A Appendices

A.1 Hyperparameters

We tuned the batch size and the learning rate using development sets in four languages,[14] and then fixed these hyperparameters for all other languages in each model. The batch size was 1 sentence in low-resource scenarios (in baseline LSup and fine-tuning of RaRe), and to 100 sentences, in high-resource settings (HSup and the pretraining phase of RaRe). The learning rate was set to 0.001 and 0.01 for the high-resource and low-resource baseline models, respectively, and to 0.005, 0.0005 for the pretraining and fine-tuning phase of RaRe based on development results for the four languages. For CoNLL datasets, we had to decrease the batch size of the pre-training phase from 100 to 20 (because of GPU memory issues).

A.2 Cross-lingual Word Embeddings

We experimented with Wiki and CommonCrawl monolingual embeddings from fastText (Bojanowski et al., 2017). Each of the 41 languages is mapped to English embedding space using three methods from MUSE: 1) supervised with bilingual dictionaries; 2) seeding using identical character sequences; and 3) unsupervised training using adversarial learning (Lample et al., 2018). The cross-lingual mappings are evaluated by precision at $k = 1$. The resulting cross-lingual embeddings are then used in NER direct transfer in a leave-one-out setting for the 41 languages (41×40 transfers), and we report the mean F_1 in Table 3. CommonCrawl doesn't perform well in bilingual induction despite having larger text corpora, and underperforms in direct transfer NER. It is also evident that using identical character strings instead of a bilingual dictionary as the seed for learning a supervised bilingual mapping barely effects the performance. This finding also applies to few-shot learning over larger ensembles: running RaRe over 40 source languages achieves an average F_1 of 77.9 when using embeddings trained with a dictionary, versus 76.9 using string identity instead. For this reason we have used the string identity method in the paper (e.g., Table 4), providing greater portability to language pairs without a bilingual dictionary. Experiments with unsupervised mappings performed substantially worse than supervised methods, and so we didn't explore these further.

	Unsup		IdentChr		Sup	
	crawl	wiki	crawl	wiki	crawl	wiki
word translation accuracy	34	24	43	**53**	50	**54**
average F_1 in direct transfer	26	21	37	**44**	39	**45**

Table 3: The effect of the choice of monolingual word embeddings (Common Crawl and Wikipedia), and their cross-lingual mapping on NER direct transfer.

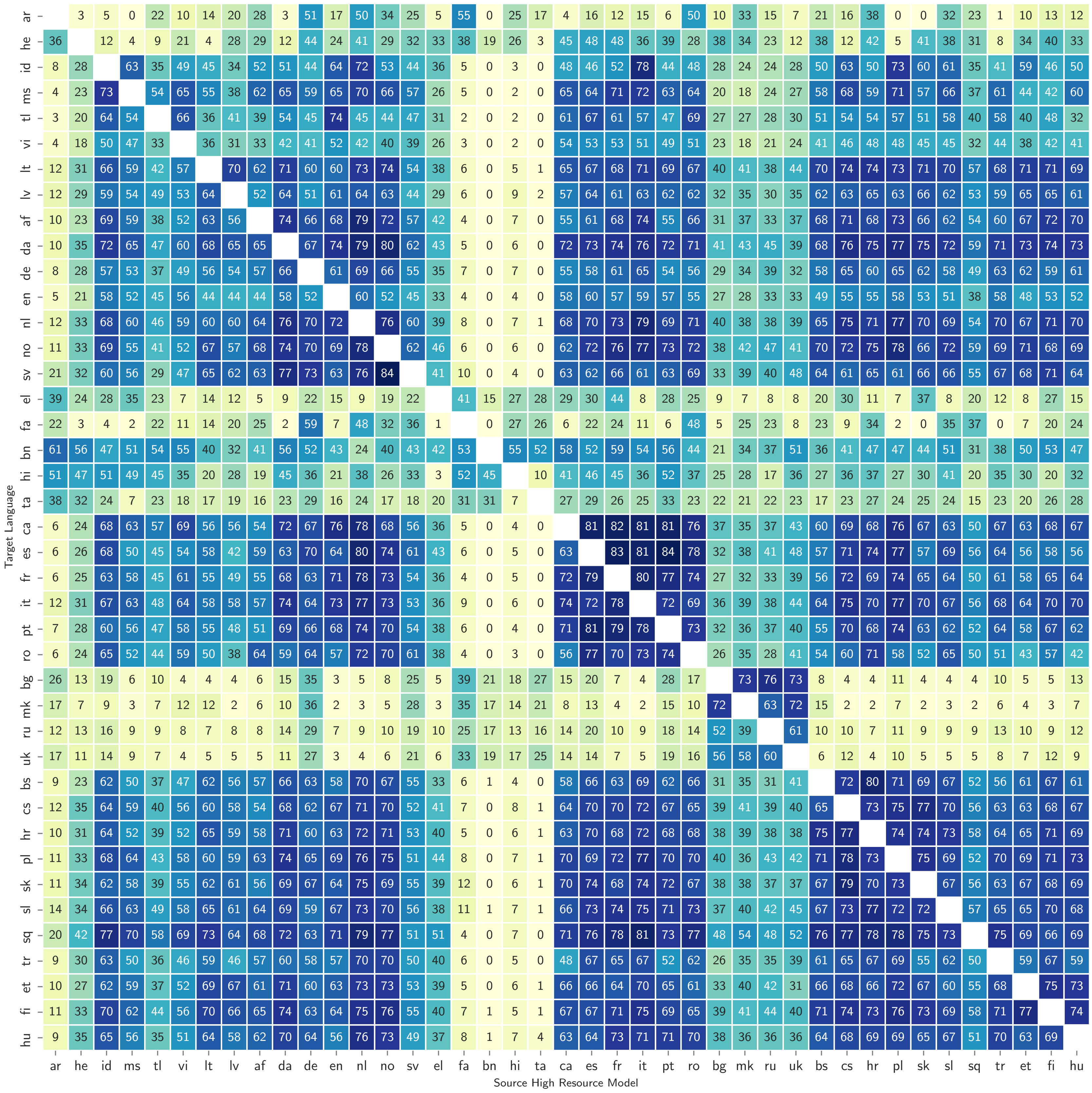
A.3 Direct Transfer Results

In Figure 5 the performance of an NER model trained in a high-resource setting on a source language applied on the other 40 target languages (leave-one-out) is shown. An interesting finding is that symmetry does not always hold (e.g. id vs. ms or fa vs. ar).

A.4 Detailed Low-resource Results

The result of applying baselines, proposed models and their variations, and unsupervised transfer model of Xie et al. (2018) are shown in Table 4.

[14] Afrikaans, Arabic, Bulgarian and Bengali.



	ar	he	id	ms	tl	vi	lt	lv	af	da	de	en	nl	no	sv	el	fa	bn	hi	ta	ca	es	fr	it	pt	ro	bg	mk	ru	uk	bs	cs	hr	pl	sk	sl	sq	tr	et	fi	hu
ar		3	5	0	22	10	14	20	28	3	51	17	50	34	25	5	55	0	25	17	4	16	12	15	6	50	10	33	15	7	21	16	38	0	0	32	23	1	10	13	12
he	36		12	4	9	21	4	28	29	12	44	24	41	29	32	33	38	19	26	3	45	48	48	36	39	28	38	34	23	12	38	12	42	5	41	38	31	8	34	40	33
id	8	28		63	35	49	45	34	52	51	44	64	72	53	44	36	5	0	3	0	48	46	52	78	44	48	28	24	24	28	50	63	50	73	60	61	35	41	59	46	50
ms	4	23	73		54	65	55	38	62	65	59	65	70	66	57	26	5	0	2	0	65	64	71	72	63	64	20	18	24	27	58	68	59	71	57	66	37	61	44	42	60
tl	3	20	64	54		66	36	41	39	54	45	74	45	44	47	31	2	0	2	0	61	67	61	57	47	69	27	27	28	30	51	54	54	57	51	58	40	58	40	48	32
vi	4	18	50	47	33		36	31	33	42	41	52	42	40	39	26	3	0	2	0	54	53	53	51	49	51	23	18	21	24	41	46	48	48	45	45	32	44	38	42	41
lt	12	31	66	59	42	57		70	62	71	60	60	73	74	54	38	6	0	5	1	65	67	68	71	69	67	40	41	38	44	70	74	74	73	71	70	57	68	71	71	69
lv	12	29	59	54	49	53	64		52	64	51	61	64	63	44	29	6	0	9	2	57	64	61	63	62	62	32	35	30	35	62	63	65	63	66	62	53	59	65	65	61
af	10	23	69	59	38	52	63	56		74	66	68	79	72	57	42	4	0	7	0	55	61	68	74	55	66	31	37	33	37	68	71	68	73	66	62	54	60	67	72	70
da	10	35	72	65	47	60	68	65	65		67	74	79	80	62	43	5	0	6	0	72	73	74	76	72	71	41	43	45	39	68	76	75	77	75	72	59	71	73	74	73
de	8	28	57	53	37	49	56	54	57	66		61	69	66	55	35	7	0	7	0	55	58	61	65	54	56	29	34	39	32	58	65	60	65	62	58	49	63	62	59	61
en	5	21	58	52	45	56	44	44	44	58	52		60	52	45	33	4	0	4	0	58	60	57	59	57	55	27	28	33	33	49	55	55	58	53	51	38	58	48	53	52
nl	12	33	68	60	46	59	60	60	64	76	70	72		76	60	39	8	0	7	1	68	70	73	79	69	71	40	38	38	39	65	75	71	77	70	69	54	70	67	71	70
no	11	33	69	55	41	52	67	57	68	74	70	69	78		62	46	6	0	6	0	62	72	76	77	73	72	38	42	47	41	70	72	75	78	66	72	59	69	71	68	69
sv	21	32	60	56	29	47	65	62	63	77	73	63	76	84		41	10	0	4	0	63	62	66	61	63	69	33	39	40	48	64	61	65	61	66	66	55	67	68	71	64
el	39	24	28	35	23	7	14	12	5	9	22	15	9	19	22		41	15	27	28	29	30	44	8	28	25	9	7	8	8	20	30	11	7	37	8	20	12	8	27	15
fa	22	3	4	2	22	11	14	20	25	2	59	7	48	32	36	1		0	27	26	6	22	24	11	6	48	5	25	23	8	23	9	34	2	0	35	37	0	7	20	24
bn	61	56	47	51	54	55	40	32	41	56	52	43	24	40	43	42	53		55	52	58	52	59	54	56	44	21	34	37	51	36	41	47	47	44	51	31	38	50	53	47
hi	51	47	51	49	45	35	20	28	19	45	36	21	38	26	33	3	52	45		10	41	46	45	36	52	37	25	28	17	36	27	36	37	27	30	41	20	35	30	20	32
ta	38	32	24	7	23	18	17	19	16	23	29	16	24	17	18	20	31	31	7		27	29	26	25	33	23	22	21	22	23	17	23	27	24	25	24	15	23	20	26	28
ca	6	24	68	63	57	69	56	56	54	72	67	76	78	68	56	36	5	0	4	0		81	82	81	81	76	37	35	37	43	60	69	68	76	67	63	50	67	63	68	67
es	6	26	68	50	45	54	58	42	59	63	70	64	80	74	61	43	6	0	5	0	63		83	81	84	78	32	38	41	48	57	71	74	77	57	69	56	64	56	58	56
fr	6	25	63	58	45	61	55	49	55	68	63	71	78	73	54	36	4	0	5	0	72	79		80	77	74	27	32	33	39	56	72	69	74	65	64	50	61	58	65	64
it	12	31	67	63	48	64	58	58	57	74	64	73	77	73	53	36	9	0	6	0	74	72	78		72	69	36	39	38	44	64	75	70	77	70	67	56	68	64	70	70
pt	7	28	60	56	47	58	55	48	51	69	66	68	74	70	54	38	6	0	4	0	71	81	79	78		73	32	36	37	40	55	70	68	74	63	62	52	64	58	67	62
ro	6	24	65	52	44	59	50	38	64	59	64	57	72	70	61	38	4	0	3	0	56	77	70	73	74		26	35	28	41	54	60	71	58	52	65	50	51	43	57	42
bg	26	13	19	6	10	4	4	4	6	15	35	3	5	8	25	5	39	21	18	27	15	20	7	4	28	17		73	76	73	8	4	4	11	4	4	4	10	5	5	13
mk	17	7	9	3	7	12	12	2	6	10	36	2	3	5	28	3	35	17	14	21	8	13	4	2	15	10	72		63	72	15	2	2	7	2	3	2	6	4	3	7
ru	12	13	16	9	9	8	7	8	8	14	29	7	9	10	19	10	25	17	13	16	14	20	10	9	18	14	52	39		61	10	10	7	11	9	9	9	13	10	9	12
uk	17	11	14	9	7	4	5	5	5	11	27	3	4	6	21	6	33	19	17	25	14	14	7	5	19	16	56	58	60		6	12	4	10	5	5	5	8	7	12	9
bs	9	23	62	50	37	47	62	56	57	66	63	58	70	67	55	33	6	1	4	0	58	66	63	69	62	66	31	35	31	41		72	80	71	69	67	52	56	61	67	61
cs	12	35	64	59	40	56	60	58	54	68	62	67	71	70	52	41	7	0	8	1	64	70	70	72	67	65	39	41	39	40	65		73	75	77	70	56	63	63	68	67
hr	10	31	64	52	39	52	65	59	58	71	60	63	72	71	53	40	5	0	6	1	63	70	68	72	68	68	38	39	38	38	75	77		74	74	73	58	64	65	71	69
pl	11	33	68	64	43	58	60	59	63	74	65	69	76	75	51	44	8	0	7	1	70	69	72	77	70	70	40	36	43	42	71	78	73		75	69	52	70	69	71	73
sk	11	34	62	58	39	55	62	61	56	69	67	64	75	69	55	39	12	0	6	1	70	74	68	74	72	67	38	38	37	37	67	79	70	73		67	56	63	67	68	69
sl	14	34	66	63	49	58	65	61	64	69	59	67	73	70	56	38	11	1	7	1	66	73	74	75	71	73	37	40	42	45	67	73	77	72	72		57	65	65	70	68
sq	20	42	77	70	58	69	73	64	68	72	63	71	79	77	51	51	4	0	7	0	71	76	78	81	73	77	48	54	48	52	76	77	78	78	75	73		75	69	66	69
tr	9	30	63	50	36	46	59	46	57	60	58	57	70	70	50	40	6	0	5	0	48	67	65	67	52	62	26	35	35	39	61	65	67	69	55	62	50		59	67	59
et	10	27	62	59	37	52	69	67	61	71	60	63	73	73	53	39	5	0	6	1	66	66	64	70	65	61	33	40	42	31	66	68	66	72	67	60	55	68		75	73
fi	11	33	70	62	44	56	70	66	65	74	63	64	75	76	55	40	7	1	5	1	67	67	71	75	69	65	39	41	44	40	71	74	73	76	73	69	58	71	77		74
hu	9	35	65	56	35	51	64	58	62	70	64	56	76	73	49	37	8	1	7	4	63	64	73	71	71	70	38	36	36	36	64	68	69	69	65	67	51	70	63	69	

Figure 5: The direct transfer performance of a source NER model trained in a high-resource setting applied on the other 40 target languages, and evaluated in terms of phrase-level F_1.

				Supervised						Unsupervised						
	#train(k)	#test(k)	BiDic.P@1	HSup	LSup	RaRe t1	RaRe t10	RaRe all	$\text{BEA}^{\text{ent}}_{\text{sup}}$ t10	RaRe $_{\text{uns}}$	BWET	$\text{BEA}^{\text{ent}}_{\text{uns}\times 2}$ t10	$\text{BEA}^{\text{ent}}_{\text{uns}}$	$\text{BEA}^{\text{tok}}_{\text{uns}}$	MV^{tok}	Oracle
af	5	1	36	84	59	73	79	79	80	76	64	79	79	74	75	80
ar	20	10	46	88	64	71	74	74	65	26	19	54	45	54	12	56
bg	20	10	55	90	61	80	81	81	81	5	51	81	65	54	4	76
bn	10	1	1	95	70	68	74	74	69	65	36	67	66	60	56	63
bs	15	1	30	92	63	80	79	80	78	76	52	80	78	77	69	82
ca	20	10	70	91	62	82	86	84	86	80	62	85	80	79	72	83
cs	20	10	64	90	62	77	78	75	78	73	59	77	75	72	71	78
da	20	10	68	90	62	77	81	81	82	79	68	83	82	79	78	80
de	20	10	73	86	58	73	74	73	72	69	63	72	71	64	68	70
el	20	10	55	89	61	67	67	67	54	13	45	49	43	34	13	45
en	20	10	—	81	47	64	65	64	65	58	—	63	61	57	56	61
es	20	10	83	90	63	83	84	84	85	76	62	85	81	76	73	84
et	15	10	41	90	64	73	77	77	78	72	58	78	78	71	73	75
fa	20	10	33	93	74	78	81	79	69	30	16	65	50	52	15	60
fi	20	10	58	89	67	78	80	80	81	76	68	81	80	69	77	78
fr	20	10	82	88	57	81	81	80	84	75	59	83	79	73	71	80
he	20	10	52	85	53	61	61	60	55	40	26	54	54	46	34	50
hi	5	1	29	85	68	64	74	73	68	48	27	64	61	58	35	54
hr	20	10	48	89	61	74	79	78	80	76	49	80	79	77	73	78
hu	20	10	64	90	59	75	79	78	80	71	55	79	79	69	73	76
id	20	10	68	91	67	82	83	81	75	59	62	73	67	61	62	79
it	20	10	77	89	60	80	81	80	82	75	59	81	78	76	72	79
lt	10	10	26	86	62	72	79	80	79	76	48	80	80	75	77	74
lv	10	10	31	91	68	70	75	75	69	68	40	69	69	67	65	66
mk	10	1	50	91	67	79	82	81	80	4	38	79	66	48	3	75
ms	20	1	48	91	66	78	80	78	74	69	62	68	67	63	68	74
nl	20	10	76	89	59	78	80	80	81	77	63	82	81	78	76	79
no	20	10	67	90	65	79	82	81	83	79	59	83	83	77	79	79
pl	20	10	66	89	61	76	79	78	81	73	63	82	80	77	76	78
pt	20	10	80	90	59	79	81	80	82	77	65	82	77	74	70	82
ro	20	10	67	92	66	80	82	82	80	76	46	78	76	74	67	77
ru	20	10	59	86	53	73	71	71	56	10	38	53	40	36	11	61
sk	20	10	52	91	62	76	79	79	80	74	50	79	76	76	71	79
sl	15	10	47	92	64	76	80	80	79	76	58	79	78	76	73	78
sq	5	1	37	88	69	79	84	84	83	82	59	83	84	76	79	79
sv	20	10	61	93	69	83	83	84	82	77	60	79	80	69	76	84
ta	15	1	7	84	54	44	53	53	46	35	12	39	42	25	29	38
tl	10	1	20	93	66	75	82	80	78	65	60	62	60	57	52	76
tr	20	10	61	90	61	75	77	77	77	70	53	77	76	67	67	71
uk	20	10	45	89	60	70	78	79	70	5	35	64	58	49	6	60
vi	20	10	54	88	55	64	72	72	61	58	53	56	55	48	47	56
μ	—	—	—	89.2	62.1	74.3	77.4	76.9	74.8	60.2	50.5	72.8	69.7	64.5	56.7	71.6
σ	—	—	—	2.8	5.2	7.3	6.4	6.4	9.6	24.1	14.7	11.5	12.6	13.7	25	11.5

Table 4: The size of training and test sets (development set size equals test set size) in thousand sentences, and the precision at 1 for Bilingual dictionaries induced from mapping languages to the English embedding space (using identical characters) is shown (BiDic.P@1). F_1 scores on the test set, comparing baseline supervised models (HSup, LSup), multilingual transfer from top k source languages (RaRe, 5 runs, $k = 1, 10, 40$), an unsupervised RaRe with uniform expertise and no fine-tuning (RaRe $_{\text{uns}}$), and aggregation methods: majority voting (MV^{tok}), $\text{BEA}^{\text{tok}}_{\text{uns}}$ and $\text{BEA}^{\text{ent}}_{\text{uns}}$ (Bayesian aggregation in token- and entity-level), and the oracle single best annotation (Oracle). We also compare with BWET (Xie et al., 2018), an unsupervised transfer model with state-of-the-art on CoNLL NER datasets. The mean and standard deviation over all 41 languages, μ, σ, are also reported.