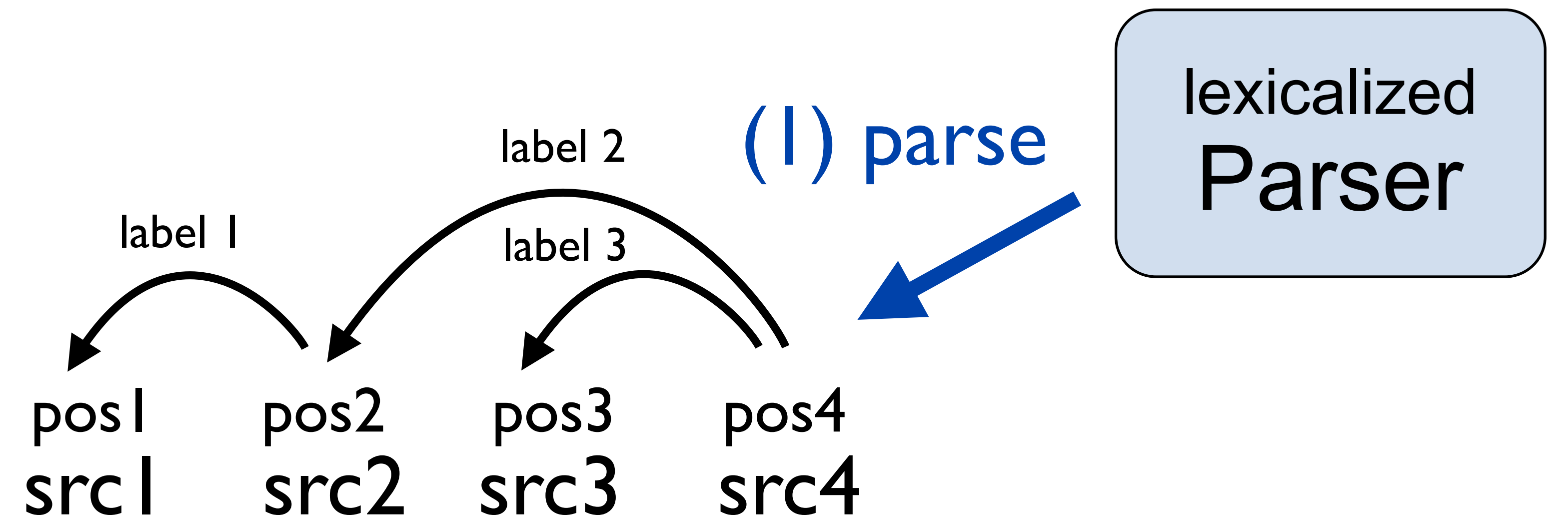
Delexicalized Model Transfer



Extensions:

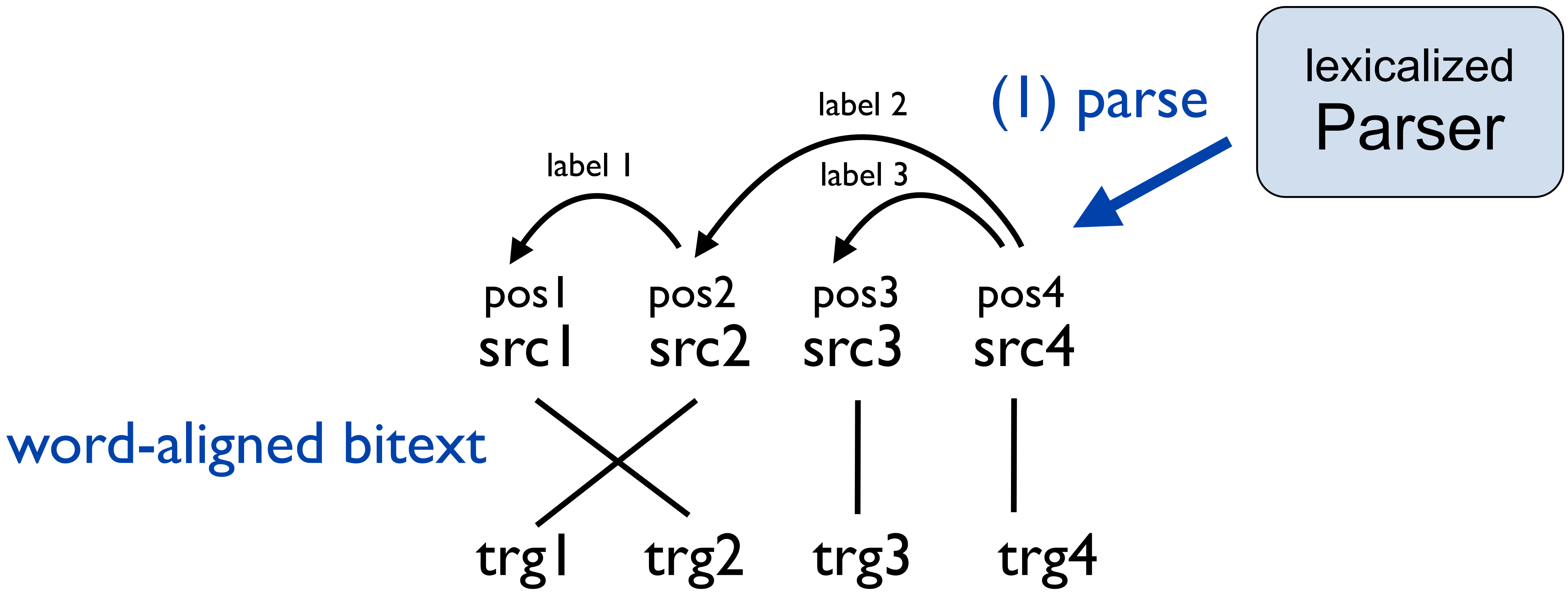
- multi-source transfer
- cross-lingual word clusters
- word embeddings
- target language adaptation

Annotation Projection

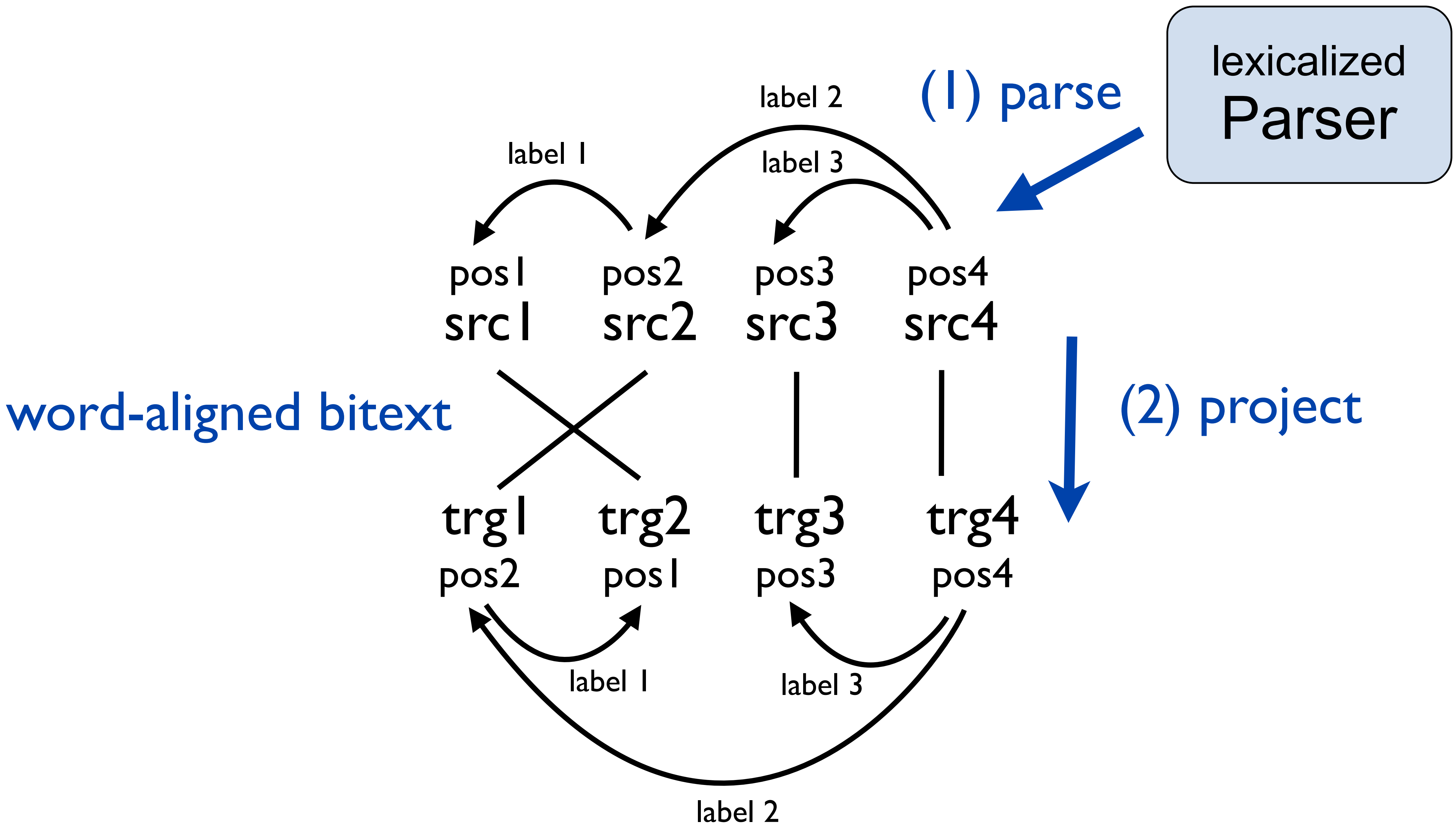


word-aligned bitext

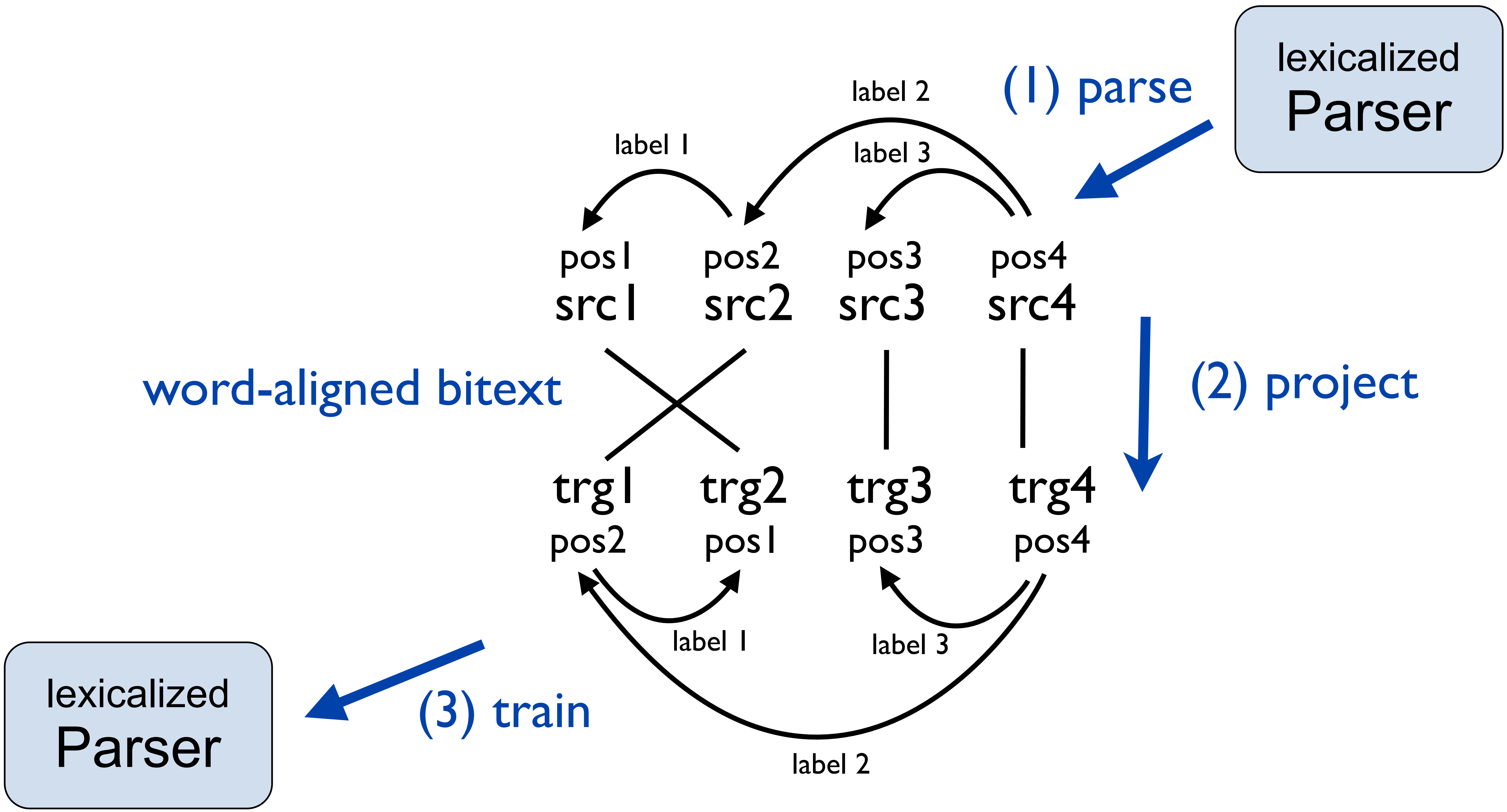
Annotation Projection



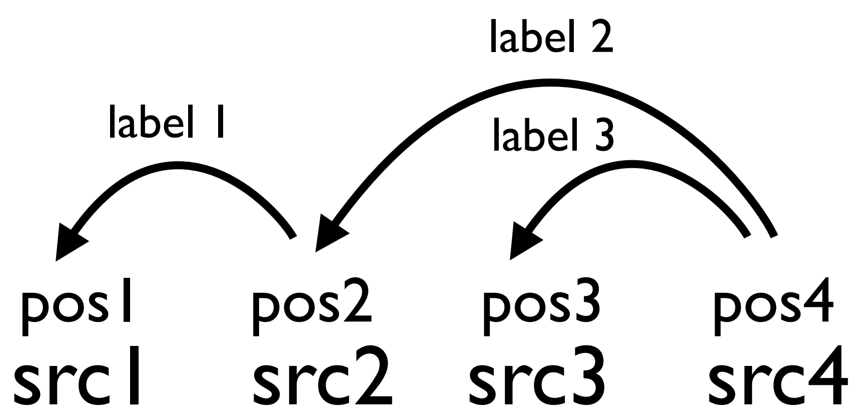
Annotation Projection



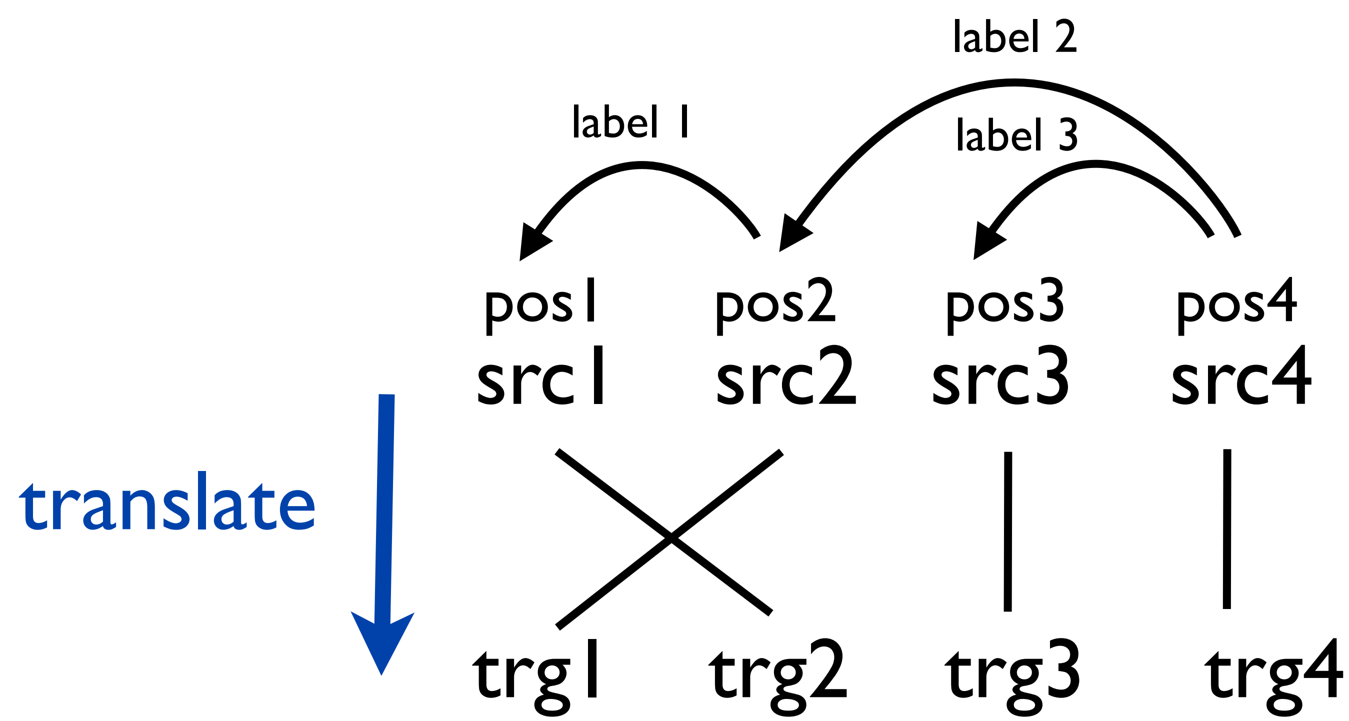
Annotation Projection



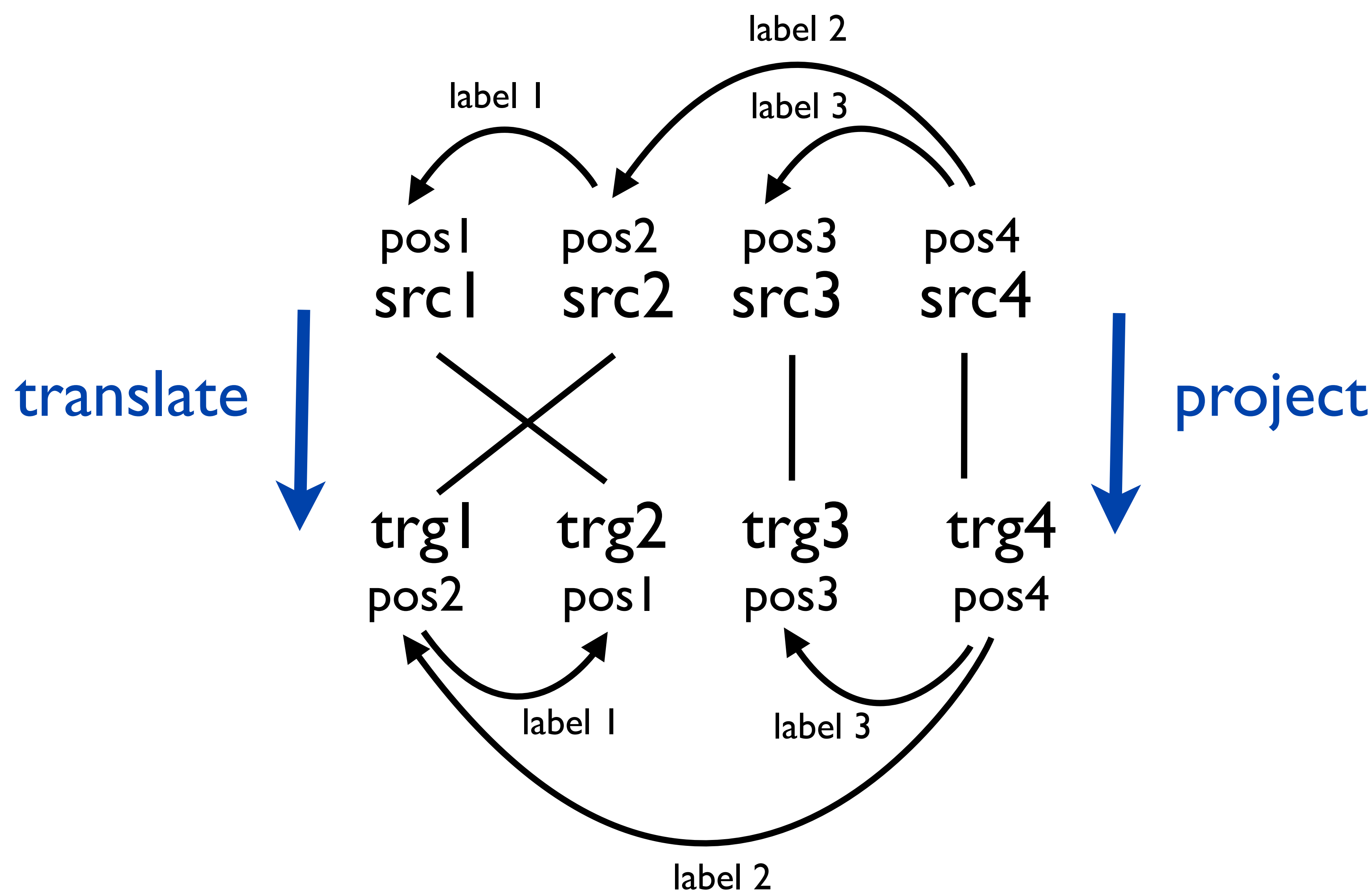
Treebank Translation



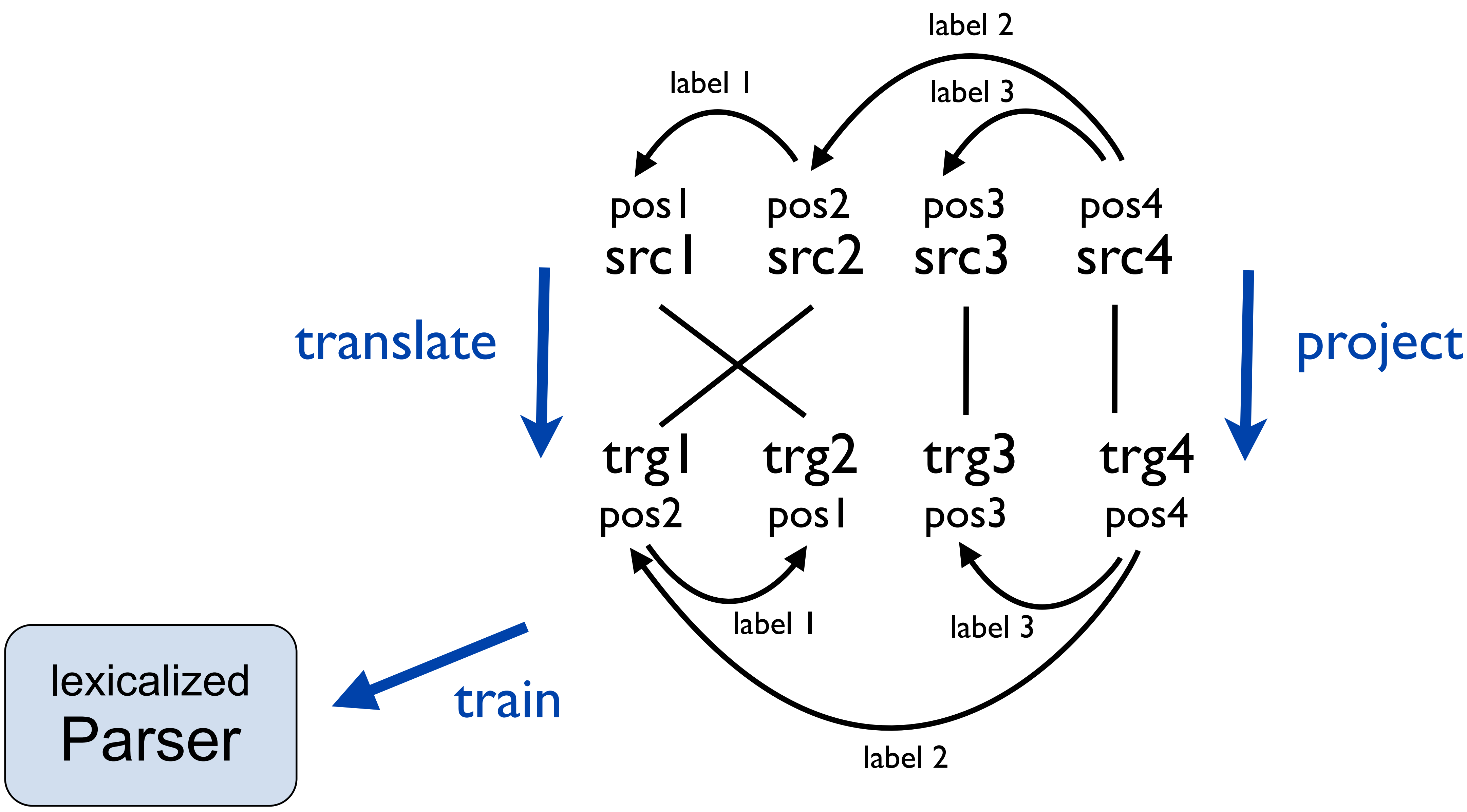
Treebank Translation



Treebank Translation



Treebank Translation



Example: Target Language = Spanish

	delexicalized	
PoS	**gold**	**predicted**
cs	43,82	33,55
de	53,63	46,35
en	60,94	52,52
es	*75,47*	*69,03*
fi	30,14	26,03
fr	66,42	58,74
hu	31,17	28,67
it	64,96	57,98
sv	51,93	37,15

Example: Target Language = Spanish

	delexicalized		annotation projection
PoS	gold	predicted	gold
cs	43,82	33,55	49,17
de	53,63	46,35	63,49
en	60,94	52,52	65,07
es	*75,47*	*69,03*	*84,05*
fi	30,14	26,03	42,37
fr	66,42	58,74	69,33
hu	31,17	28,67	48,97
it	64,96	57,98	65,76
sv	51,93	37,15	59,06

Example: Target Language = Spanish

	delexicalized		annotation projection	
PoS	**gold**	**predicted**	**gold**	**predicted**
cs	43,82	33,55	49,17	46,83
de	53,63	46,35	63,49	61,31
en	60,94	52,52	65,07	62,62
es	*75,47*	*69,03*	*84,05*	*80,16*
fi	30,14	26,03	42,37	40,96
fr	66,42	58,74	69,33	66,18
hu	31,17	28,67	48,97	47,36
it	64,96	57,98	65,76	63,31
sv	51,93	37,15	59,06	57,43

Example: Target Language = Spanish

	delexicalized		annotation projection		
PoS	**gold**	**predicted**	**gold**	**predicted**	**projected**
cs	43,82	33,55	49,17	46,83	36,85
de	53,63	46,35	63,49	61,31	53,15
en	60,94	52,52	65,07	62,62	56,69
es	*75,47*	*69,03*	*84,05*	*80,16*	*80,16*
fi	30,14	26,03	42,37	40,96	23,5
fr	66,42	58,74	69,33	66,18	61,81
hu	31,17	28,67	48,97	47,36	26,82
it	64,96	57,98	65,76	63,31	55,98
sv	51,93	37,15	59,06	57,43	52,06

Example: Target Language = Spanish

	annotation projection		
PoS	**gold**	**predicted**	**projected**
cs	49,17	46,83	36,85
de	63,49	61,31	53,15
en	65,07	62,62	56,69
es	*84,05*	*80,16*	*80,16*
fi	42,37	40,96	23,5
fr	69,33	66,18	61,81
hu	48,97	47,36	26,82
it	65,76	63,31	55,98
sv	59,06	57,43	52,06

Example: Target Language = Spanish

	annotation projection			treebank translation
PoS	**gold**	**predicted**	**projected**	**gold**
cs	49,17	46,83	36,85	49,81
de	63,49	61,31	53,15	64,88
en	65,07	62,62	56,69	67,2
es	*84,05*	*80,16*	*80,16*	*84,05*
fi	42,37	40,96	23,5	36,11
fr	69,33	66,18	61,81	71,15
hu	48,97	47,36	26,82	43,16
it	65,76	63,31	55,98	68,74
sv	59,06	57,43	52,06	59,8

Example: Target Language = Spanish

	annotation projection			treebank translation	
PoS	**gold**	**predicted**	**projected**	**gold**	**predicted**
cs	49,17	46,83	36,85	49,81	48,07
de	63,49	61,31	53,15	64,88	62,34
en	65,07	62,62	56,69	67,2	64,48
es	*84,05*	*80,16*	*80,16*	*84,05*	*80,16*
fi	42,37	40,96	23,5	36,11	34,45
fr	69,33	66,18	61,81	71,15	67,7
hu	48,97	47,36	26,82	43,16	41,07
it	65,76	63,31	55,98	68,74	66,1
sv	59,06	57,43	52,06	59,8	57,41

Example: Target Language = Spanish

	annotation projection			treebank translation		
PoS	**gold**	**predicted**	**projected**	**gold**	**predicted**	**projected**
cs	49,17	46,83	36,85	49,81	48,07	40,02
de	63,49	61,31	53,15	64,88	62,34	53,3
en	65,07	62,62	56,69	67,2	64,48	56,18
es	*84,05*	*80,16*	*80,16*	*84,05*	*80,16*	*80,16*
fi	42,37	40,96	23,5	36,11	34,45	26,86
fr	69,33	66,18	61,81	71,15	67,7	63,77
hu	48,97	47,36	26,82	43,16	41,07	25,81
it	65,76	63,31	55,98	68,74	66,1	61,82
sv	59,06	57,43	52,06	59,8	57,41	51,26

Discussion

Be careful with delexicalized models

- models are not easy to transfer
- robust universal features are difficult to find

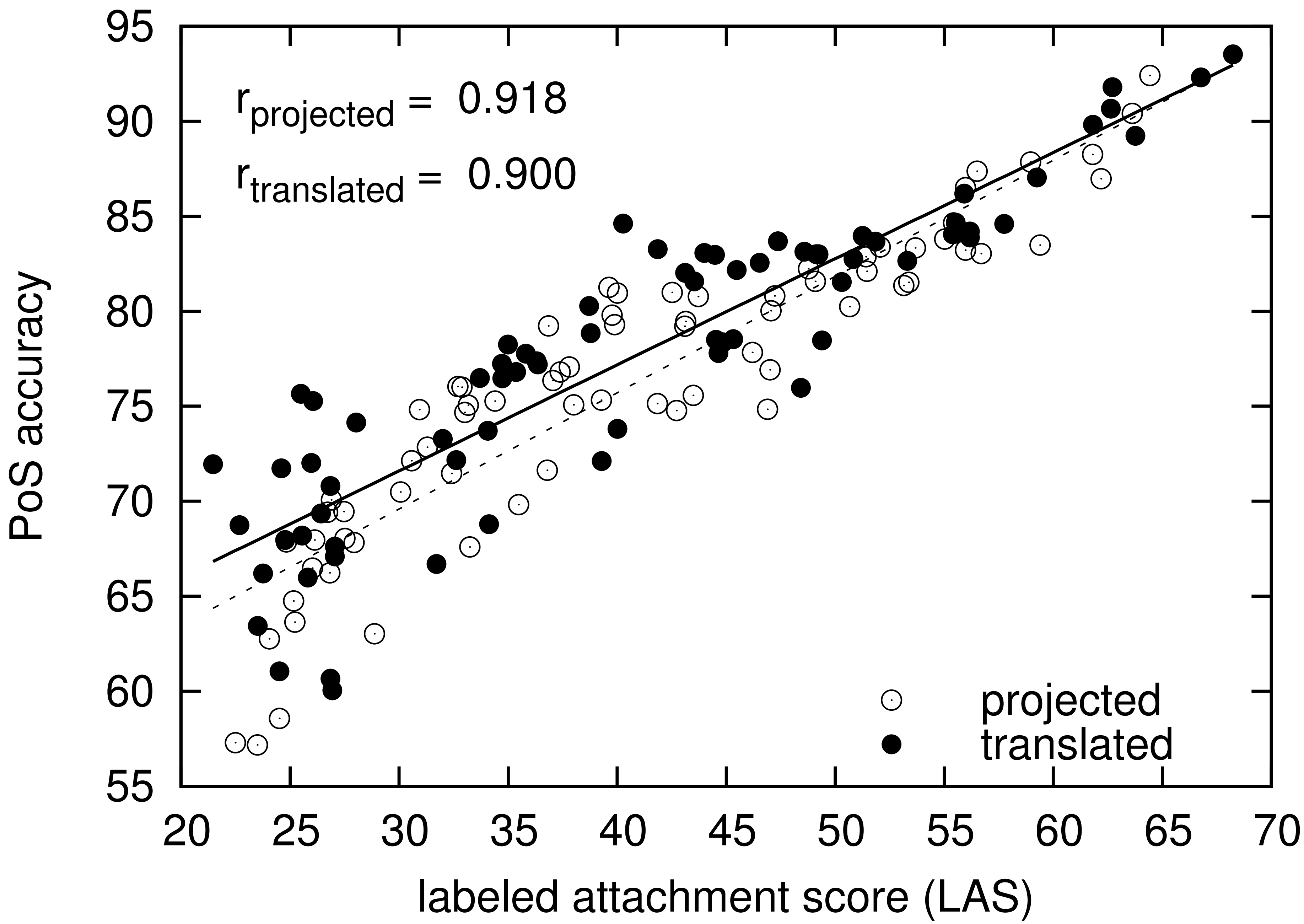
Cross-lingual methods work quite well

- if PoS labels are reliable
- languages are rather closely related

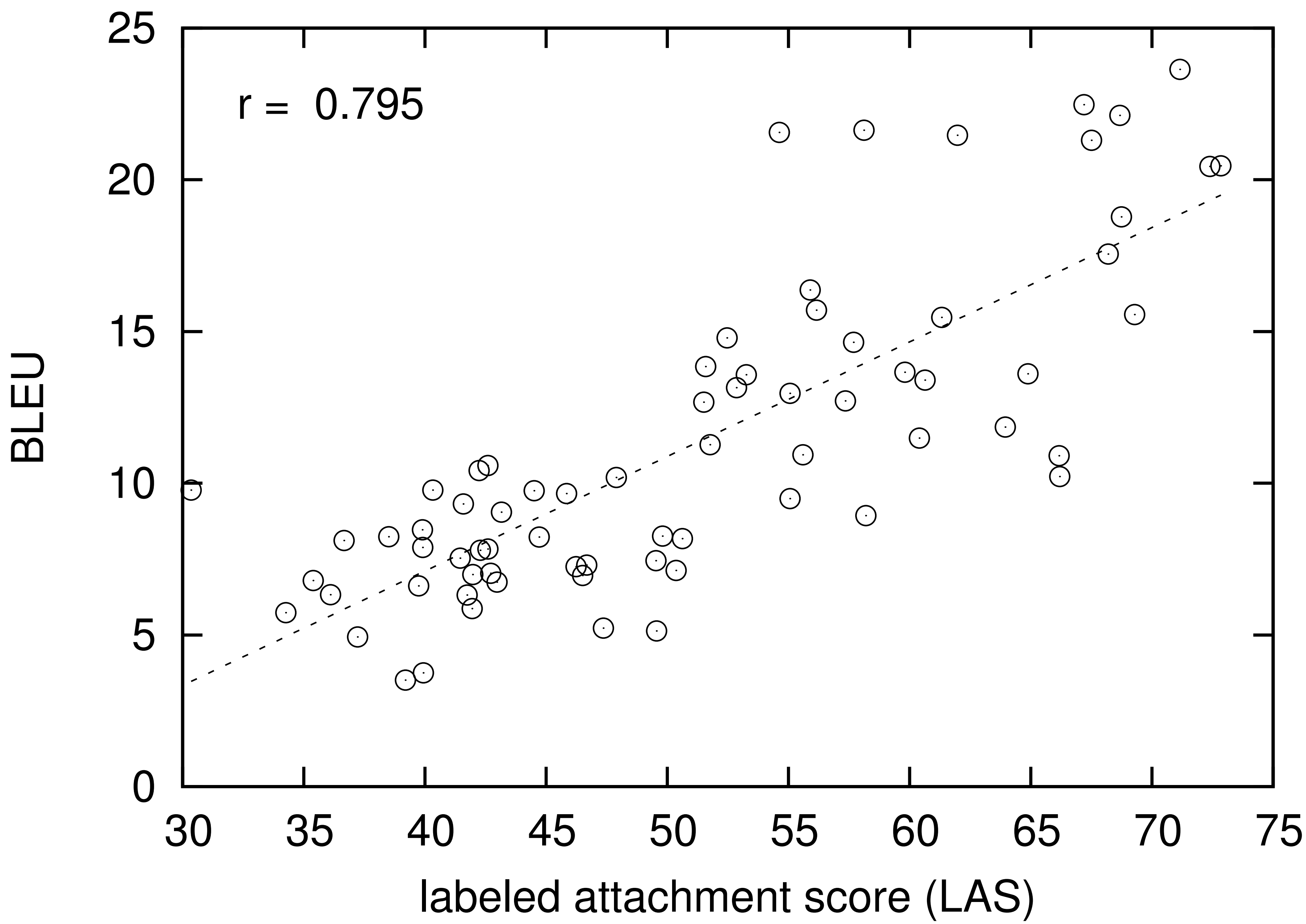
Automatic treebank translation is a valid option

- but requires reasonable translation performance

The Impact of PoS Tagging Performance



Translation Quality vs. Parsing Quality



Many Languages, One Parser

Waleed Ammar[◇] **George Mulcaire**[♡] **Miguel Ballesteros**[♠◇] **Chris Dyer**[◇] **Noah A. Smith**[♡]
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[♡]Computer Science & Engineering, University of Washington, Seattle, WA, USA
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cdyer@cs.cmu.edu, nasmith@cs.washington.edu

- Parsing with multiple source and target languages
- Multilingual word embeddings and typological features
- Target language may not be included in source set

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Submission batch: 3/2016; Revision batch: 5/2016; Published 7/2016.

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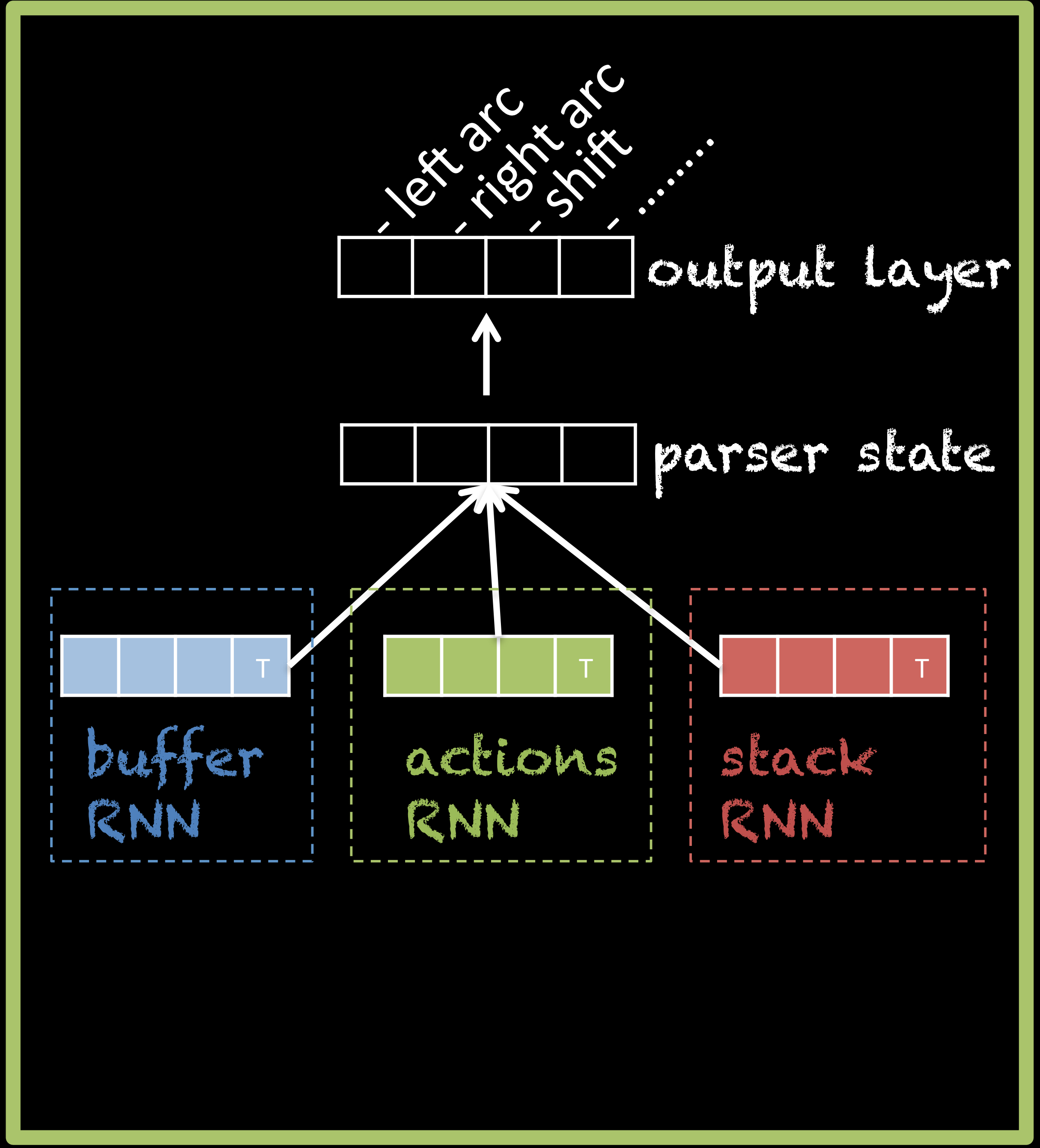
- Parsing with multiple source and target languages
- Multilingual word embeddings and typological features
- Target language may not be included in source set

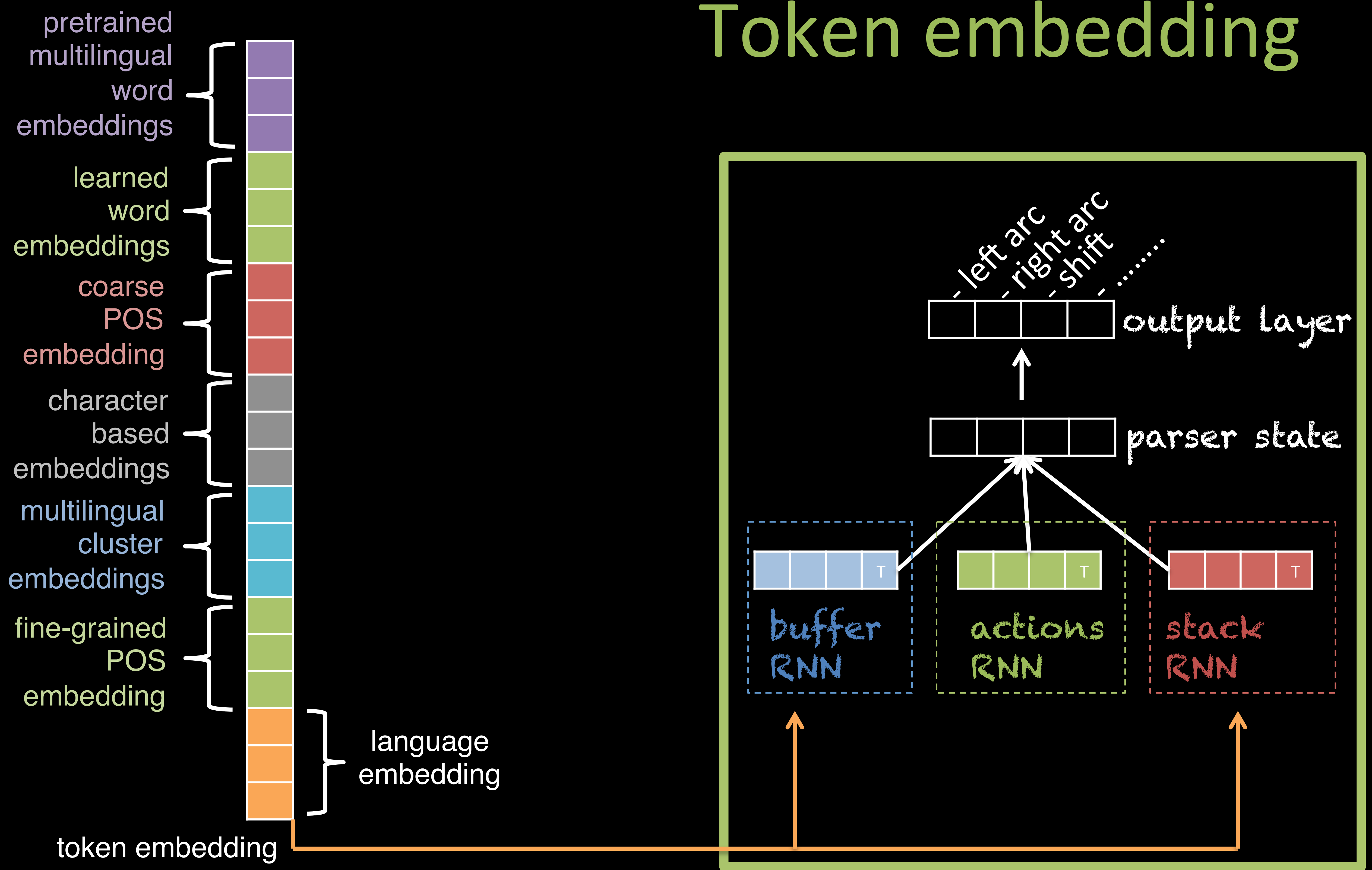
Thanks to Waleed for sharing slides!

The parsing model

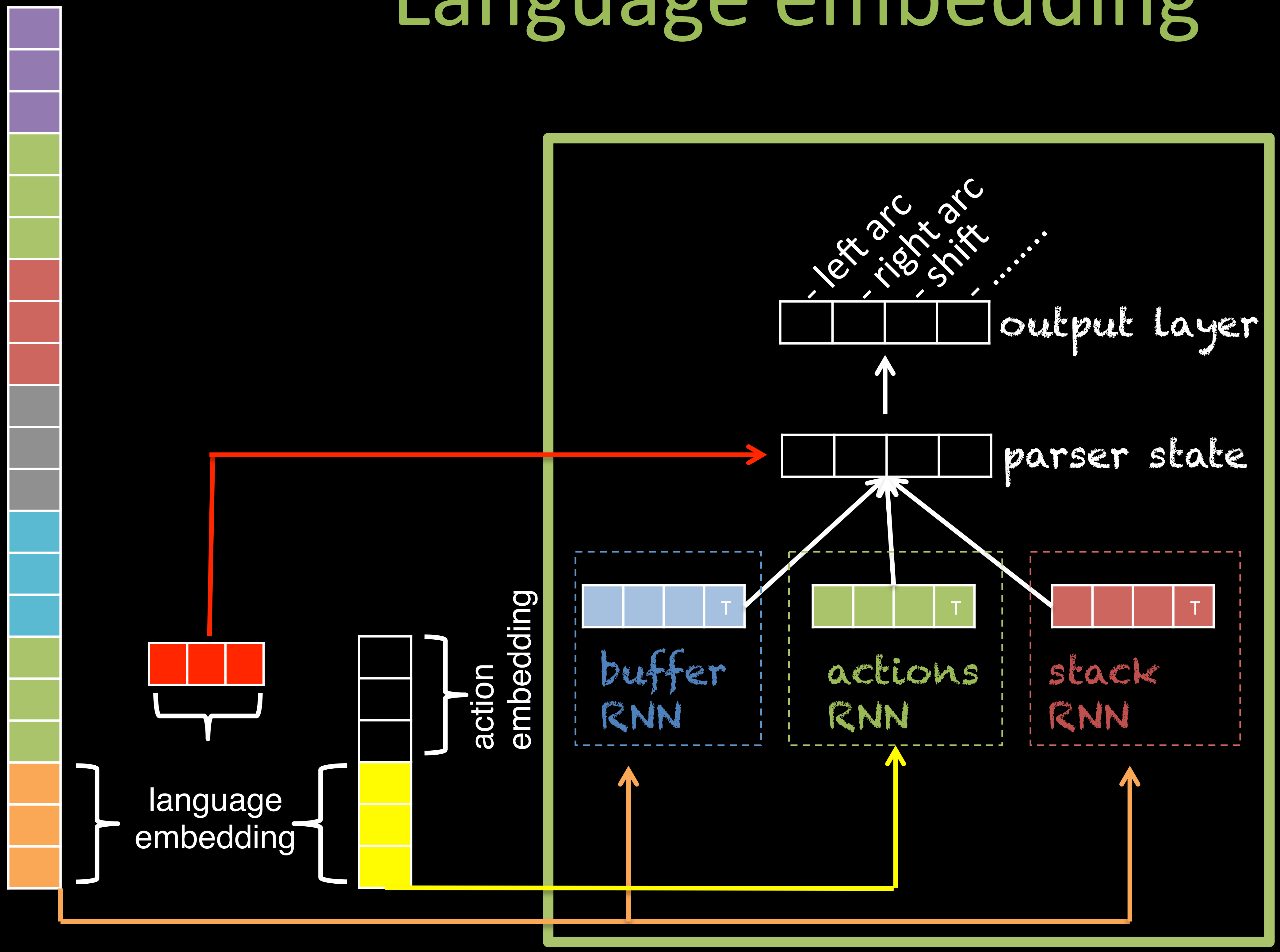


Ref: Dyer et al. 2015

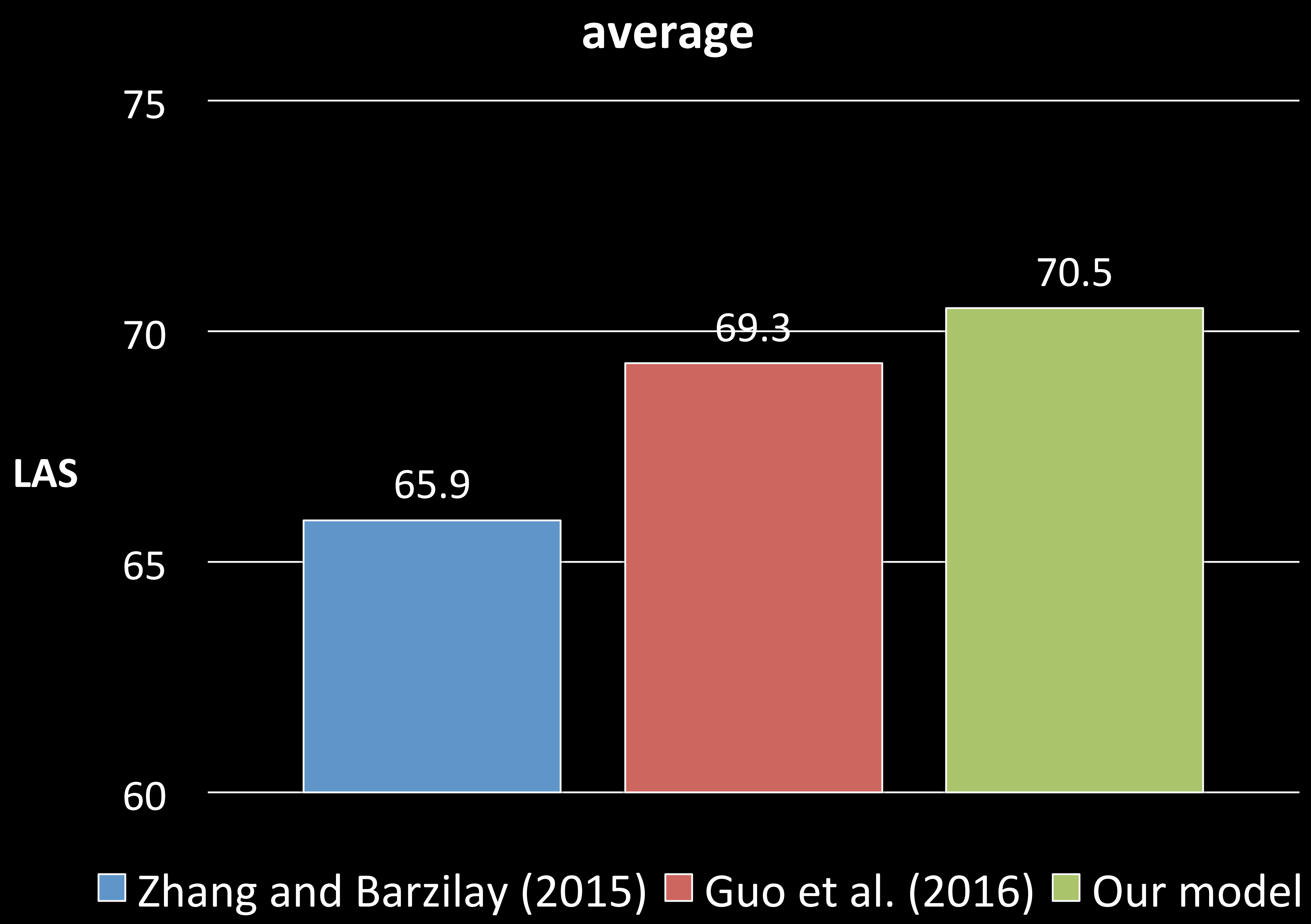
Token embedding



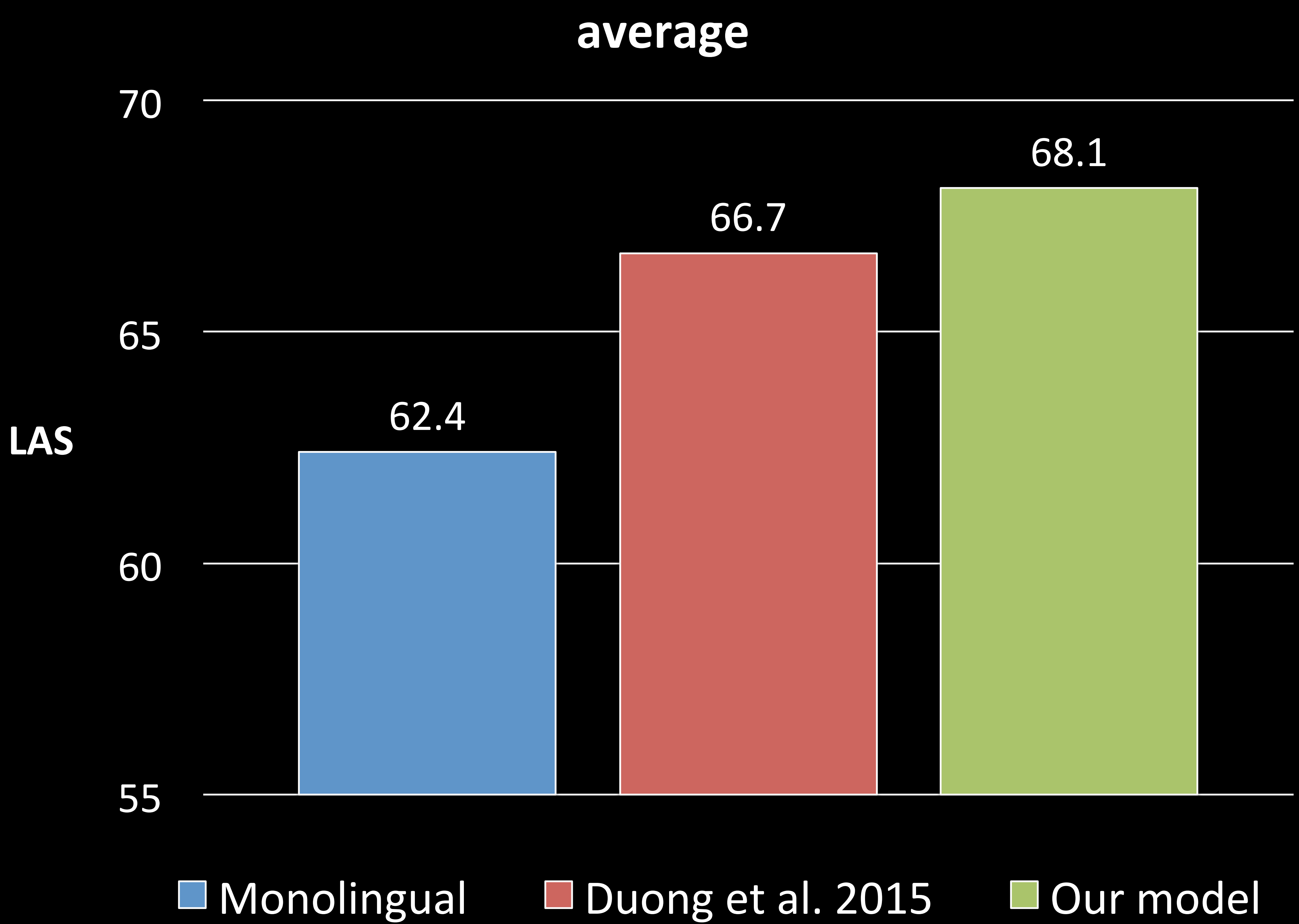
Language embedding



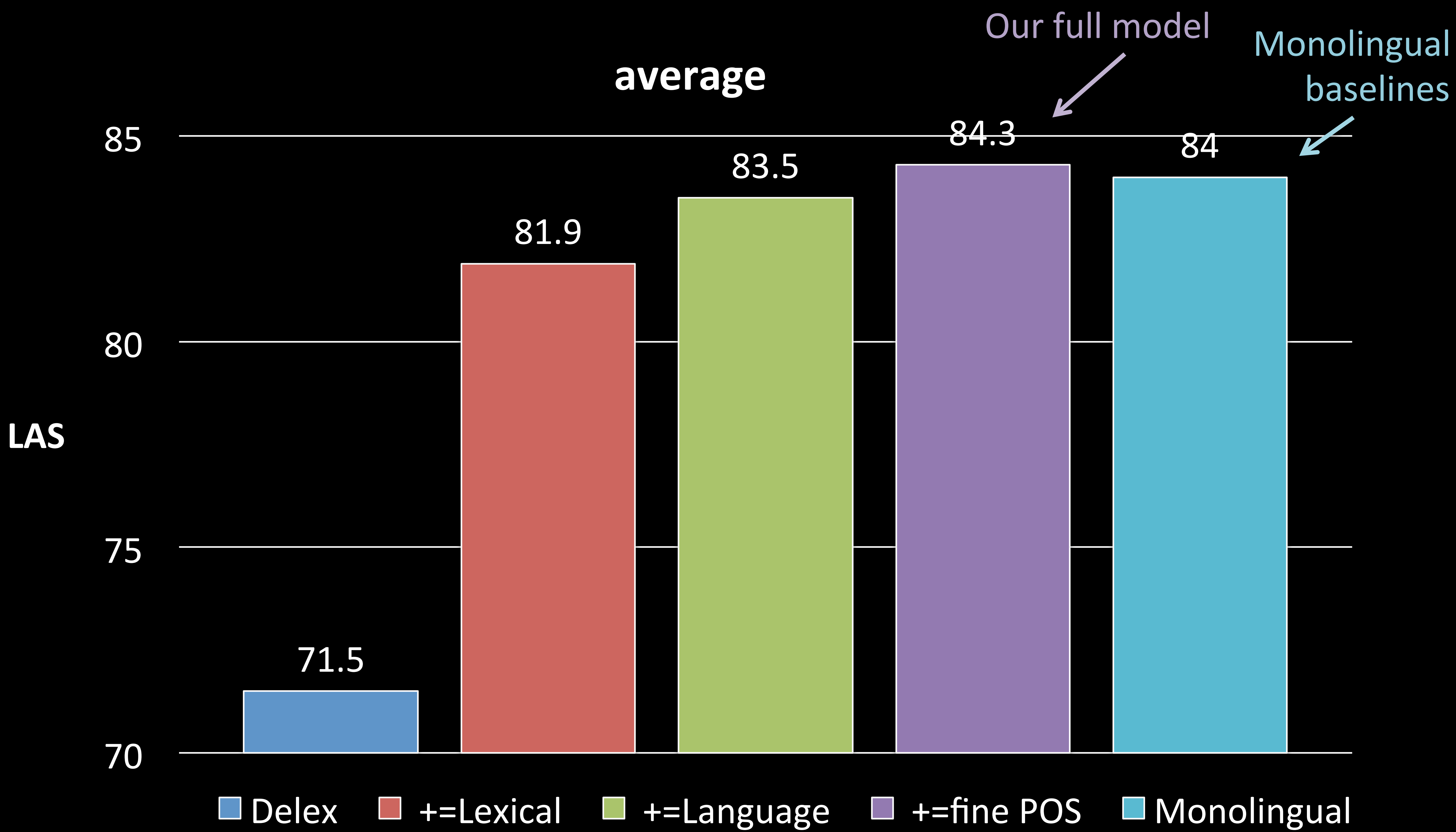
How does the model compare to previous work when target language has no training data?



How does the model compare to previous work when target language has a 3K-word training set?

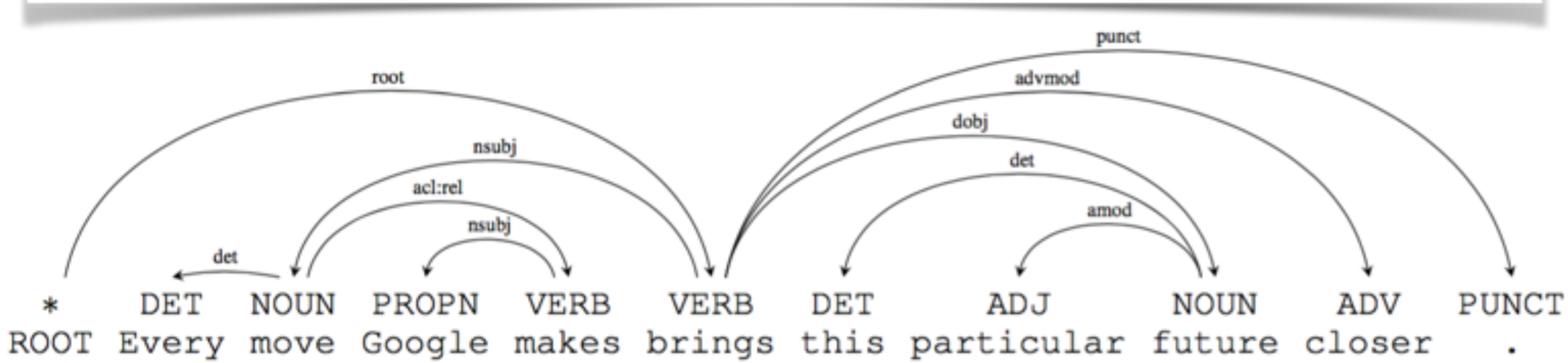


Does the model match the performance of the monolingual parsers when target language has lots of training data?



Need More Data?

Wang and Eisner (2016) The Galactic Dependencies Treebanks: Getting More Data by Synthesizing New Languages



Language	Sentence
English	Every move Google makes brings this particular future closer.
English[French/N]	Every move Google makes brings this future particular closer.
English[Hindi/V]	Every move Google makes this particular future closer brings.
English[French/N, Hindi/V]	Every move Google makes this future particular closer brings.

Figure 1: The original UD tree for a short English sentence, and its "translations" into three synthetic languages, which are obtained by manipulating the tree. (Moved constituents are underlined.) Each language has a different distribution over surface part-of-speech sequences.

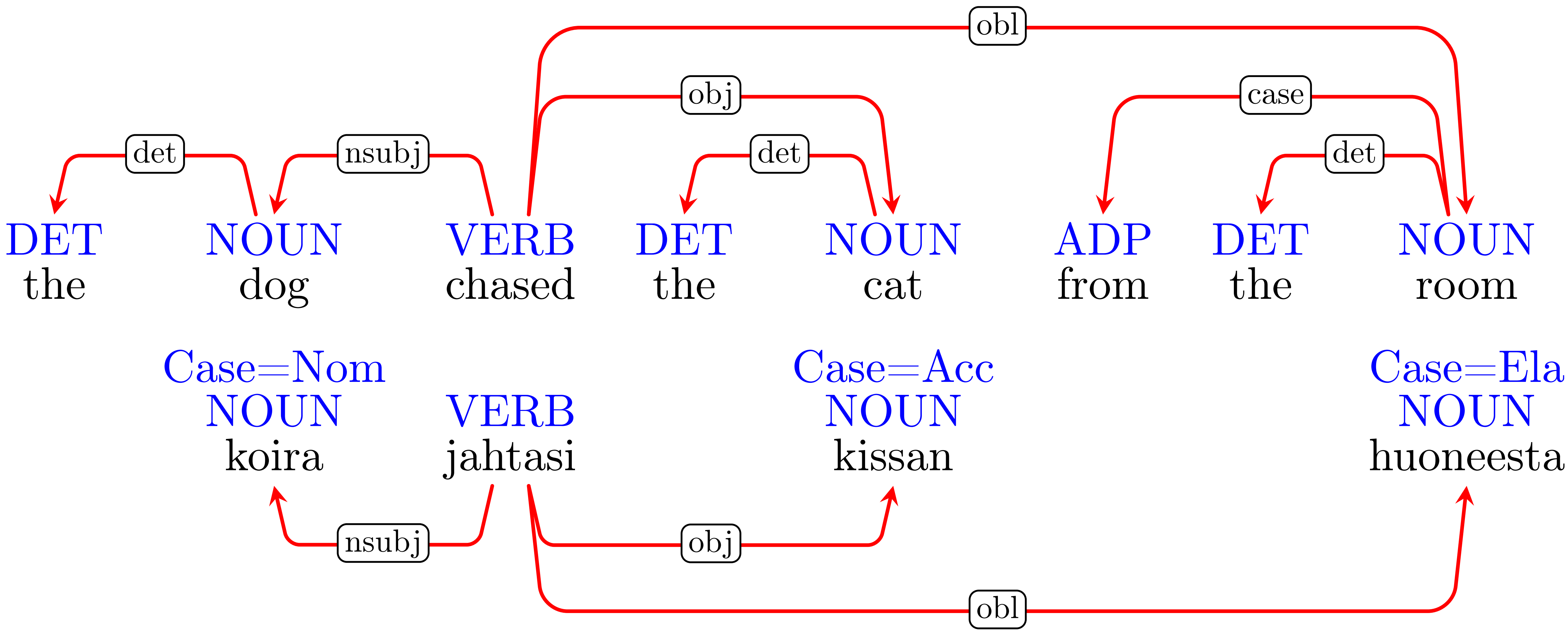
Parser Evaluation

CoNLL shared tasks on dependency parsing 2006–2007:

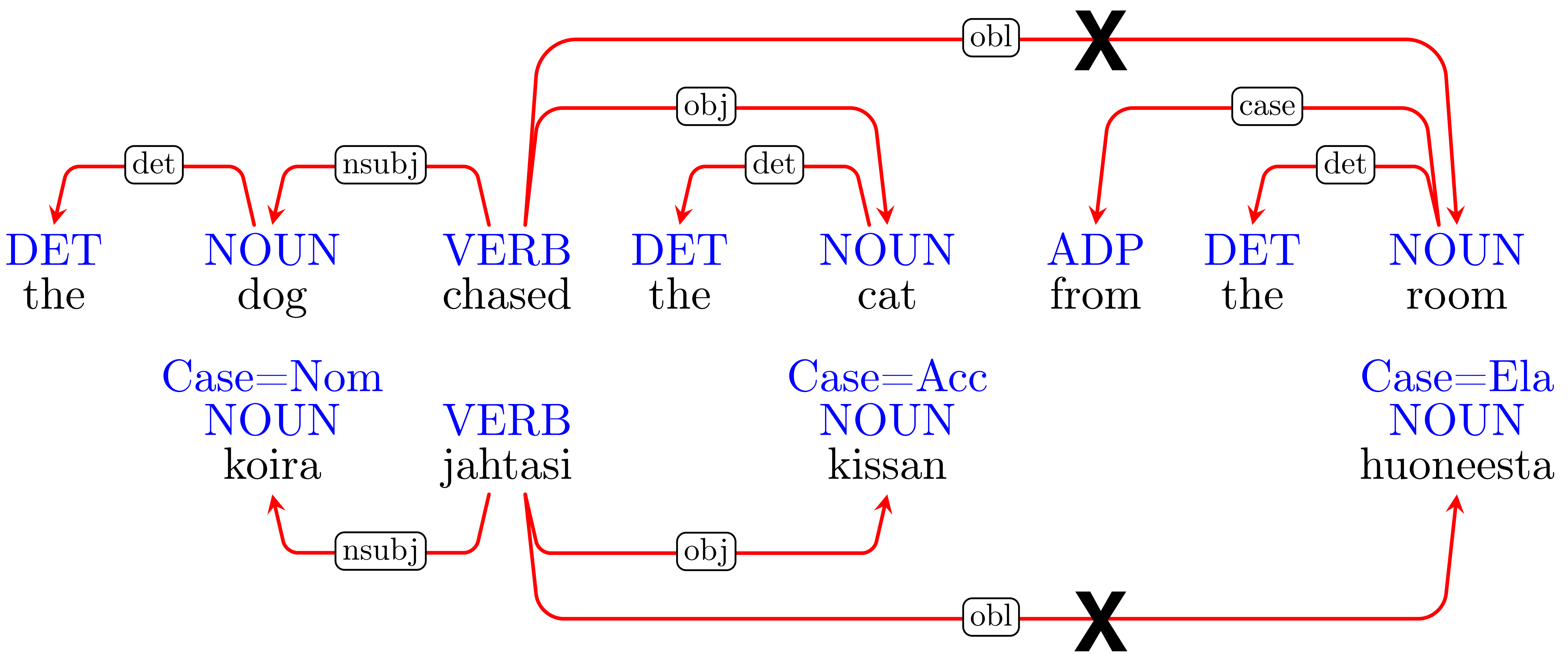
- Large variation in parsing accuracy across languages
- Hard to analyze differences because of inconsistent annotations

CoNLL shared task on UD parsing 2017:

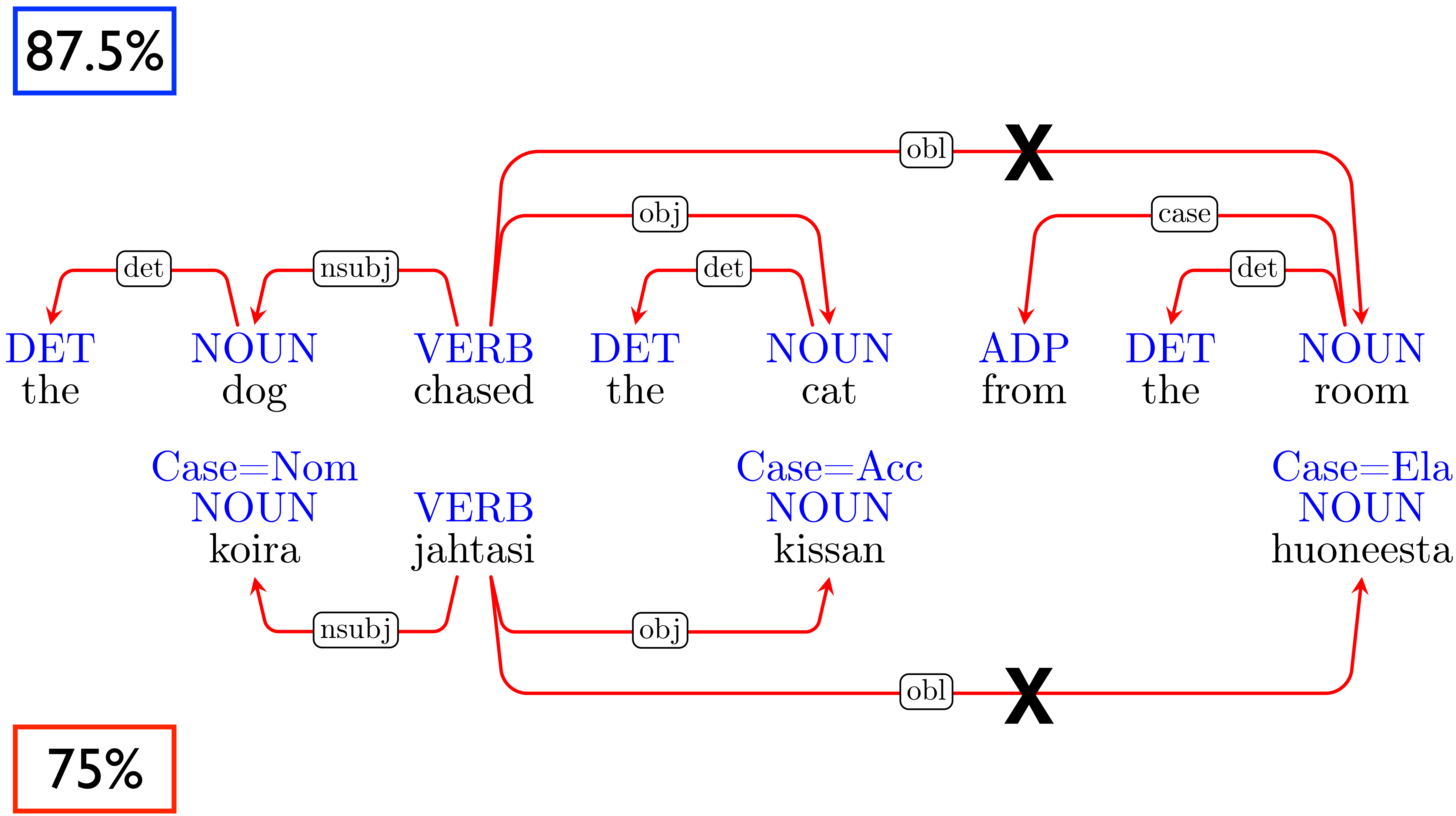
- Cross-linguistically consistent annotation
- Can we now compare numbers across languages?



obl
obj
case
det
nsubj
det
det
DET
the
NOUN
dog
VERB
chased
DET
the
NOUN
cat
ADP
from
DET
the
NOUN
room
Case=Nom
NOUN
koira
VERB
jahtasi
Case=Acc
NOUN
kissan
Case=Ela
NOUN
huoneesta
nsubj
obj
obl



DET
the
NOUN
dog
VERB
chased
DET
the
NOUN
cat
ADP
from
DET
the
NOUN
room
det
nsubj
obj
obl
X
det
case
det
Case=Nom
NOUN
koira
VERB
jahtasi
Case=Acc
NOUN
kissan
Case=Ela
NOUN
huoneesta
nsubj
obj
obl
X



87.5%
obl
X
obj
case
det
nsubj
det
det
DET the
NOUN dog
VERB chased
DET the
NOUN cat
ADP from
DET the
NOUN room
Case=Nom NOUN koira
VERB jahtasi
Case=Acc NOUN kissan
Case=Ela NOUN huoneesta
nsubj
obj
obl
X
75%

A New Proposal

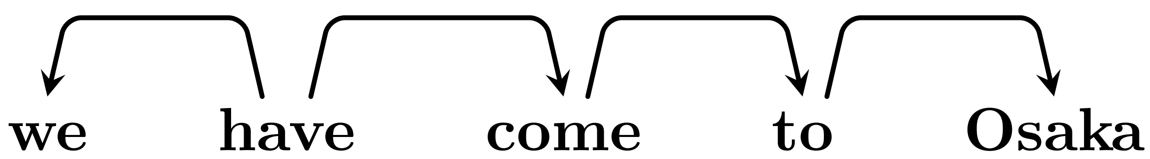
Core	Func	Punct	Other
nsubj obj iobj csubj ccomp xcomp	aux cop mark det clf case cc	punct	...

LAS = Labeled F-score on All – Punct

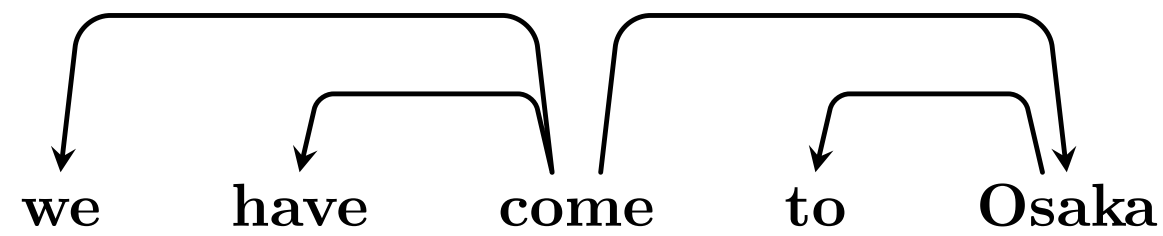
CNC = Labeled F-score on All – (Punct U Func)

Language	Main Metrics			Func		Core	
	LAS	CNC	Diff	Freq	F	Freq	F
Estonian	85.90	86.08	0.18	11.85	85.03	27.36	84.71
Finnish	78.45	77.22	−1.23	17.26	84.48	23.51	77.19
Finnish-FTB	76.17	74.61	−1.56	19.87	82.50	25.58	73.59
Polish	86.21	84.47	−1.75	21.64	92.51	30.49	84.67
Czech	83.23	81.04	−2.20	24.08	90.22	22.53	81.51
Hungarian	82.87	80.62	−2.25	25.78	89.36	23.48	81.40
Ancient Greek	57.80	55.47	−2.34	20.02	67.71	32.82	54.18
Croatian	79.89	77.52	−2.37	28.04	86.01	20.30	79.21
Latin	60.27	57.81	−2.45	18.51	71.06	31.64	60.20
Tamil	70.87	68.25	−2.62	13.58	88.29	21.30	60.68
Arabic	74.61	71.66	−2.95	28.30	82.18	22.82	68.95
Slovenian	86.06	83.08	−2.98	29.33	93.23	20.08	82.65
Latin-ITT	74.67	71.43	−3.24	33.54	81.10	29.72	72.19
Old Church Slavonic	78.37	75.08	−3.29	23.02	89.42	38.06	76.67
Bulgarian	85.74	82.01	−3.73	31.33	93.87	27.49	78.12
Persian	79.57	75.73	−3.84	29.42	88.86	16.45	63.09
Danish	80.01	76.12	−3.89	34.14	87.56	27.79	81.03
Latin-PROIEL	68.40	64.49	−3.91	23.60	81.18	35.27	65.67
Basque	74.13	70.19	−3.94	23.66	86.97	26.02	63.70
English	83.80	79.70	−4.10	32.44	92.30	27.29	84.73
Gothic	73.66	69.50	−4.16	26.36	85.32	37.32	72.84
Norwegian	86.49	82.30	−4.19	35.20	94.22	28.87	85.31
Swedish	80.00	75.81	−4.19	32.98	88.63	27.00	81.59
Greek	81.36	75.04	−6.32	40.06	90.96	24.99	77.82
Italian	87.69	80.76	−6.94	43.97	96.54	20.02	79.21
Spanish	84.76	77.70	−7.06	43.58	93.84	18.95	80.39
Portuguese	86.24	79.09	−7.15	42.27	96.03	30.79	82.47
Hindi	84.20	77.01	−7.20	37.68	96.10	20.36	64.81
Ancient Greek-PROIEL	71.00	63.71	−7.29	32.07	86.53	34.28	63.93
Hebrew	80.94	72.97	−7.97	37.70	94.01	25.09	67.82
Romanian	71.05	63.02	−8.03	33.19	86.97	26.15	53.90
Irish	72.98	64.45	−8.54	35.41	88.52	30.21	61.91
Average	78.36	74.18	−4.17	29.06	87.86	26.69	73.32

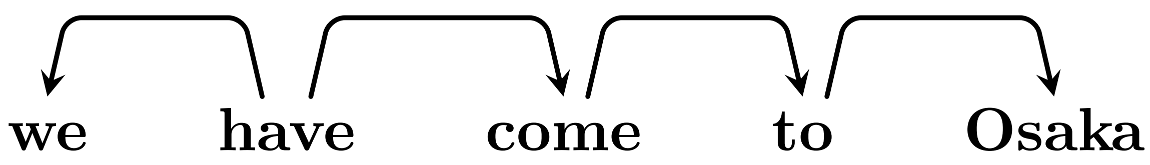
“Function-Head Dependencies”



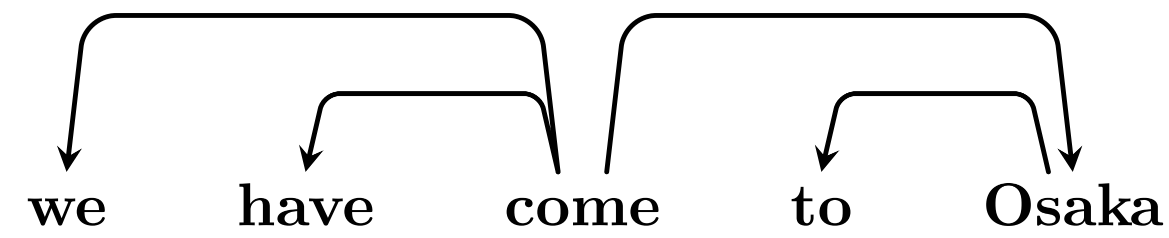
“Content-Head Dependencies”



“Function-Head Dependencies”

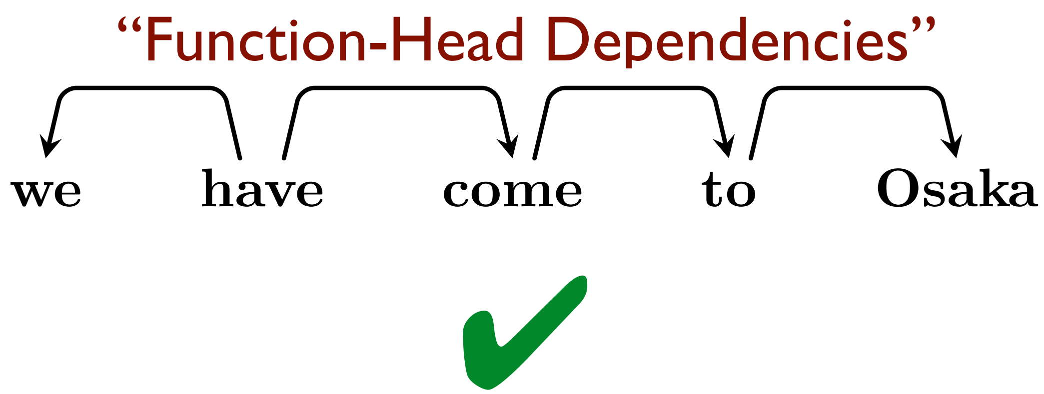


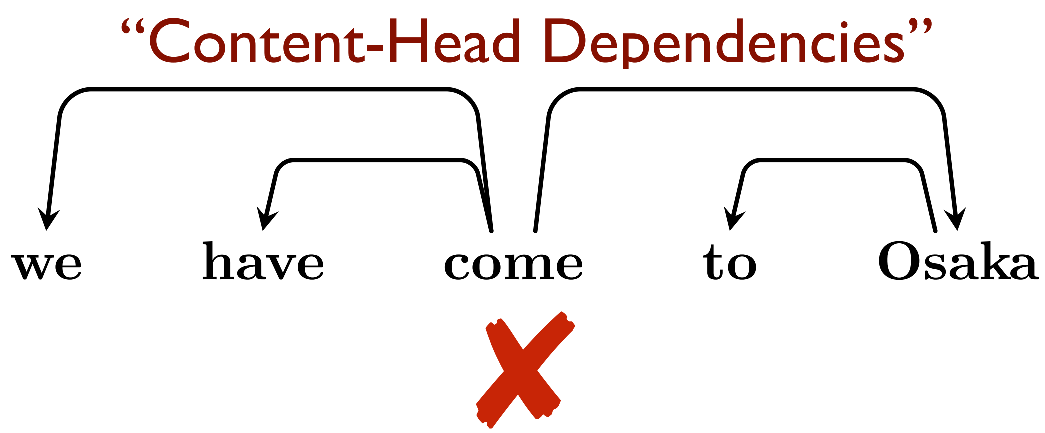
“Content-Head Dependencies”



Bad for parsing?

“It is now fairly well known that, while dependency representations in which content words are made heads tend to help semantically oriented downstream applications, dependency parsing numbers are higher if you make auxiliary verbs heads […] and if you make prepositions the head of prepositional phrases.” (De Marneffe et al., 2014)


"Function-Head Dependencies"
we
have
come
to
Osaka


"Content-Head Dependencies"
we
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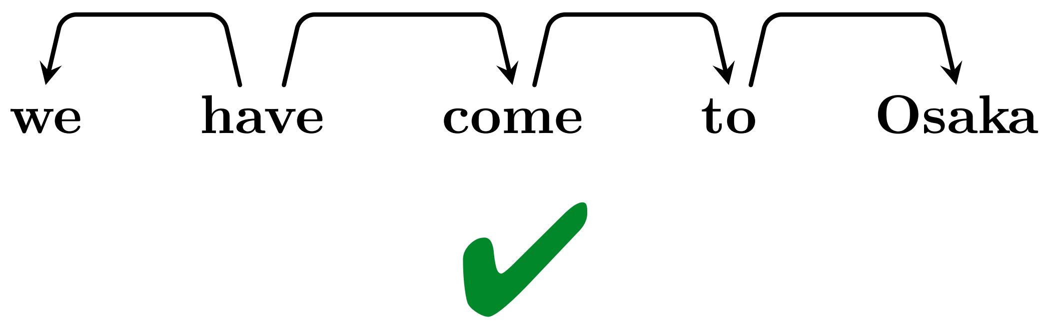
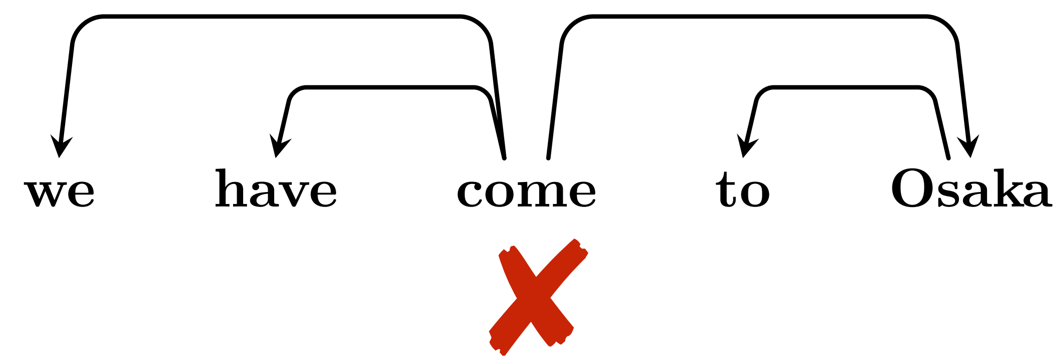
“Function-Head Dependencies”

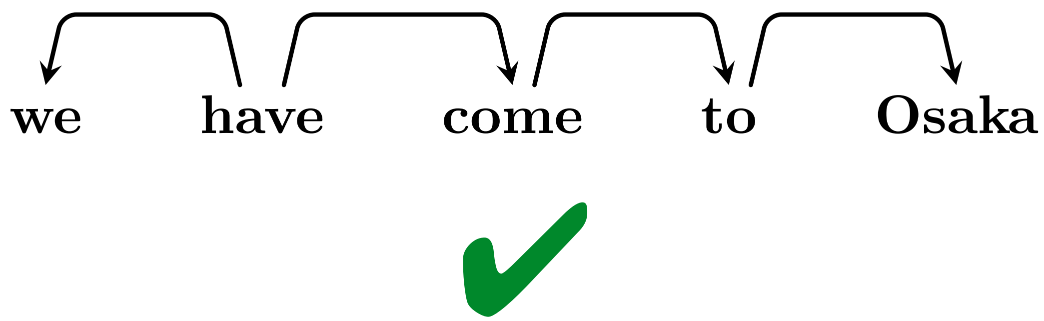


“Content-Head Dependencies”



Schwartz et al. (2012) Learnability-Based Syntactic Annotation Design

"Function-Head Dependencies"



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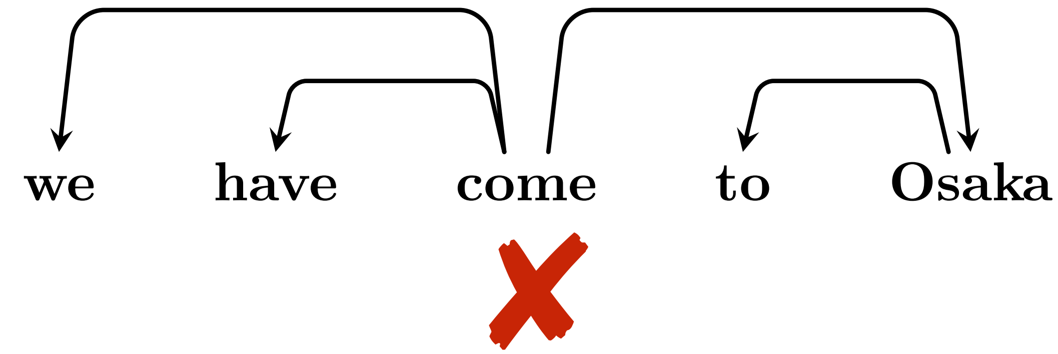
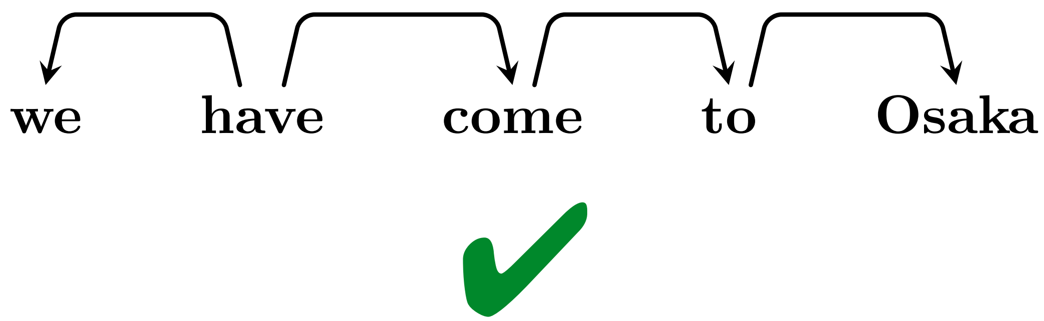


Schwartz et al. (2012) Learnability-Based Syntactic Annotation Design

	Function head	**Content head**

“Function-Head Dependencies”



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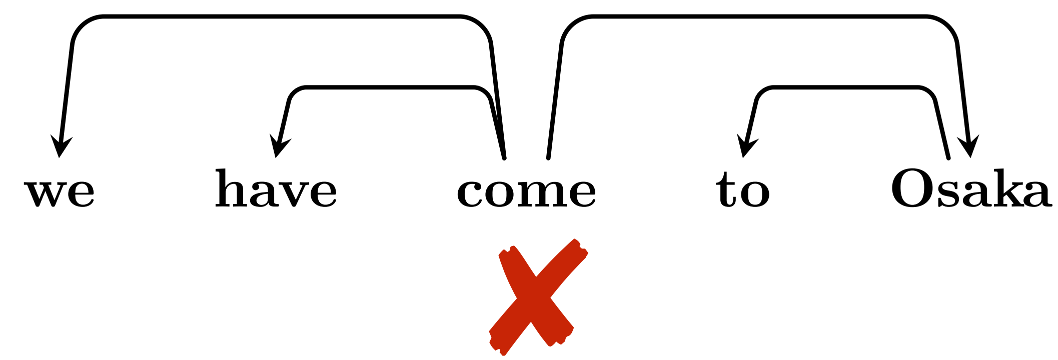
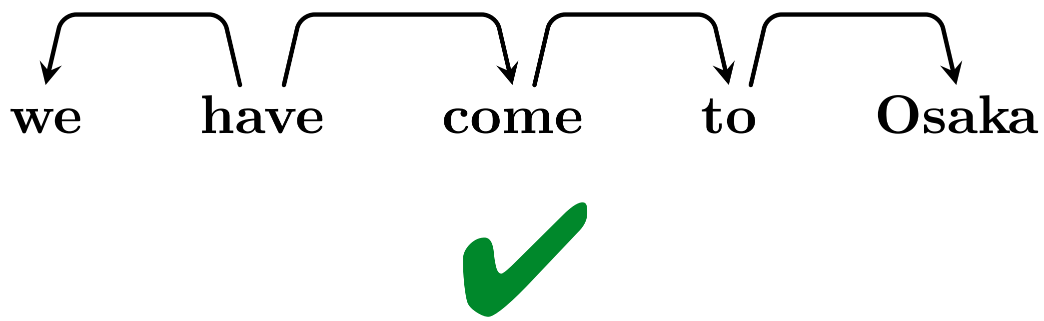


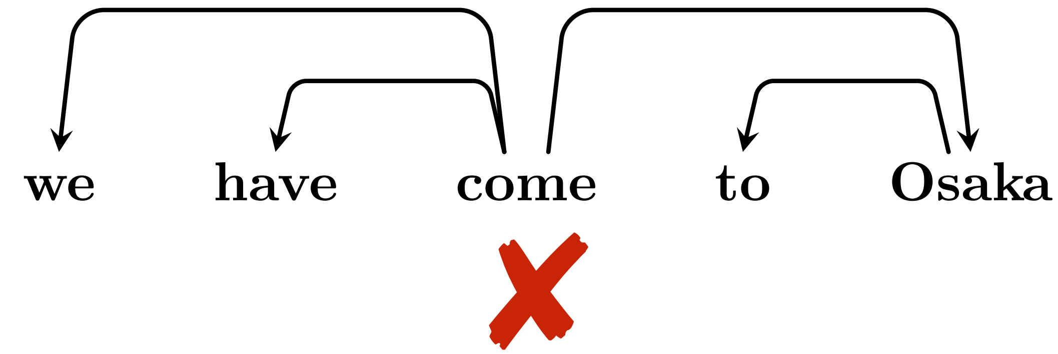
Schwartz et al. (2012) Learnability-Based Syntactic Annotation Design

	Function head	Content head
Prep – Noun	✔	✘

"Function-Head Dependencies"



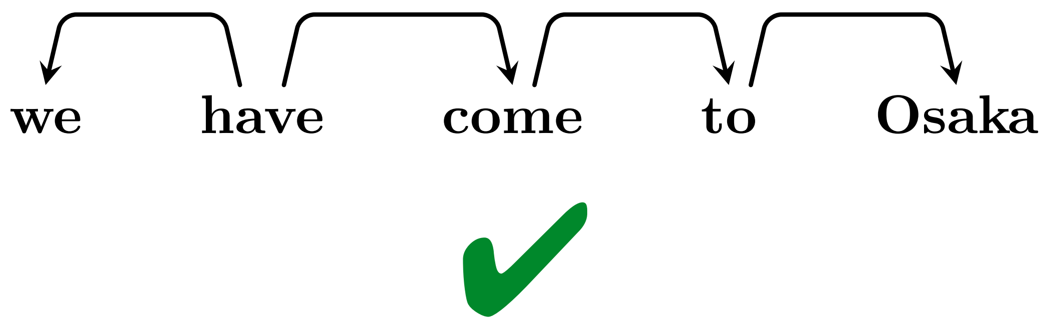
"Content-Head Dependencies"



Schwartz et al. (2012) Learnability-Based Syntactic Annotation Design

	Function head	Content head
Prep – Noun	✔	✘
Det – Noun	✘	✔

“Function-Head Dependencies”



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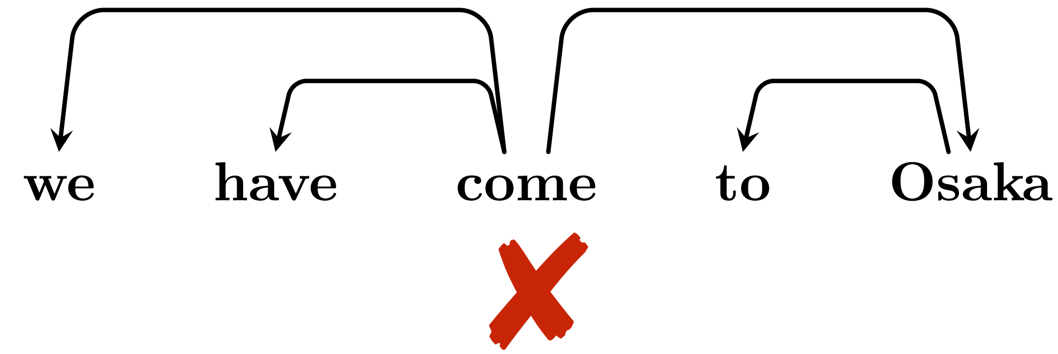
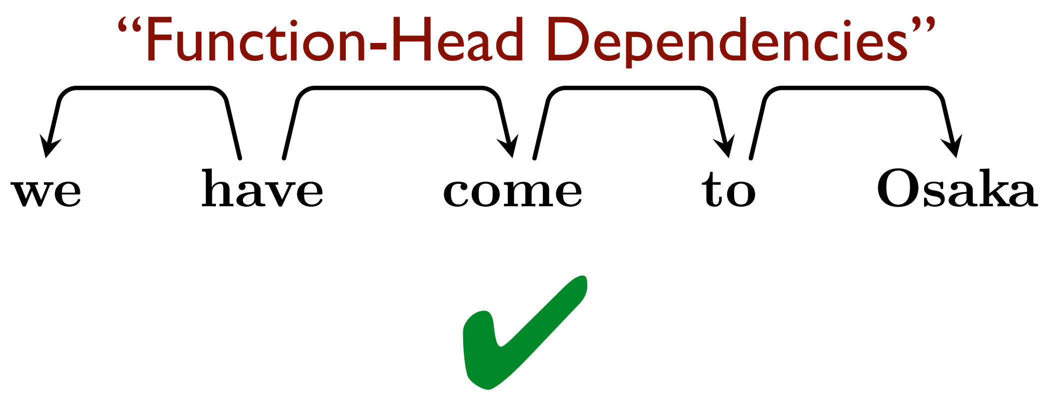
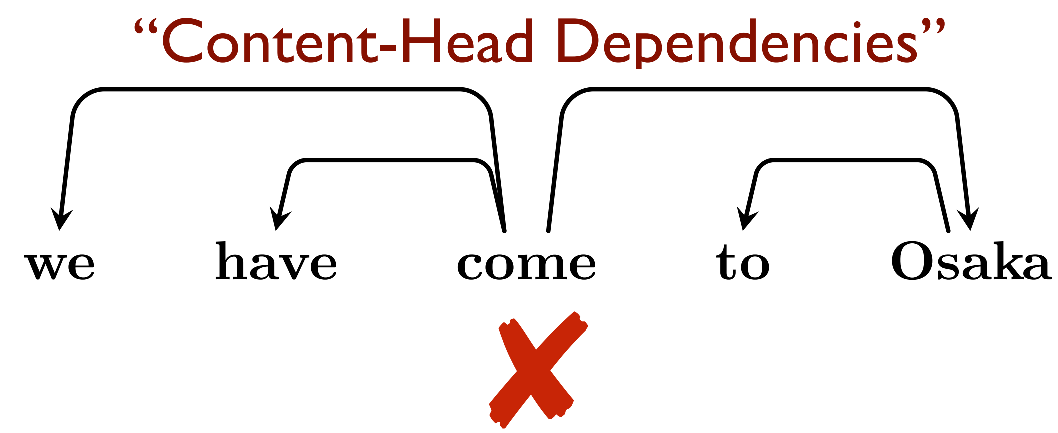


Schwartz et al. (2012) Learnability-Based Syntactic Annotation Design

	Function head	Content head
Prep – Noun	✔	✘
Det – Noun	✘	✔
CC – Conj	✘	✔

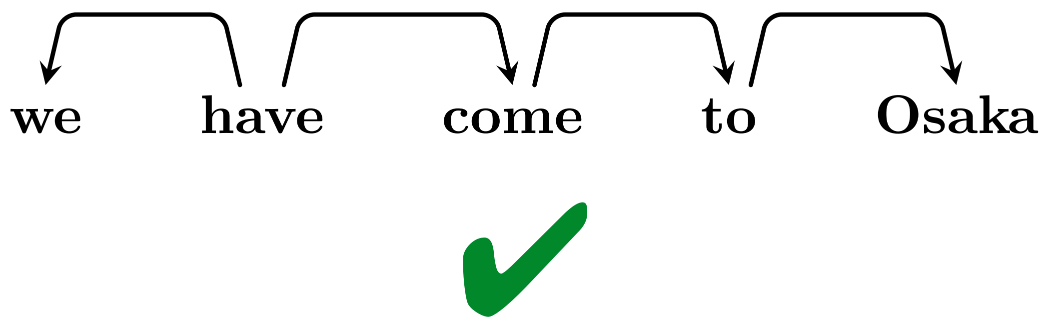




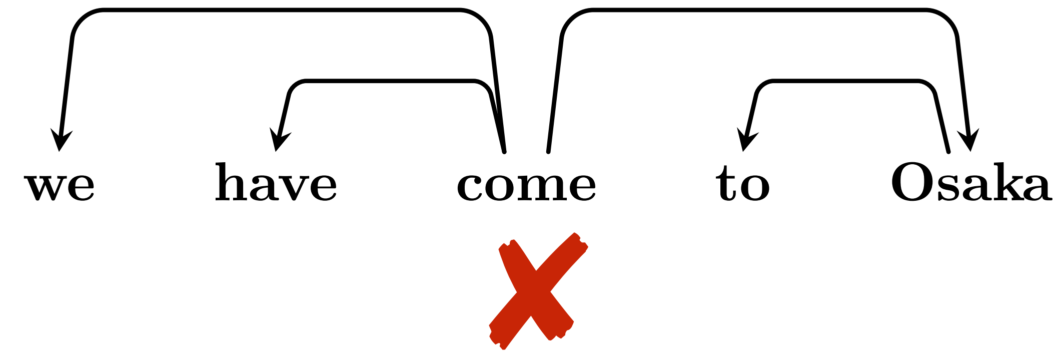
Schwartz et al. (2012) Learnability-Based Syntactic Annotation Design

	Function head	Content head
Prep – Noun	✔	✘
Det – Noun	✘	✔
CC – Conj	✘	✔
Aux – Verb	?	?

“Function-Head Dependencies”



“Content-Head Dependencies”



Schwartz et al. (2012) Learnability-Based Syntactic Annotation Design

	Function head	Content head
Prep – Noun	✔	✘
Det – Noun	✘	✔
CC – Conj	✘	✔
Aux – Verb	?	?
Mark – Infinitive	?	?

UD Parsing

UD Parsing

Silveira and Manning (2015) Monolingual parsing using transform-detransform	English	aux case cop	Inconclusive results

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Attardi et al. (2015) Monolingual parsing using different representations	Italian	case cop	UD > ISDT

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Attardi et al. (2015) Monolingual parsing using different representations	Italian	case cop	UD > ISDT
Rosa (2015) Multi-source delexicalized transfer parsing	All	case	UD > PDT

UD Parsing

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Not so bad after all?

- No clear evidence that “content-head” is harder to parse in general
- In the cross-lingual setting, it even seems to work better

UD Parsing

Not so bad after all?

- No clear evidence that "content-head" is harder to parse in general
- In the cross-lingual setting, it even seems to work better

Can we do better?

- Exploit the full representation – lexical and functional heads
- Use typology of syntactic relations as a bias for learning

Beyond Parsing

Transforming Dependency Structures to Logical Forms for Semantic Parsing

Siva Reddy[†a] **Oscar Täckström**[‡] **Michael Collins**[‡b] **Tom Kwiatkowski**[‡]
Dipanjan Das[‡] **Mark Steedman**[†] **Mirella Lapata**[†]
[†]ILCC, School of Informatics, University of Edinburgh
[‡] Google, New York

- Rules for mapping dependency trees to logical forms
- State-of-the-art on multiple question-answering tasks
- New paper: one set of rules for multiple languages

Transactions of the Association for Computational Linguistics, vol. 4, pp. 127–140, 2016. Action Editor: Christopher Potts.
Submission batch: 12/2015; Published 4/2016.

Transforming Dependency Structures to Logical Forms for Semantic Parsing

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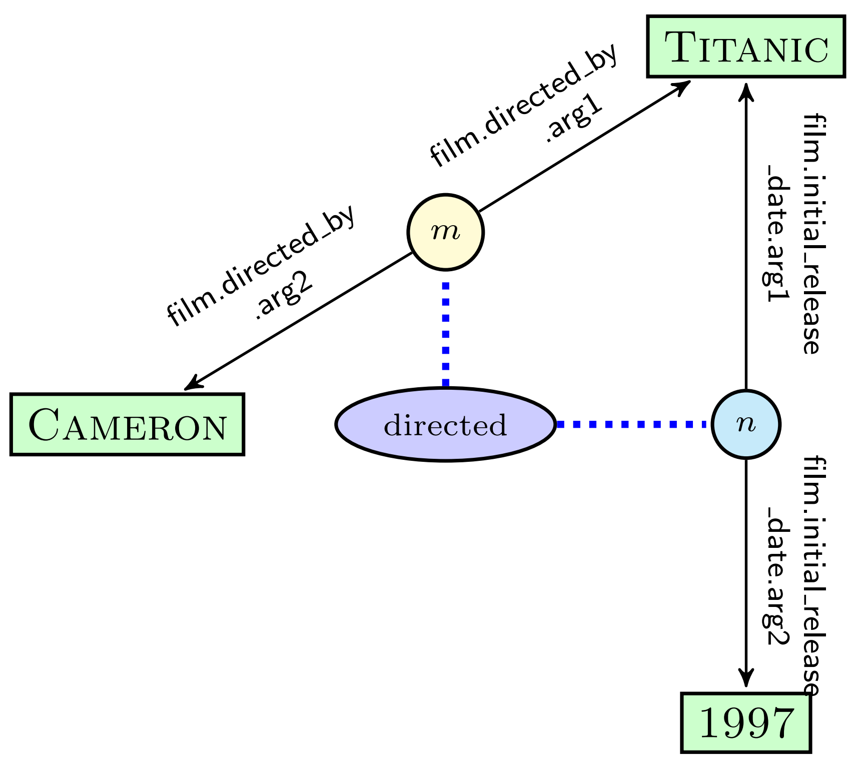
- Rules for mapping dependency trees to logical forms
- State-of-the-art on multiple question-answering tasks
- New paper: one set of rules for multiple languages

Thanks to Oscar for sharing slides!

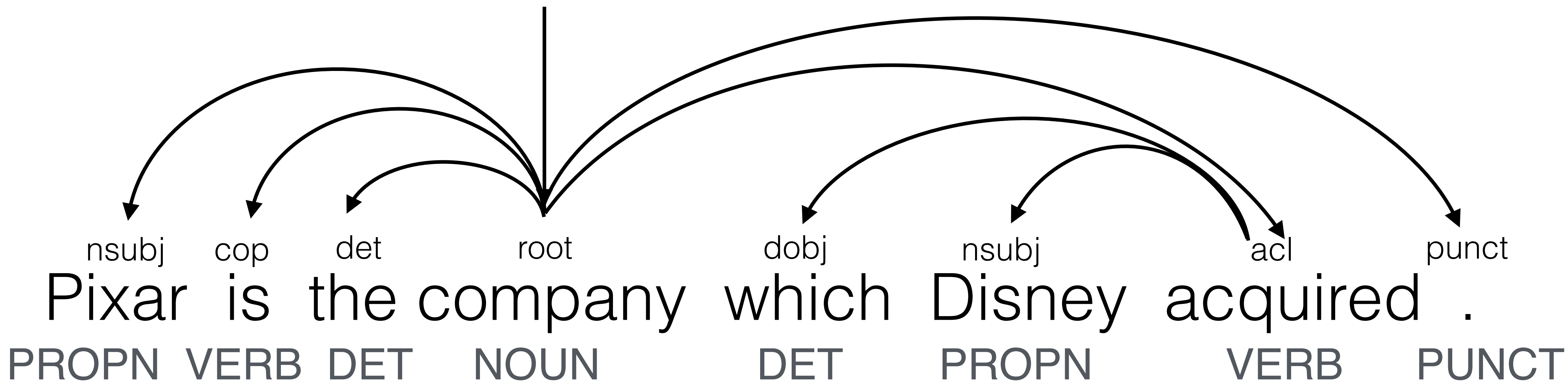
Who directed Titanic?

$$\lambda z.\exists xy.\mathrm{directed}(z_e) \wedge \mathrm{Titanic}(y_a) \wedge \mathrm{Q}(x_a) \wedge \mathrm{arg}_1(z_e, x_a) \wedge \mathrm{arg}_2(z_e, y_a)$$

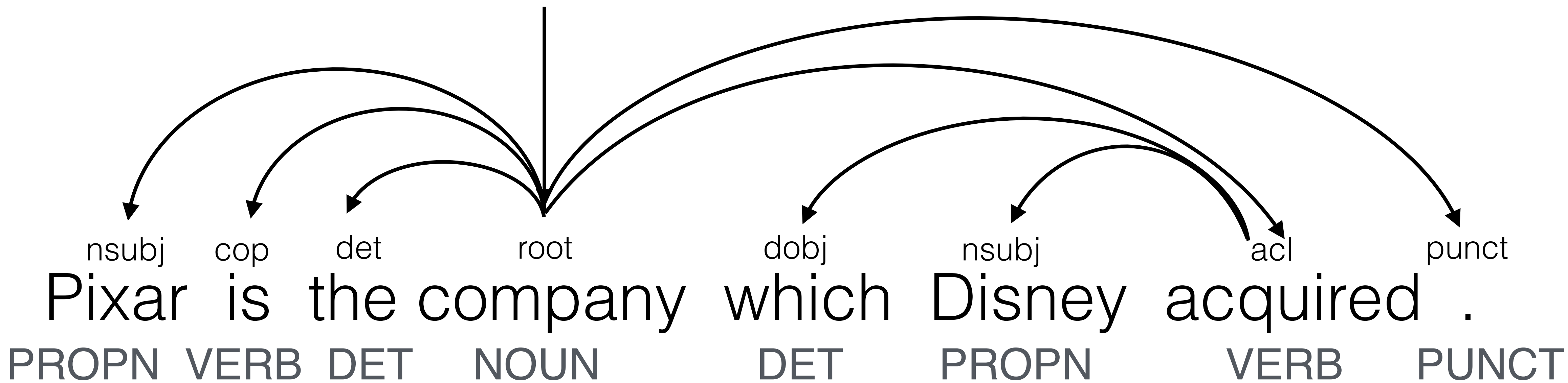


Knowledge Graph

Take syntactic dependencies



Take syntactic dependencies



Deterministically infer logical form(s)

$$\exists z.\mathrm{company}(\mathrm{Pixar}) \wedge \mathrm{acquired}(z_e) \wedge \mathrm{arg}_1(z_e, \mathrm{Disney}) \wedge \mathrm{arg}_2(z_e, \mathrm{Pixar})$$

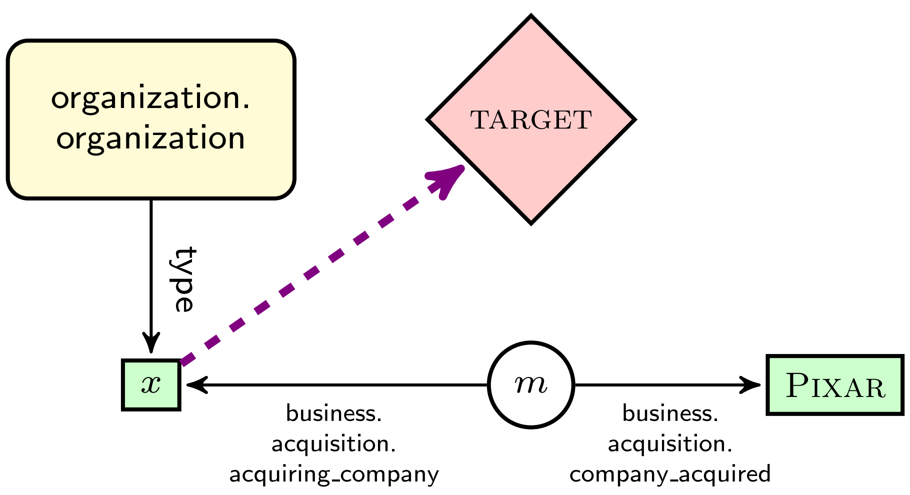
Deterministically Convert to Logical Form(s)

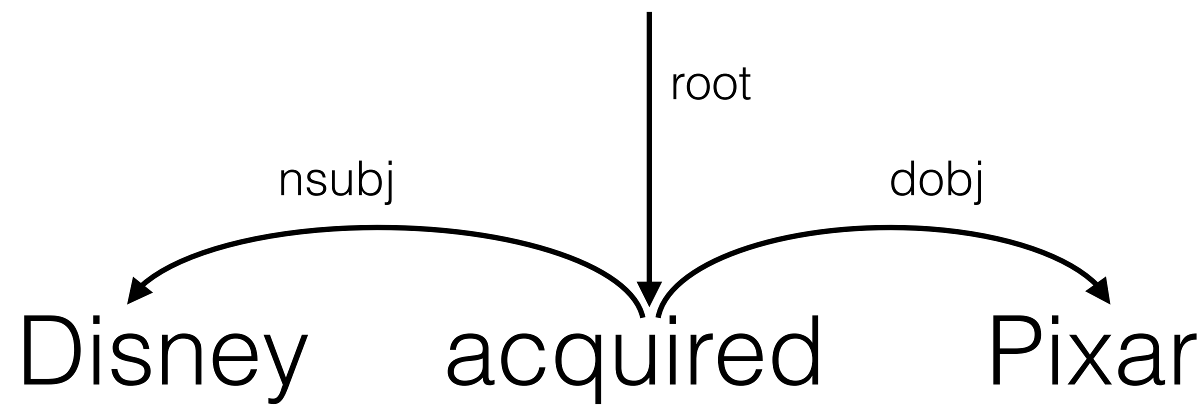
$$\exists z.\text{company}(\text{Pixar}) \land \text{acquired}(z_e) \land \text{arg}_1(z_e, \text{Disney}) \land \text{arg}_2(z_e, \text{Pixar})$$

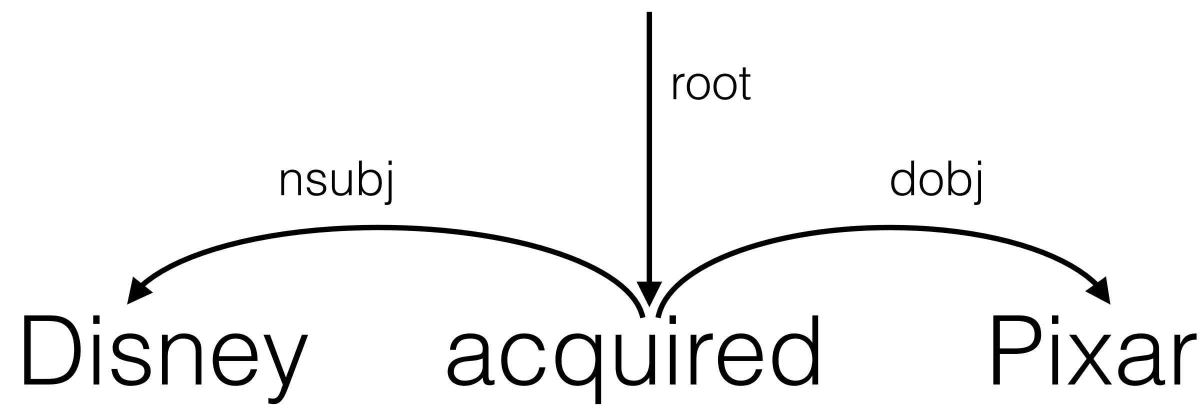
Deterministically Convert to Logical Form(s)

$$\exists z.\text{company}(\text{Pixar}) \wedge \text{acquired}(z_e) \wedge \text{arg}_1(z_e, \text{Disney}) \wedge \text{arg}_2(z_e, \text{Pixar})$$

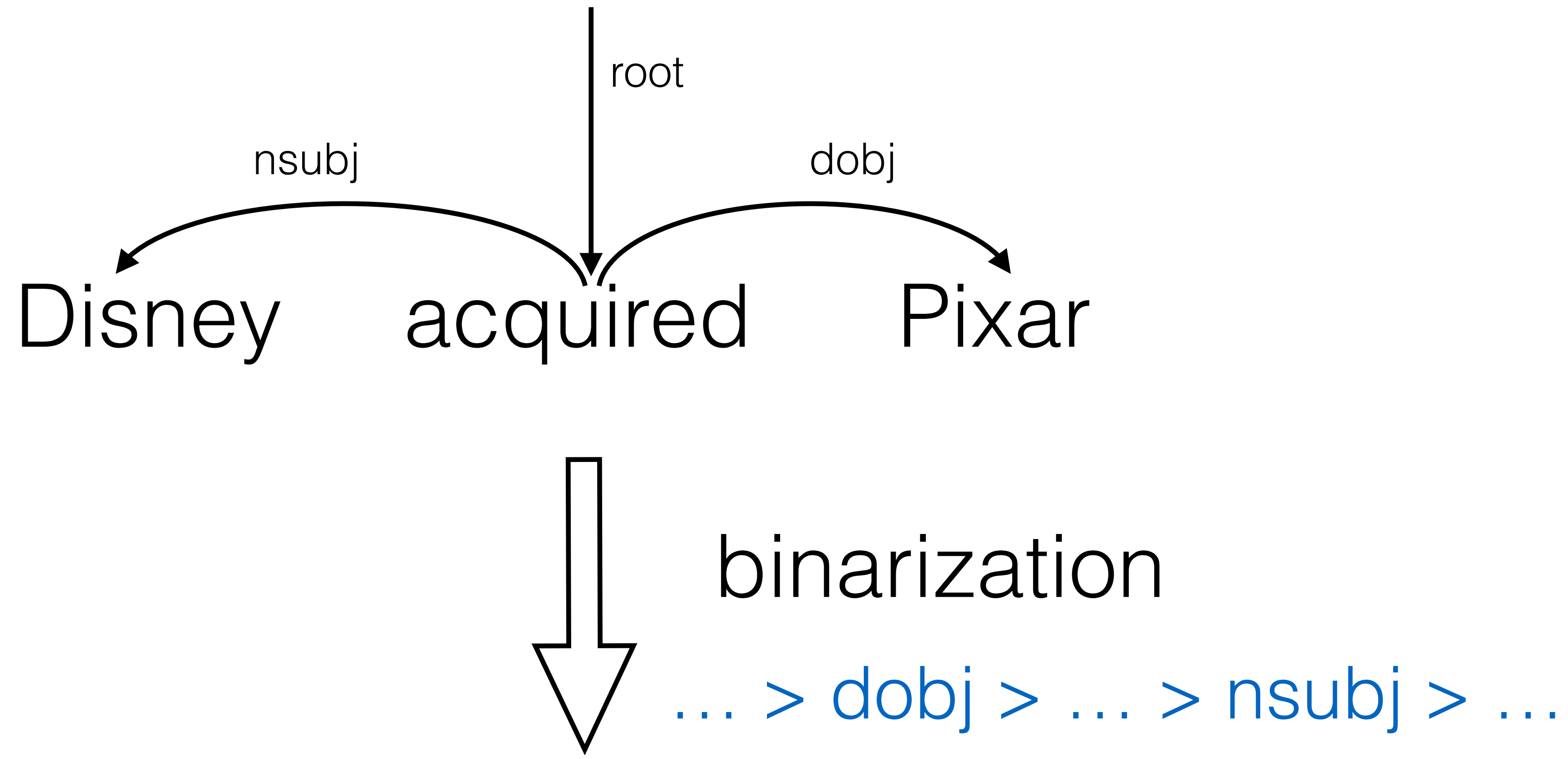
Learn model to map logical form to KG to answer question

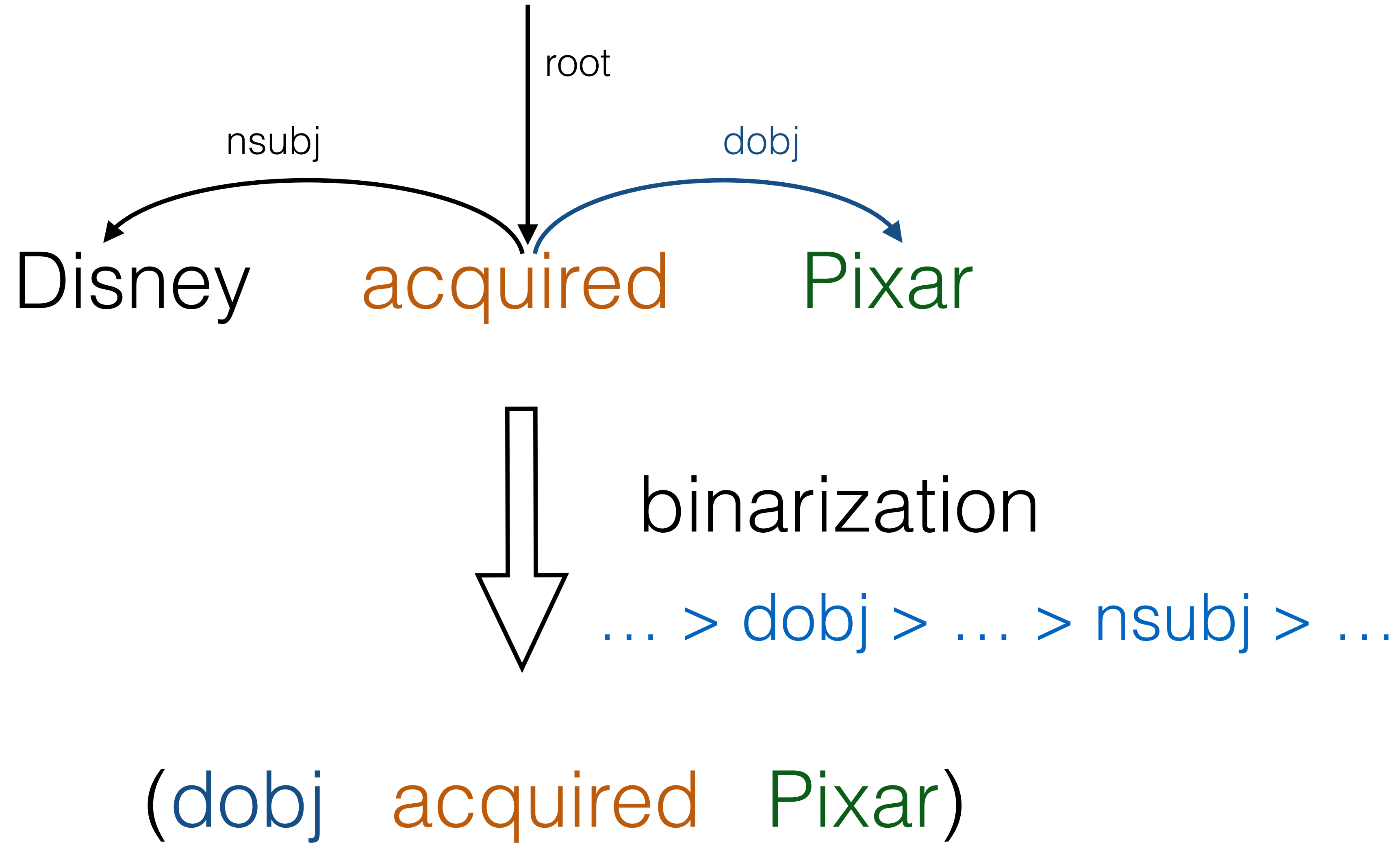


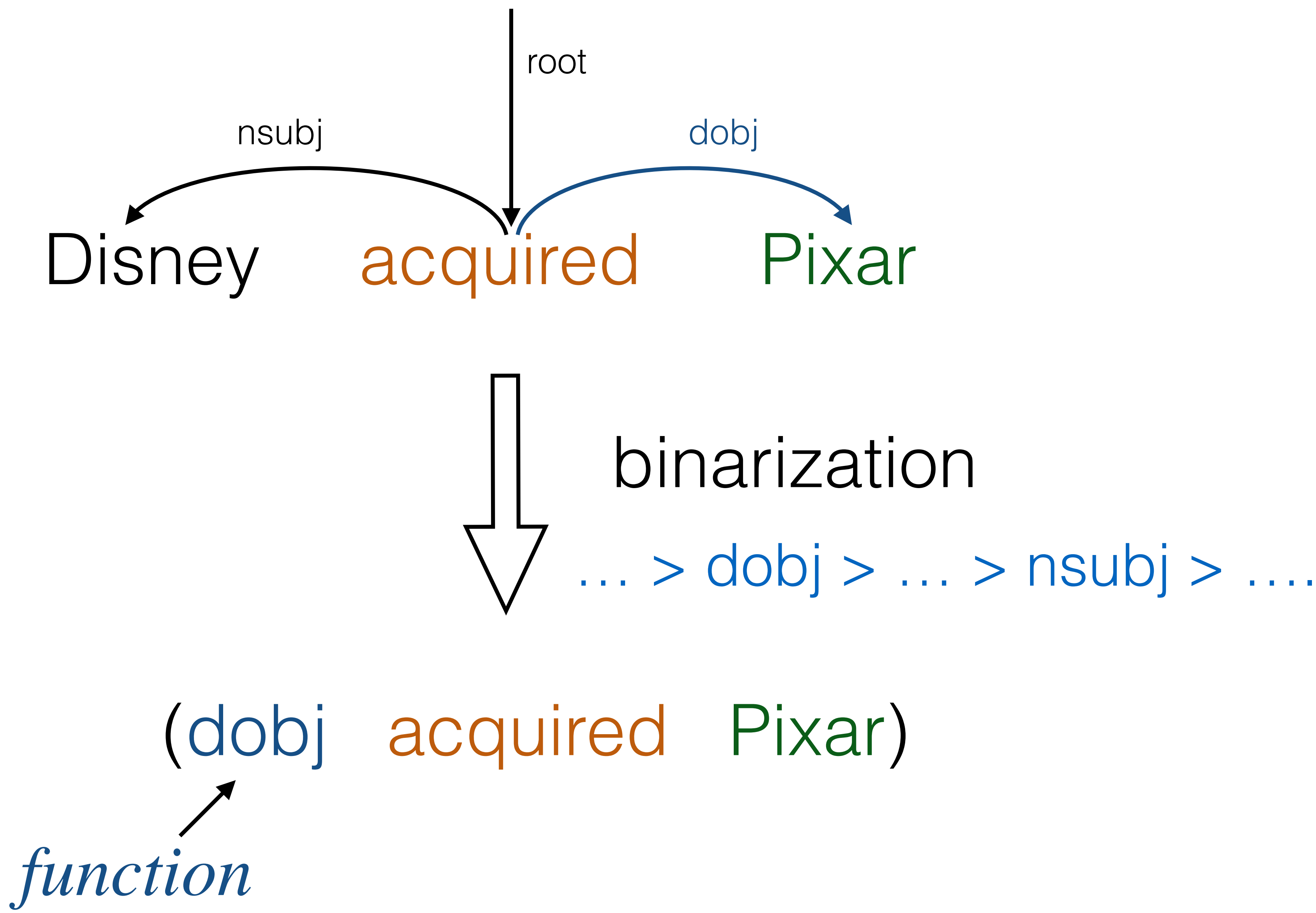

root
nsubj
dobj
Disney
acquired
Pixar

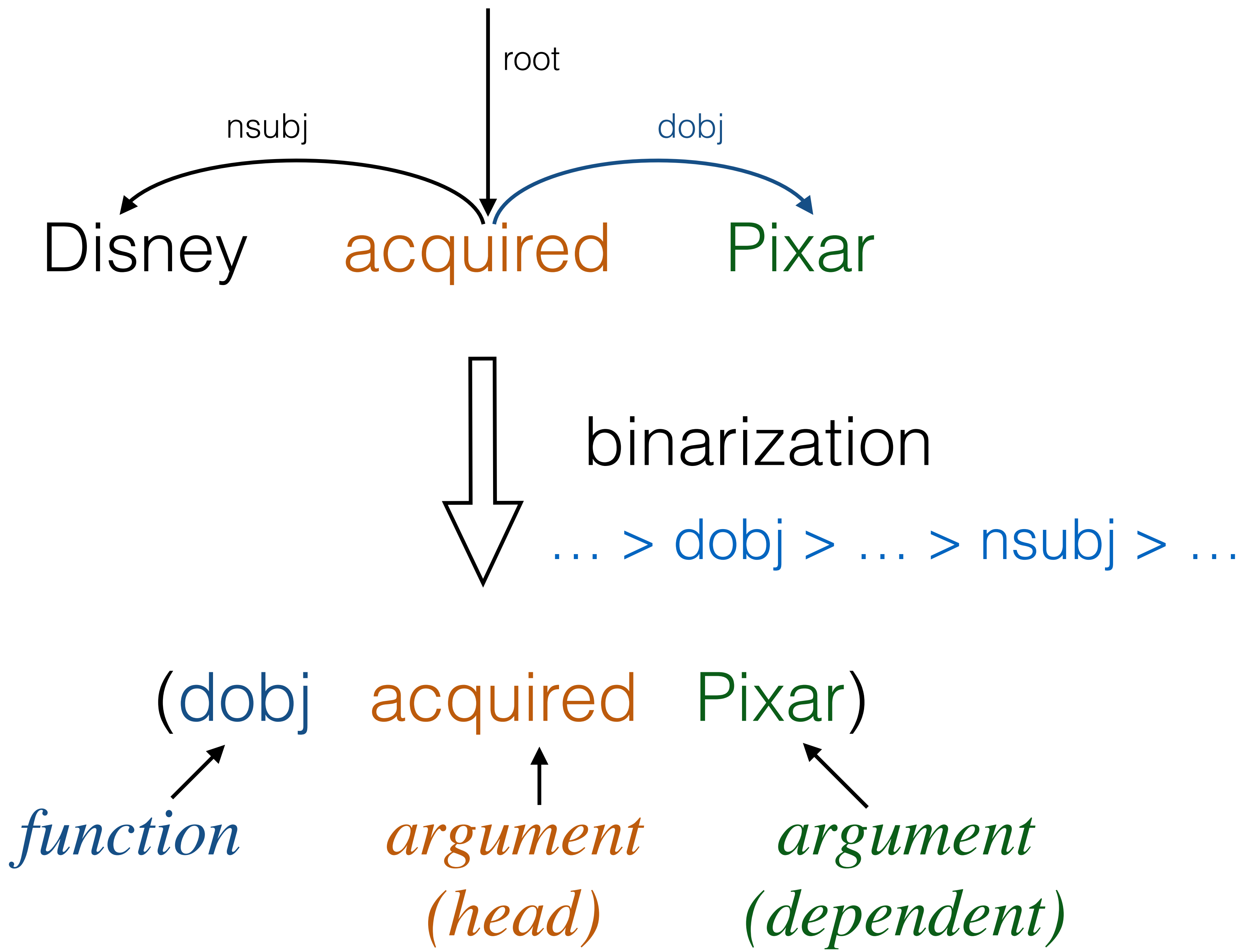


Dependencies drive the composition

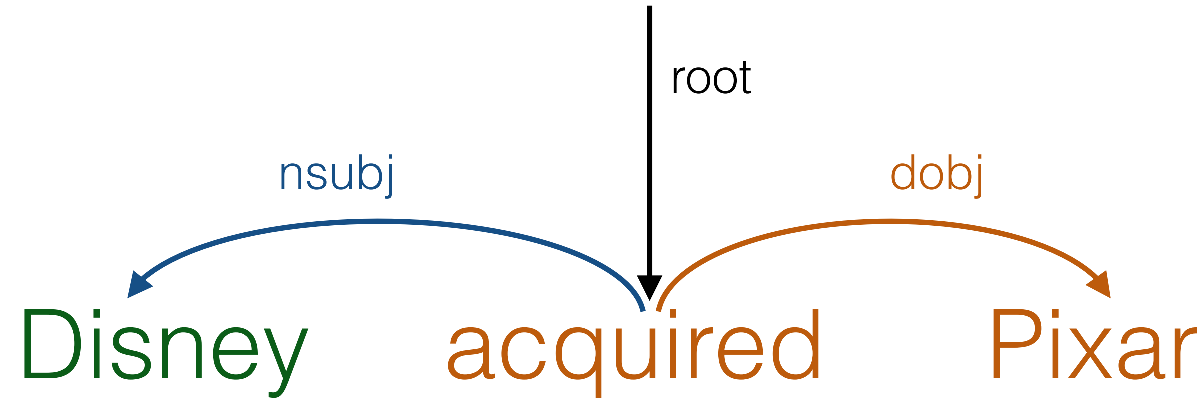

root
nsubj
dobj
Disney acquired Pixar
binarization
… > dobj > … > nsubj > ….


root
nsubj
dobj
Disney
acquired
Pixar
binarization
… > dobj > … > nsubj > ….
(dobj acquired Pixar)

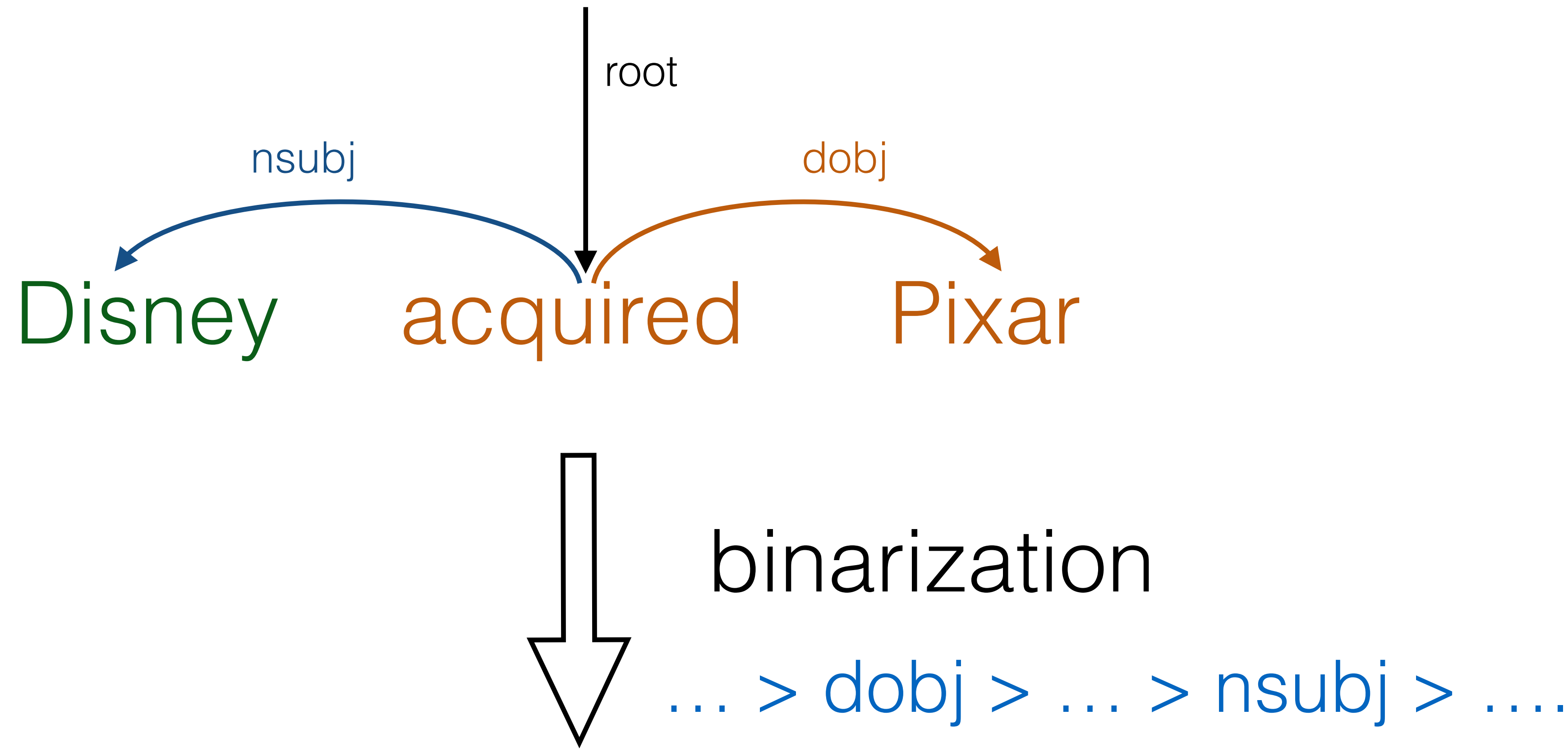

root
nsubj
dobj
Disney
acquired
Pixar
binarization
… > dobj > … > nsubj > ….
(dobj acquired Pixar)
function



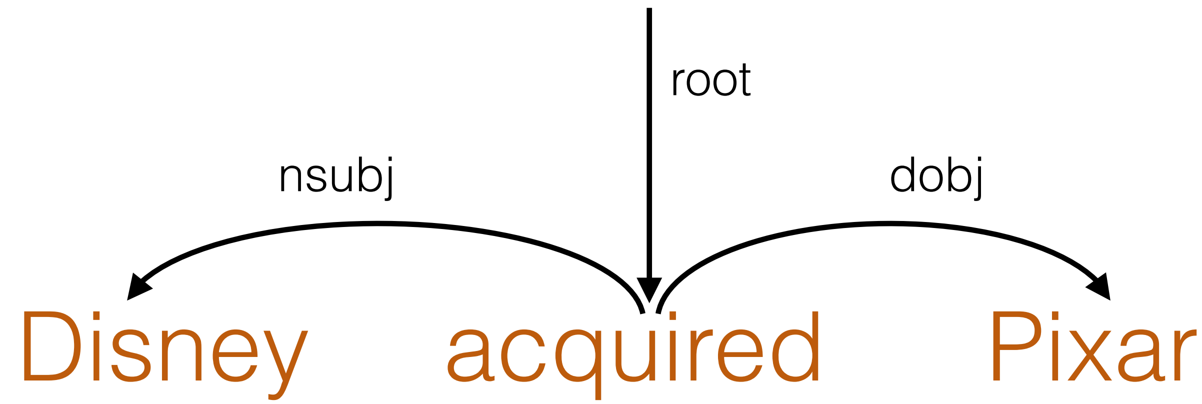
root
nsubj
dobj
Disney acquired Pixar
binarization
… > dobj > … > nsubj > ….
(dobj acquired Pixar)
function
argument (head)
argument (dependent)



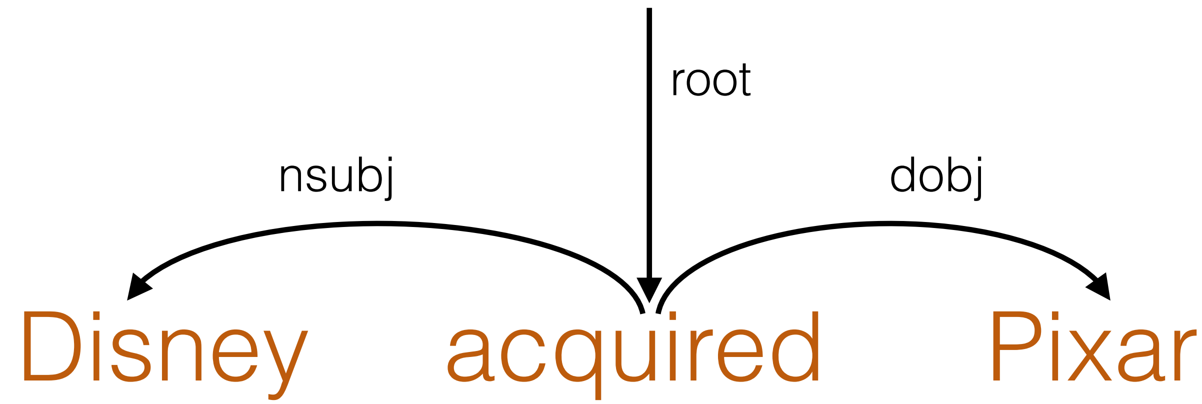
(nsubj (dobj acquired Pixar) Disney)



(nsubj (dobj acquired Pixar) Disney)



(nsubj (dobj acquired Pixar) Disney)



binarization

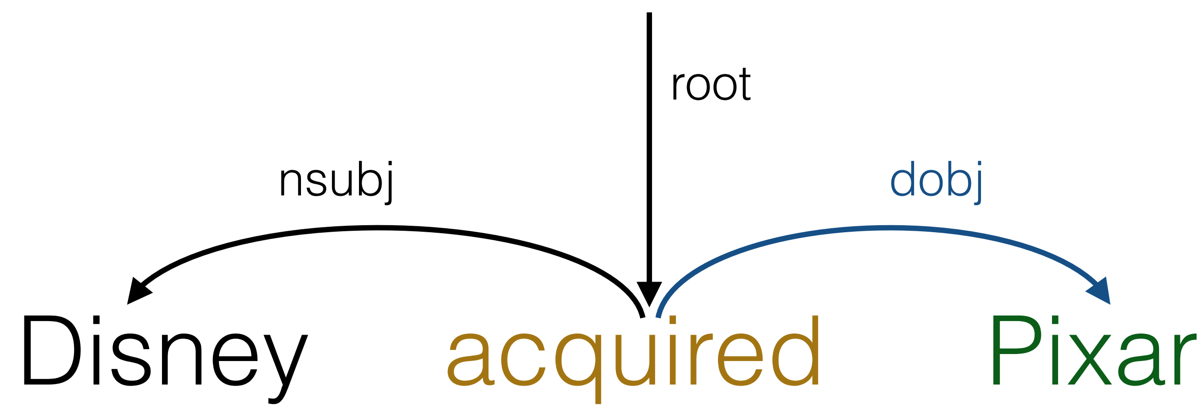
… > dobj > … > nsubj > ….

(nsubj (dobj acquired Pixar) Disney)

substitution + composition

$$\lambda z.\exists xy.\mathrm{acquired}(z_e) \wedge \mathrm{Pixar}(y_a) \wedge \mathrm{Disney}(x_a) \wedge \mathrm{arg}_1(z_e, x_a) \wedge \mathrm{arg}_2(z_e, y_a)$$

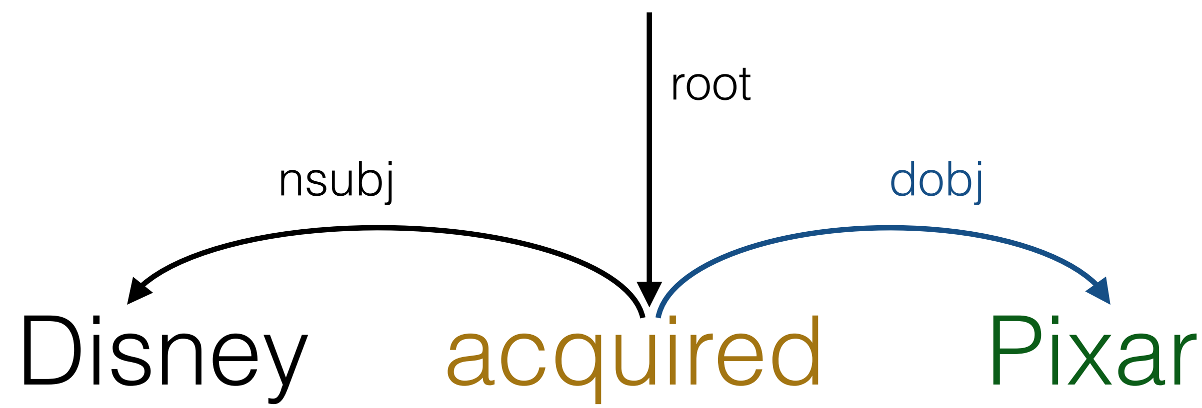
A Single Type System



All constituents are of the same lambda expression type

TYPE[acquired] = **TYPE**[Pixar] = **TYPE**[(dobj acquired Pixar)]

A Single Type System



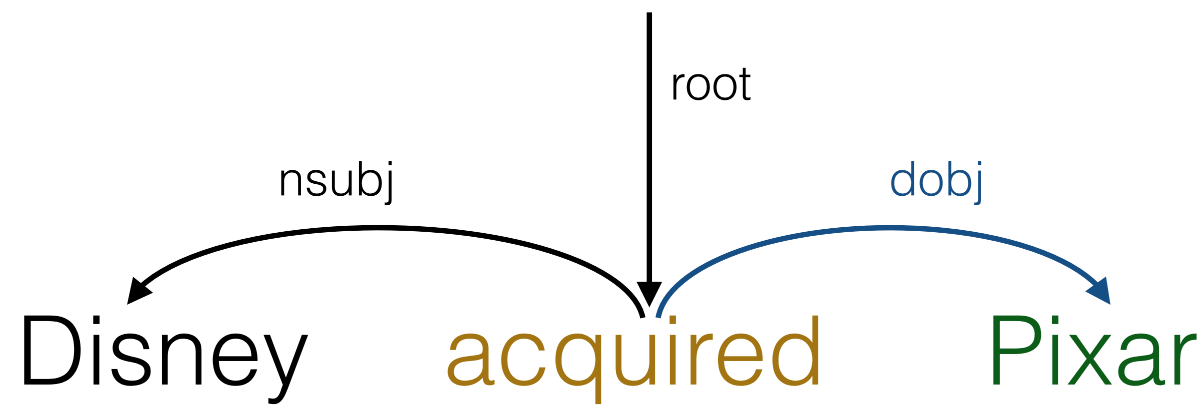
Lambda Calculus Basic Types

Individuals: **Ind** (also denoted by $_{.a}$)

Events: **Event** (also denoted by $_{.e}$)

Truth values: **Bool**

Substitution

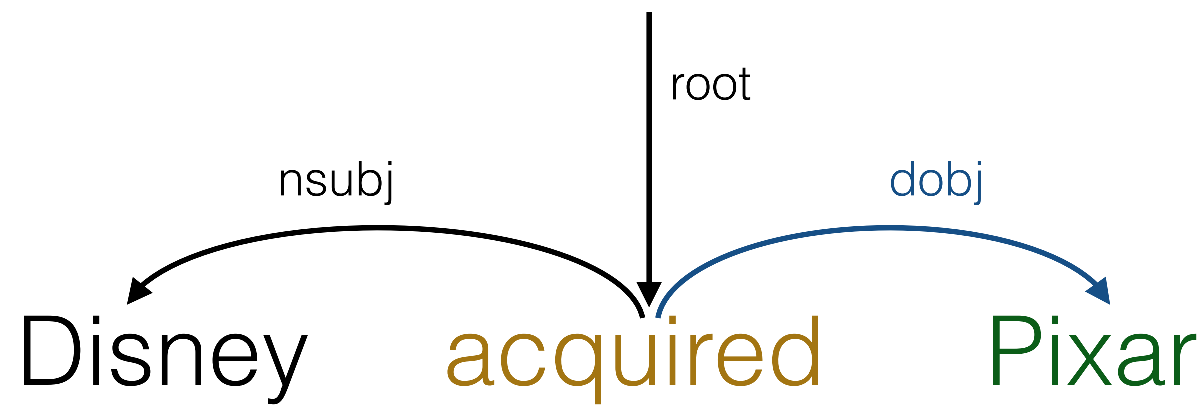


Lambda Expressions for Words (**Ind** x **Event** -> **Bool**):

acquired $\Rightarrow \lambda x.\mathrm{acquired}(x_e)$

Pixar $\Rightarrow \lambda x.\mathrm{Pixar}(x_a)$

Substitution

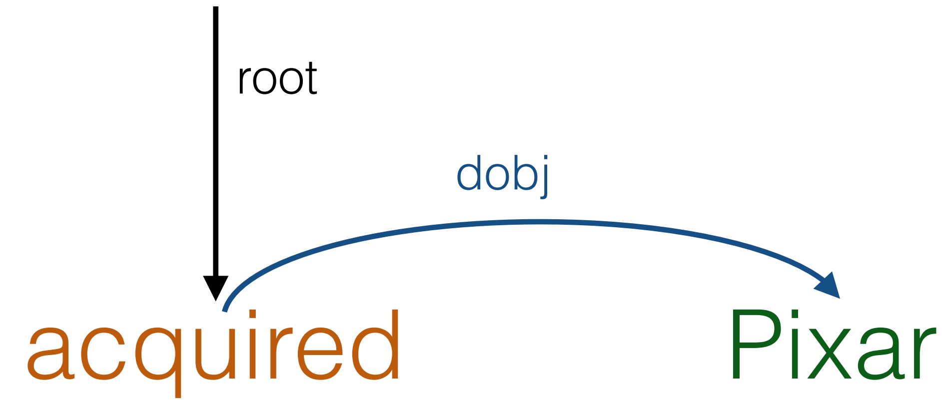


Lambda Expressions for Dependency Labels:

$$\text{dobj} \Rightarrow \lambda f g z .\, \exists x .\, f(z) \wedge g(x) \wedge \mathrm{arg}_2(z_e, x_a)$$

mirrors the tree structure

Composition



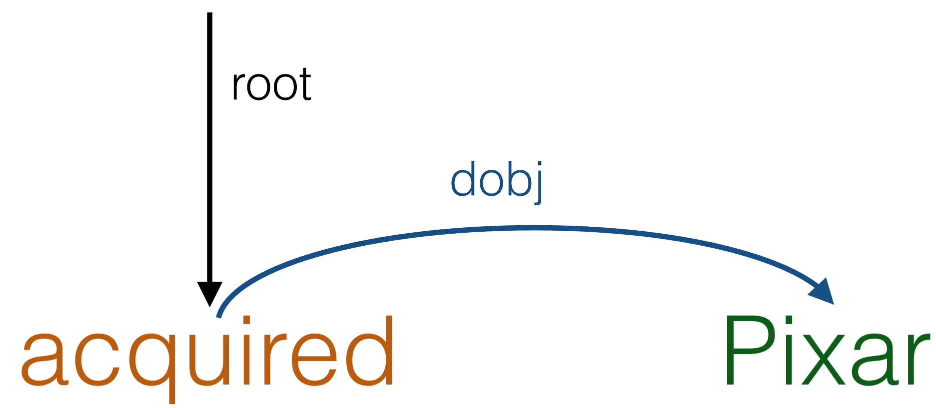
(dobj acquired Pixar)

$$\lambda f g z. \exists y. f(z) \wedge g(y) \wedge \mathrm{arg}_2(z_e, y_a)$$

$$\lambda z.\mathrm{acquired}(z_e)$$

$$\lambda y.\mathrm{Pixar}(y_a)$$

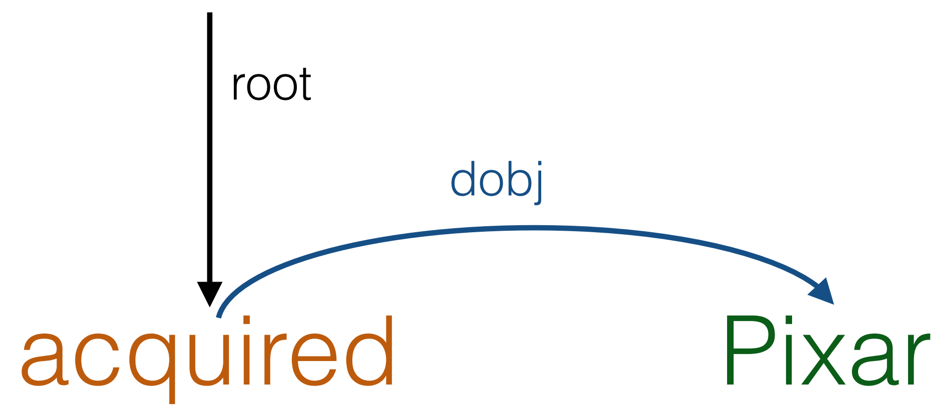
Composition



(dobj acquired Pixar)

$$\frac{\begin{matrix} \lambda f g z . \exists y . \\ f(z) \wedge g(y) \wedge \\ \mathrm{arg}_2(z_e, y_a) \end{matrix} \quad \lambda z . \mathrm{acquired}(z_e) \quad \lambda y . \mathrm{Pixar}(y_a)}{\begin{matrix} \lambda g z .\ \exists y .\ \mathrm{acquired}(z_e) \wedge g(y) \\ \wedge\ \mathrm{arg}_2(z_e, y_a) \end{matrix}}$$

Composition

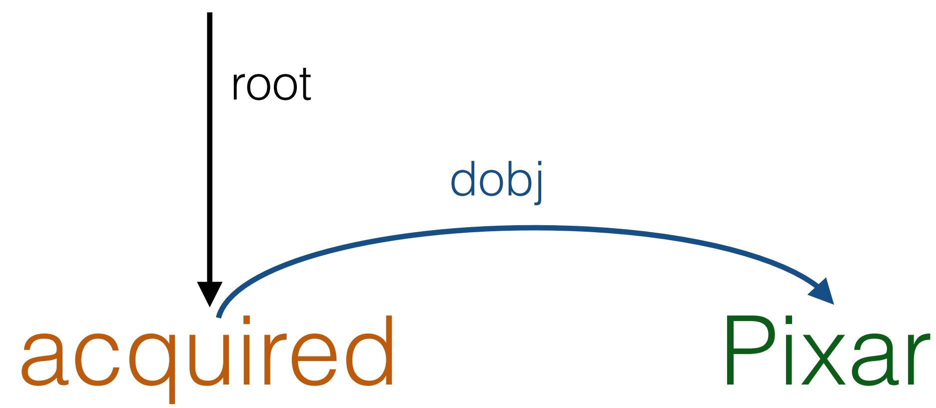


(dobj acquired Pixar)

$\lambda f g z. \exists y. \boxed{f(z)} \wedge g(y) \wedge \text{arg}_2(z_e, y_a)$ $\quad$ $\lambda z.\text{acquired}(z_e)$ $\quad$ $\lambda y.\text{Pixar}(y_a)$

$$\frac{\lambda f g z. \exists y. \boxed{f(z)} \wedge g(y) \wedge \text{arg}_2(z_e, y_a) \qquad \lambda z.\text{acquired}(z_e)}{\lambda g z.\ \exists y. \boxed{\text{acquired}(z_e)} \wedge g(y) \wedge \text{arg}_2(z_e, y_a)}$$

Composition



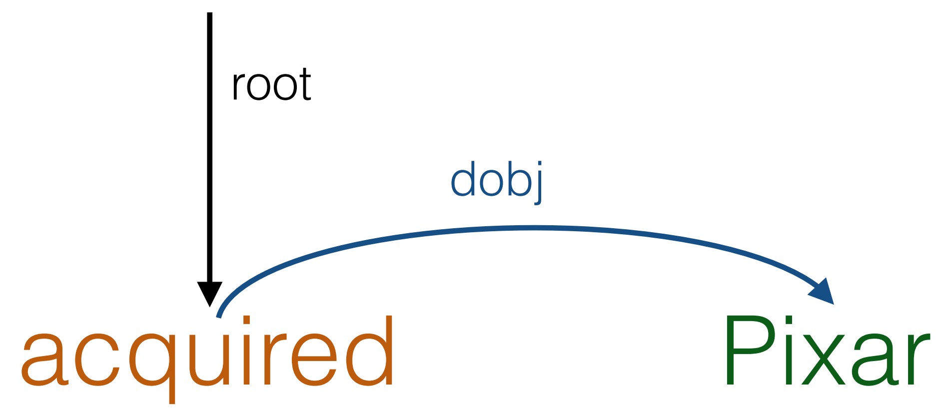
(dobj acquired Pixar)

$$\lambda f g z. \exists y. \boxed{f(z)} \wedge g(y) \wedge \arg_2(z_e, y_a) \qquad \lambda z.\text{acquired}(z_e) \qquad \lambda y.\text{Pixar}(y_a)$$

$$\lambda g z.\ \exists y. \boxed{\text{acquired}(z_e)} \wedge g(y) \wedge \arg_2(z_e, y_a)$$

$$\lambda z.\ \exists y.\ \text{acquired}(z_e) \wedge \text{Pixar}(y_a) \wedge \arg_2(z_e, y_a)$$

Composition



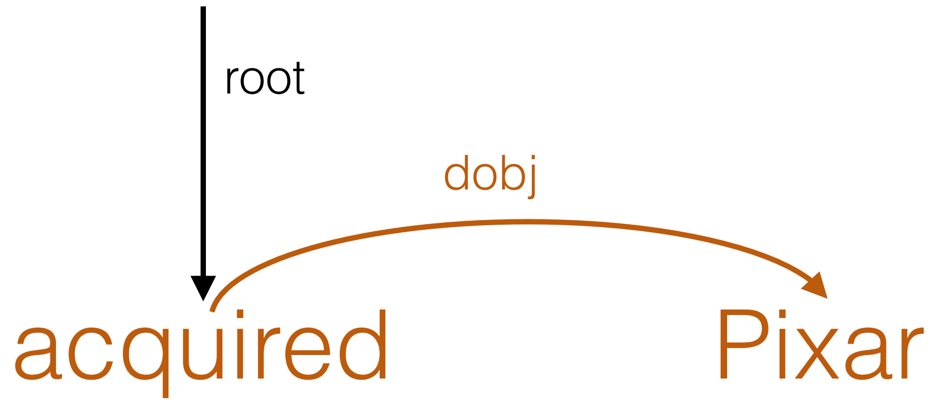
(dobj acquired Pixar)

$$\lambda f g z. \exists y. \boxed{f(z)} \wedge \boxed{g(y)} \wedge \arg_2(z_e, y_a) \qquad \lambda z.\text{acquired}(z_e) \qquad \lambda y.\text{Pixar}(y_a)$$

$$\lambda g z.\ \exists y. \boxed{\text{acquired}(z_e)} \wedge g(y) \wedge \arg_2(z_e, y_a)$$

$$\lambda z.\ \exists y.\ \text{acquired}(z_e) \wedge \boxed{\text{Pixar}(y_a)} \wedge \arg_2(z_e, y_a)$$

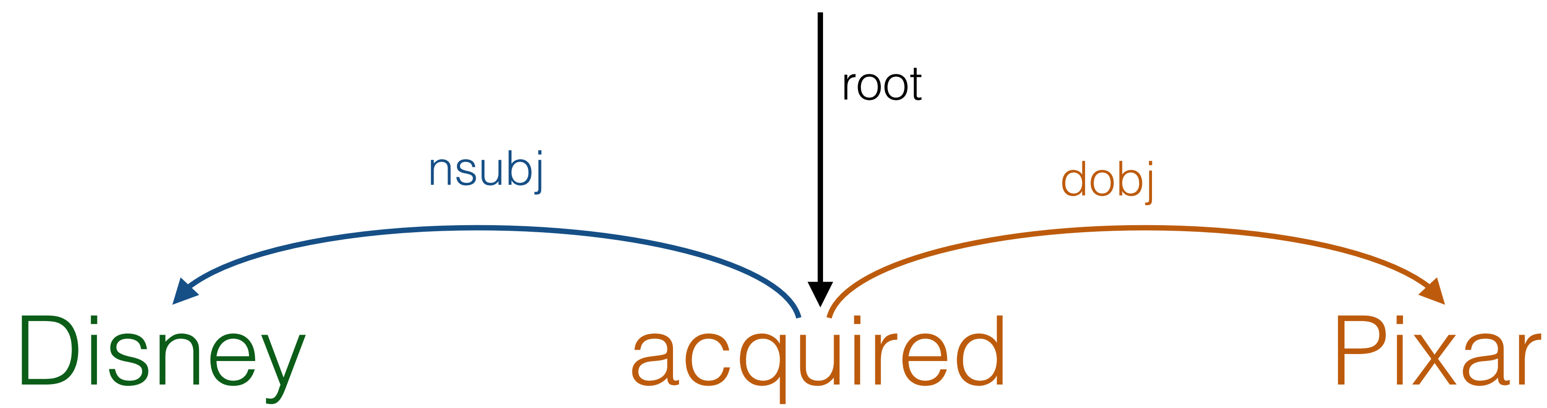
Composition



(dobj acquired Pixar)

$$\lambda z.\ \exists y.\ \mathrm{acquired}(z_e) \wedge \mathrm{Pixar}(y_a)$$
$$\wedge\ \mathrm{arg}_2(z_e, y_a)$$

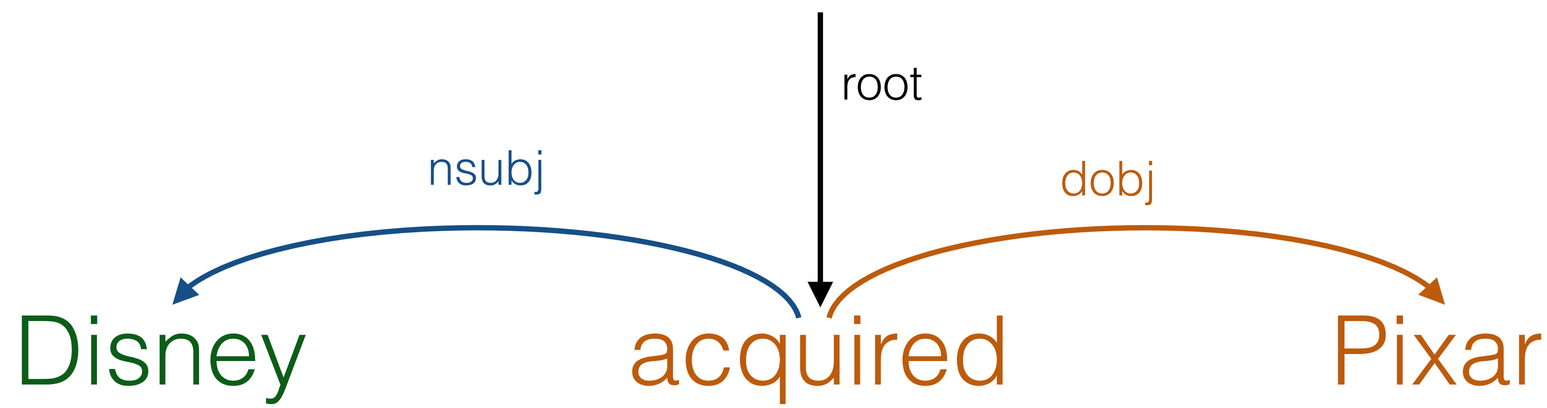
Composition



(nsubj (dobj acquired Pixar) Disney)

$$\lambda f g z.\ \exists x.\ f(z) \wedge g(x) \wedge \arg_1(z_e, x_a) \qquad \frac{\text{(dobj acquired Pixar)}}{\lambda z.\ \exists y.\ \text{acquired}(z_e) \wedge \text{Pixar}(y_a) \wedge \arg_2(z_e, y_a)} \qquad \lambda x.\text{Disney}(x_a)$$

Composition



(nsubj (dobj acquired Pixar) Disney)

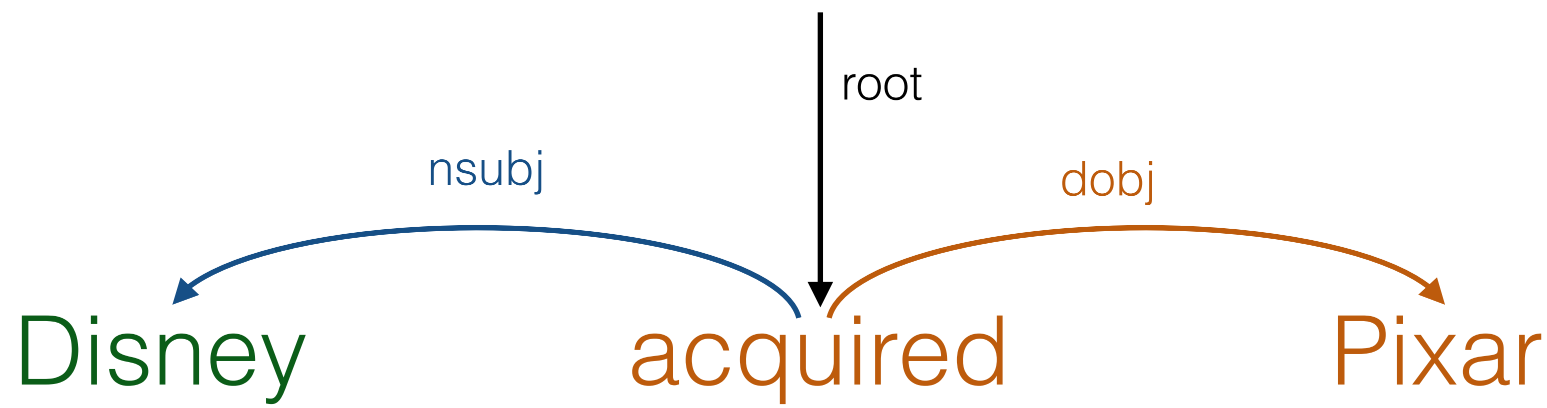
$\lambda f g z.\ \exists x.\ f(z) \wedge g(x) \wedge \mathrm{arg}_1(z_e, x_a)$

$$\frac{\text{(dobj acquired Pixar)}}{\lambda z.\ \exists y.\ \mathrm{acquired}(z_e) \wedge \mathrm{Pixar}(y_a) \wedge \mathrm{arg}_2(z_e, y_a)}$$

$\lambda x.\mathrm{Disney}(x_a)$

$$\lambda g z. \exists x y. \mathrm{acquired}(z_e) \wedge \mathrm{Pixar}(y_a) \wedge \mathrm{g}(x) \wedge \mathrm{arg}_1(z_e, x_a) \wedge \mathrm{arg}_2(z_e, y_a)$$

Composition



(nsubj (dobj acquired Pixar) Disney)

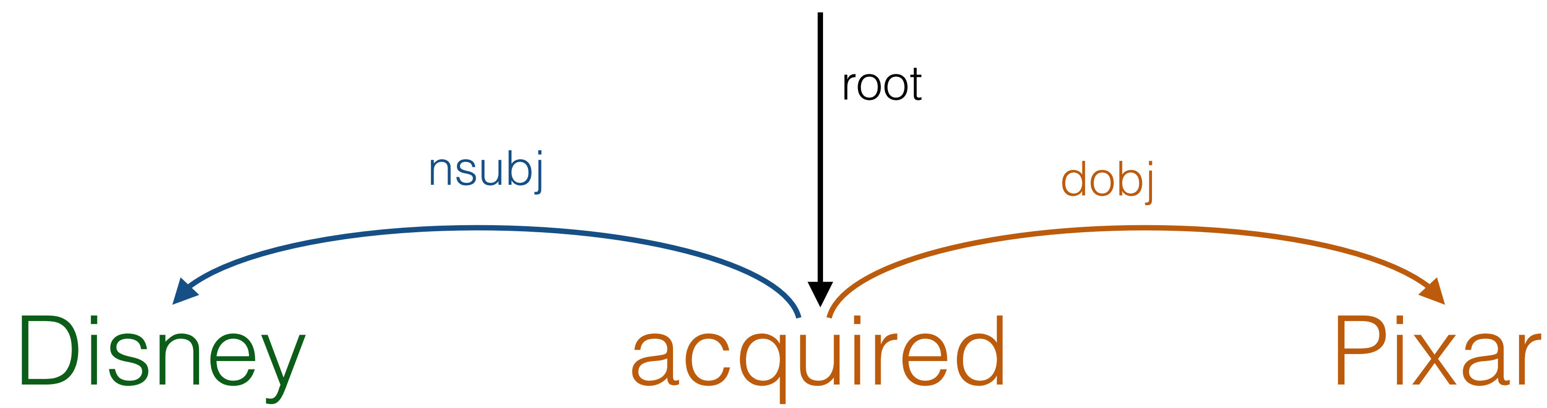
$$\lambda f g z.\ \exists x.\ \boxed{f(z)} \wedge g(x) \wedge \mathrm{arg}_1(z_e, x_a)$$

$$\lambda z.\ \exists y.\ \mathrm{acquired}(z_e) \wedge \mathrm{Pixar}(y_a) \wedge \mathrm{arg}_2(z_e, y_a)$$

$$\lambda x.\mathrm{Disney}(x_a)$$

$$\lambda g z. \exists x y. \boxed{\mathrm{acquired}(z_e) \wedge \mathrm{Pixar}(y_a)} \wedge \mathrm{g}(x) \wedge \mathrm{arg}_1(z_e, x_a) \wedge \boxed{\mathrm{arg}_2(z_e, y_a)}$$

Composition



(nsubj (dobj acquired Pixar) Disney)

$$\lambda f g z.\ \exists x.\ \boxed{f(z)} \wedge g(x) \wedge \mathrm{arg}_1(z_e, x_a)$$

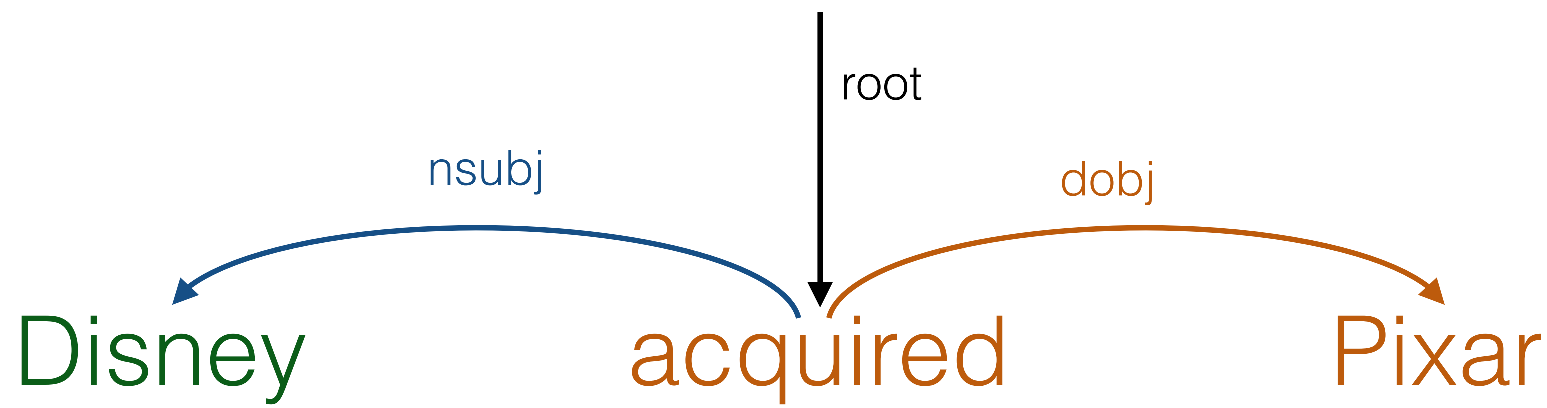
$$\lambda z.\ \exists y.\ \mathrm{acquired}(z_e) \wedge \mathrm{Pixar}(y_a) \wedge \mathrm{arg}_2(z_e, y_a)$$

$$\lambda x.\mathrm{Disney}(x_a)$$

$$\lambda g z.\exists x y.\boxed{\mathrm{acquired}(z_e) \wedge \mathrm{Pixar}(y_a)} \wedge \mathrm{g}(x) \wedge \mathrm{arg}_1(z_e, x_a) \wedge \boxed{\mathrm{arg}_2(z_e, y_a)}$$

$$\lambda z.\exists x y.\mathrm{acquired}(z_e) \wedge \mathrm{Pixar}(y_a) \wedge \mathrm{Disney}(x_a) \wedge \mathrm{arg}_1(z_e, x_a) \wedge \mathrm{arg}_2(z_e, y_a)$$

Composition



(nsubj (dobj acquired Pixar) Disney)

$$\lambda f g z.\ \exists x.\ \boxed{f(z)} \wedge \boxed{g(x)} \wedge \arg_1(z_e, x_a)$$

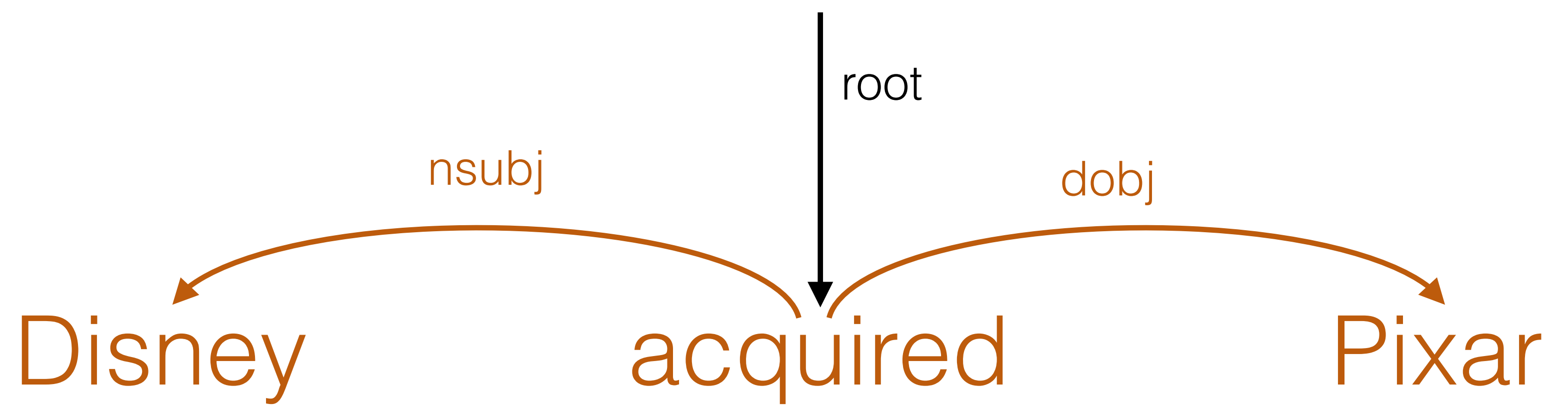
$$\lambda z.\ \exists y.\ \text{acquired}(z_e) \wedge \text{Pixar}(y_a) \wedge \arg_2(z_e, y_a)$$

$$\lambda x.\text{Disney}(x_a)$$

$$\lambda g z.\exists x y.\boxed{\text{acquired}(z_e) \wedge \text{Pixar}(y_a)} \wedge \text{g}(x) \wedge \arg_1(z_e, x_a) \wedge \boxed{\arg_2(z_e, y_a)}$$

$$\lambda z.\exists x y.\text{acquired}(z_e) \wedge \text{Pixar}(y_a) \wedge \boxed{\text{Disney}(x_a)} \wedge \arg_1(z_e, x_a) \wedge \arg_2(z_e, y_a)$$

Composition



(nsubj (dobj acquired Pixar) Disney)

$$\lambda z.\exists xy.\mathrm{acquired}(z_e) \wedge \mathrm{Pixar}(y_a) \wedge \mathrm{Disney}(x_a) \wedge \\ \mathrm{arg}_1(z_e, x_a) \wedge \mathrm{arg}_2(z_e, y_a)$$

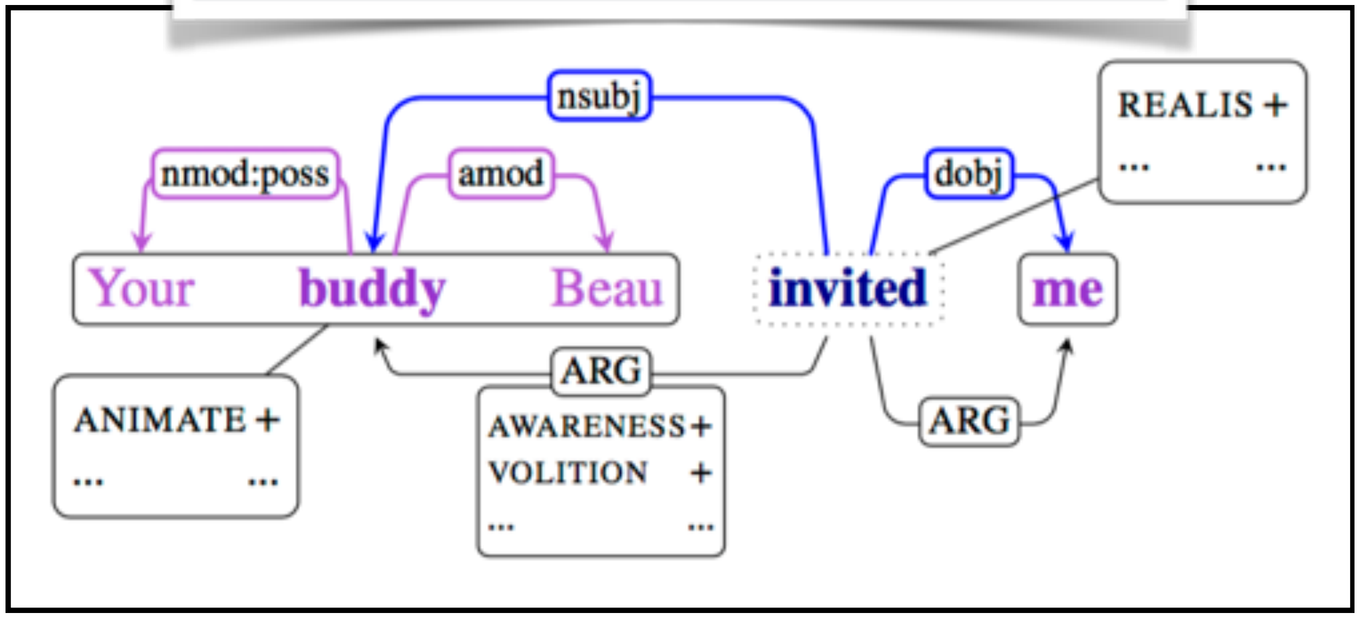
Comparison with CCG

CCG	**DepLambda**
Lexicalized semantics	Simple lexical semantics
Words drive composition	Dependencies drive composition
Argument and adjunct distinction	Every dependent is an adjunct
Complex types are powerful	Simplicity gives robustness

Other NLP Work

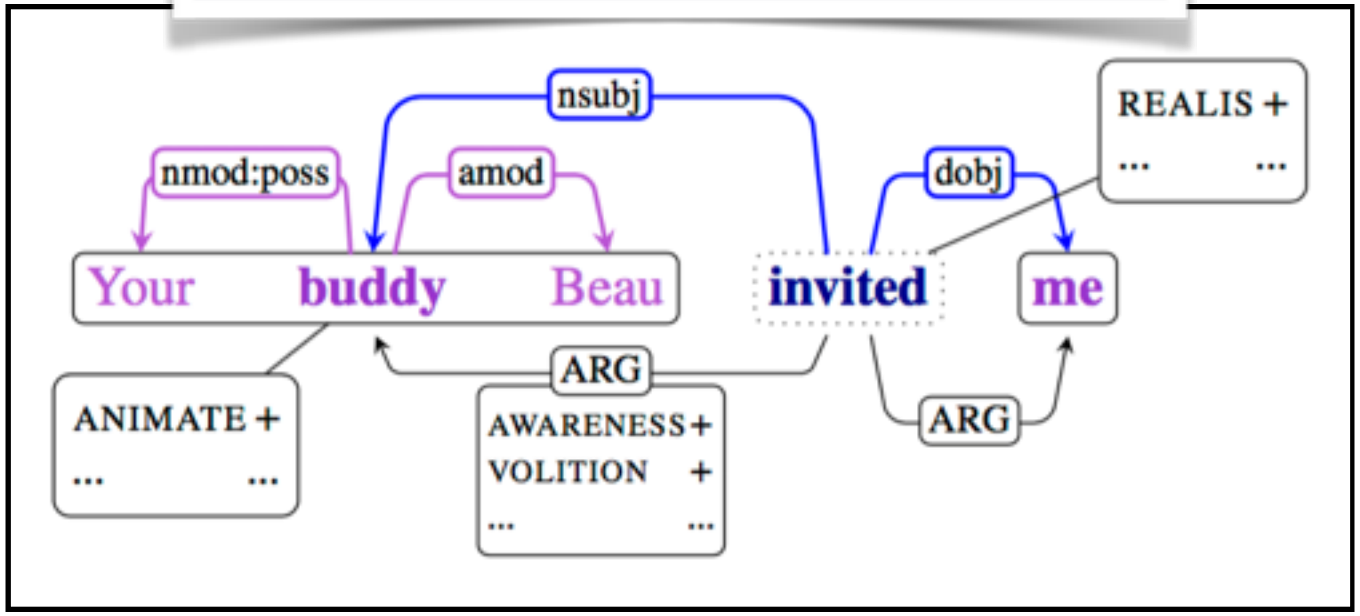
Other NLP Work

White et al. (2016) Universal Decompositional Semantics on Universal Dependencies

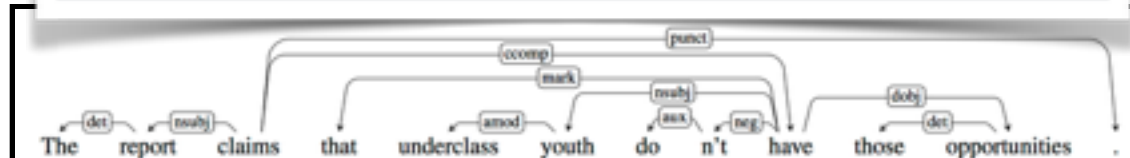


Other NLP Work

White et al. (2016) Universal Decompositional Semantics on Universal Dependencies



Sarabi and Blanco (2016) Understanding Negation in Positive Terms Using Syntactic Dependencies?

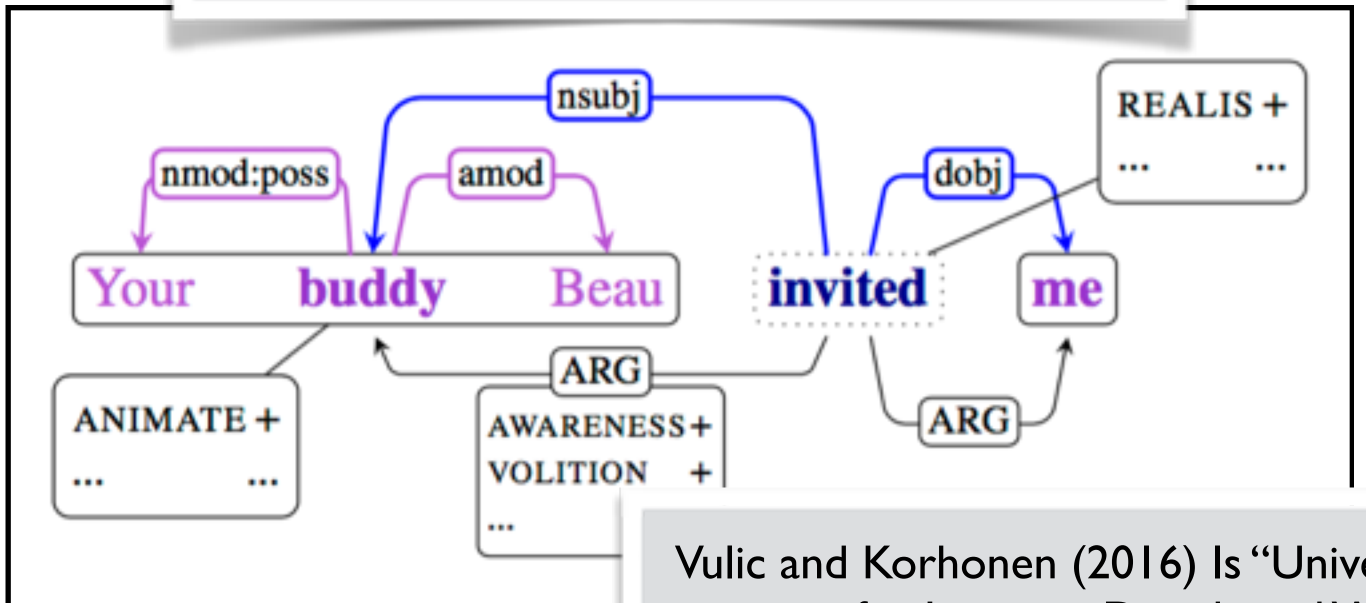


Negated statement: The report claims that underclass youth don't have those opportunities.			
Positive counterpart	Step 1		The report claims that underclass youth do have those opportunities.
	Step 2		The report claims that underclass youth have those opportunities.
	Step 3		The report claims that underclass youth have those opportunities. (idem)
Relevant tokens	Underclass youth have those opportunities.		
Potential positive interpretations	*none*	coarse	Underclass youth [some verb] those opportunities, *but not have*.
	nsubj	coarse	[Some people] have those opportunities, but not *Underclass youth*.
	amod	fine	[Some adjective] youth have those opportunities, but not *Underclass youth*.
	nsubj	fine	Underclass [some people] have those opportunities, but not *Underclass youth*.
	dobj	coarse	Underclass youth have [something], but not *those opportunities*.
	det	fine	Underclass youth have [some] opportunities, but not *those opportunities*.
	dobj	fine	Underclass youth have those [something], but not *those opportunities*.

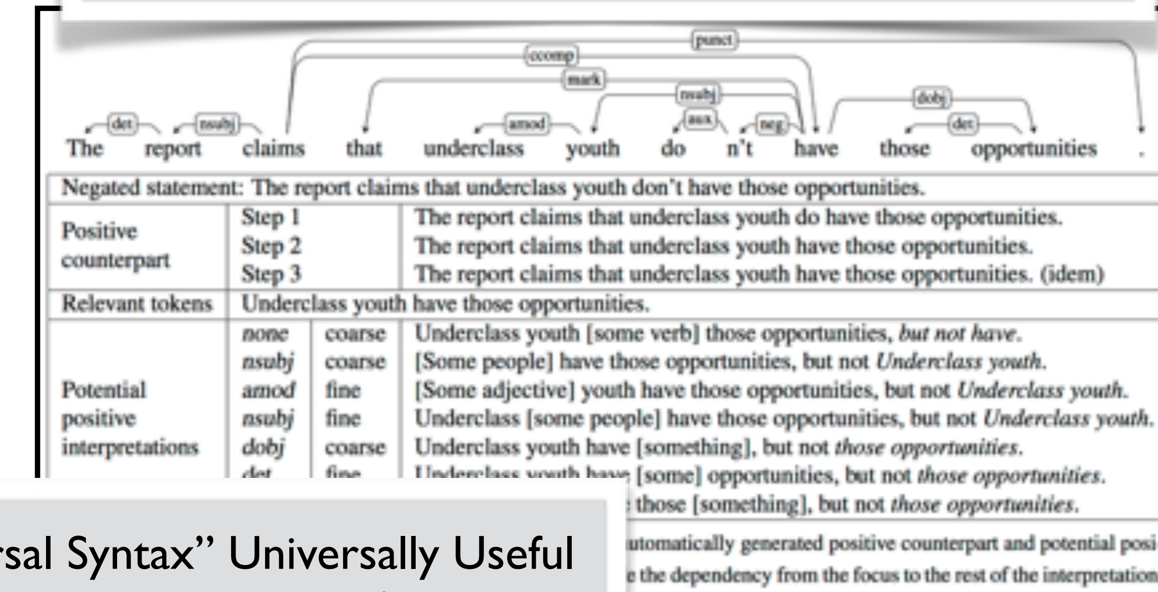
Table 1: Negated statement and syntactic dependencies (top), and automatically generated positive counterpart and potential positive interpretations (bottom). For potential interpretations, we include the dependency from the focus to the rest of the interpretation.

Other NLP Work

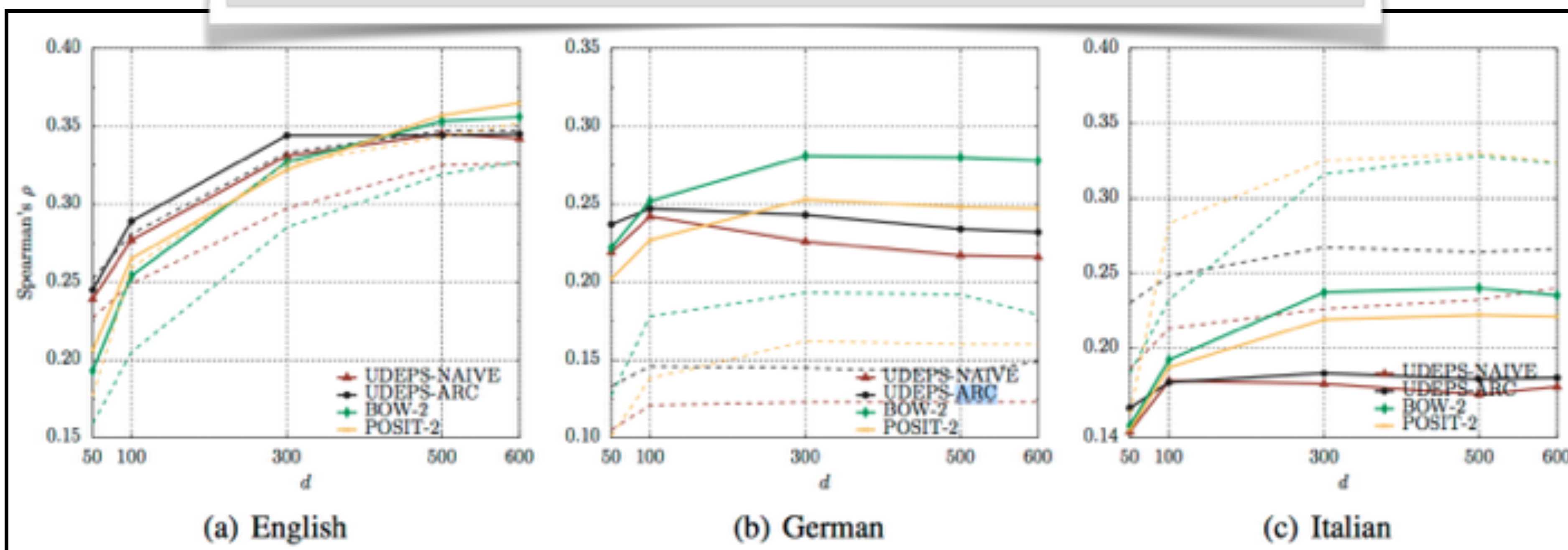
White et al. (2016) Universal Decompositional Semantics on Universal Dependencies



Sarabi and Blanco (2016) Understanding Negation in Positive Terms Using Syntactic Dependencies?



Vulic and Korhonen (2016) Is "Universal Syntax" Universally Useful for Learning Distributed Word Representations?



Conclusion

UD is widely used for parsing within and across languages

- We may have to tweak representations for parsing
- We should definitely think more about evaluation metrics

UD is starting to be used for other NLP tasks

- Several initiatives to build semantic representations on top of UD
- Scattered work on embeddings, sentiment analysis and more