

Table 6: SentEval Probing task accuracies. Classification is performed using a simple logistic regression enabling fair evaluation of the richness of a sentence embedding. We report two baselines from ?.

Tasks	Surface Information		Syntactic Information			Semantic Information				
	SentLen	WC	TreeDepth	TopConst	BShift	Tense	SubjNum	ObjNum	SOMO	CoordInv
<i>Word Embeddings</i>										
Bov-fastText ((?))	54.8	91.6	32.3	63.1	50.8	87.8	81.9	79.3	50.3	52.7
Our model (g_{emb}) - Max	62.4	43.0	32.5	76.3	74.5	88.1	85.7	82.7	54.7	56.9
Our model (g_{emb}) - Average	72.1	70.0	38.5	79.9	81.4	89.7	88.5	86.5	57.4	63.0
<i>BiLSTM-max encoders</i>										
SkipThought (?)	59.6	35.7	42.7	70.5	73.4	90.1	83.3	79.0	70.3	70.1
Our model (Encoder NER g_{ner})	50.7	3.24	19.5	34.2	57.2	66.6	63.5	61.6	50.7	52.0
Our model (Encoder EMD g_{emd})	43.3	1.8	19.3	30.0	56.3	64.0	60.1	57.9	51.3	50.4
Our model (Encoder RE g_{re})	56.8	1.2	19.3	24.5	53.9	62.3	60.8	57.1	50.4	52.2
Our model (Encoder CR g_{cr})	61.9	11.0	29.5	55.9	70.0	82.8	83.0	76.5	53.3	58.7

Table 7: Speed of training: Difference in number of updates necessary before convergence: Multi-task (Full Model: A-GM) compared to single task. We report the differences in F_1 performance. Lower time is better, higher performance is better.

Setup	Model	Time Δ	Performance Δ
(B)	NER	-16%	-0.02
(C)	EMD	-44%	+1.14
(D)	RE	+78%	+6.76
(E-GM)	Coref-GM	-28%	+0.91

adopt a simpler strategy for each parameter update: a task is randomly selected and a batch of the associated dataset is sampled for the current update. More recently, ? (?) explored various batch-level sampling strategies and showed that an anti-curriculum learning strategy (?) is most effective. In contrast, we propose a novel proportional sampling strategy, which we find to be more effective.

Regarding the selection of the set of tasks, our work is closest to (?; ?). ? (?) combine coreference resolution, entity linking (sometimes referred to as *Wikification*) and mention detection. ? (?) combine entity tagging, coreference resolution and relation extraction. These two works are based on graphical models with hand-engineered factors. We are using a neural-net-based approach fully trainable in an end-to-end fashion, with no need for external NLP tools (such as in (?)) or hand-engineered features. Coreference resolution is rarely used in combination with other tasks. The main work we are aware of is (?), which uses coreference clusters to improve reading comprehension and the works on language modeling by ? (?) and ? (?).

Regarding the combination of entity mention detection and relation, we refer to our baselines detailed above. Here again, our predictors do not require additional features like dependency trees (?) or hand-engineered heuristics (?).

Conclusion

We proposed a hierarchically supervised multi-task learning model focused on a set of semantic task. This model achieved state-of-the-art results on the tasks of Named Entity Recognition, Entity Mention Detection and Relation Extraction and competitive results on Coreference Resolution while using simpler training and regularization procedures

than previous works. The tasks share common embeddings and encoders allowing an easy information flow from the lowest level to the top of the architecture. We analyzed several aspects of the representations learned by this model as well as the effect of each tasks on the overall performances of the model.

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