Linguistic Knowledge Can Enhance Encoder-Decoder Models (*If You Let It*)

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Introduction

- Motivations:
  - Understanding “how linguistic concepts that were common as features in NLP systems are captured in neural networks” (Belinkov & Glass, *Transactions of the Association for Computational Linguistics 2019*) has been the focus of many recent studies
  - Fine-tuning on a intermediate supporting task and then on the target task consecutively is highly beneficial to improve pre-trained model’s performance (Weller et al., *ACL 2022*)

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⬇

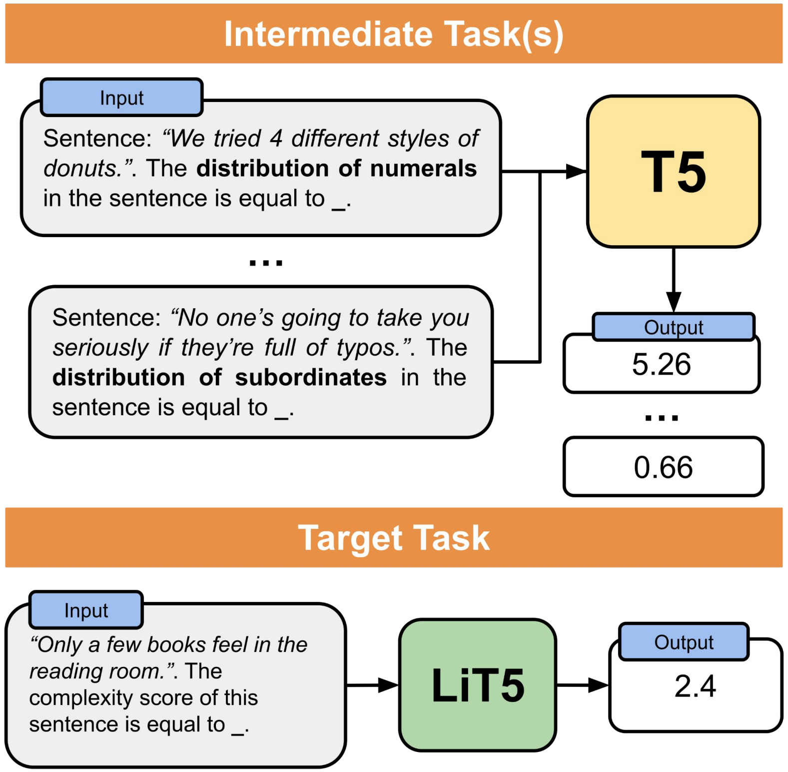
Does a step of intermediate fine-tuning on linguistic tasks enhance the prediction on a target task that strongly relies on linguistic knowledge?

Our Approach

- Two-step approach:
  - Fine-tune the T5 models on several intermediate tasks
    - Multi- and single-task fine-tuning
  - Fine-tune the Linguistically-Informed (LI) models on the target task

- We saved checkpoints every 5 epochs, in order to monitor the impact of the approach at increasing snapshots of the models

- We tested the approach both in Italian and English and in a cross-lingual scenario



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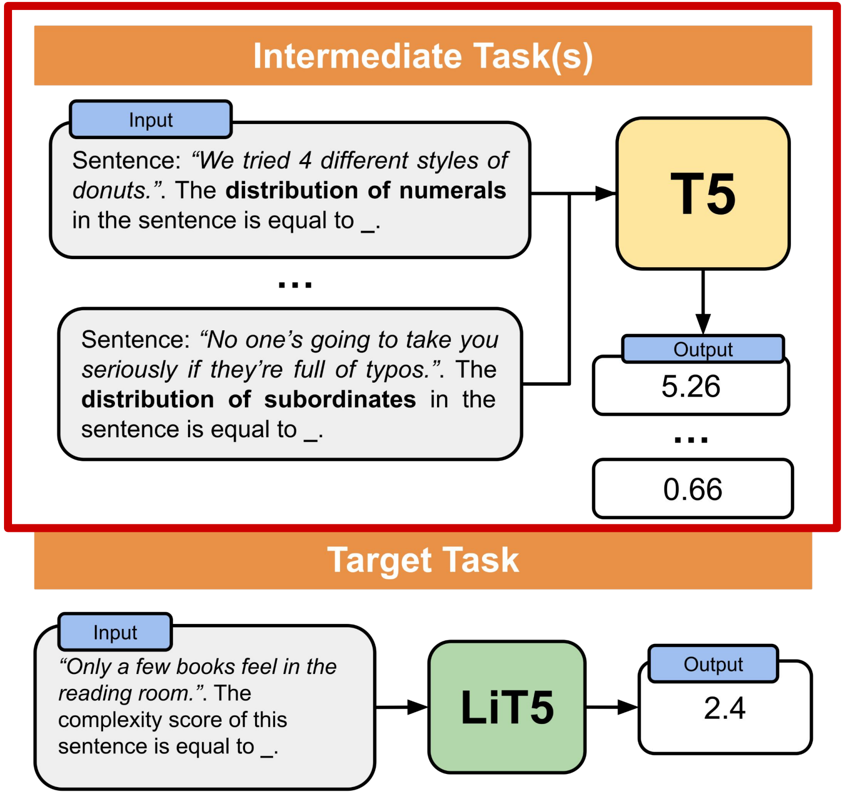

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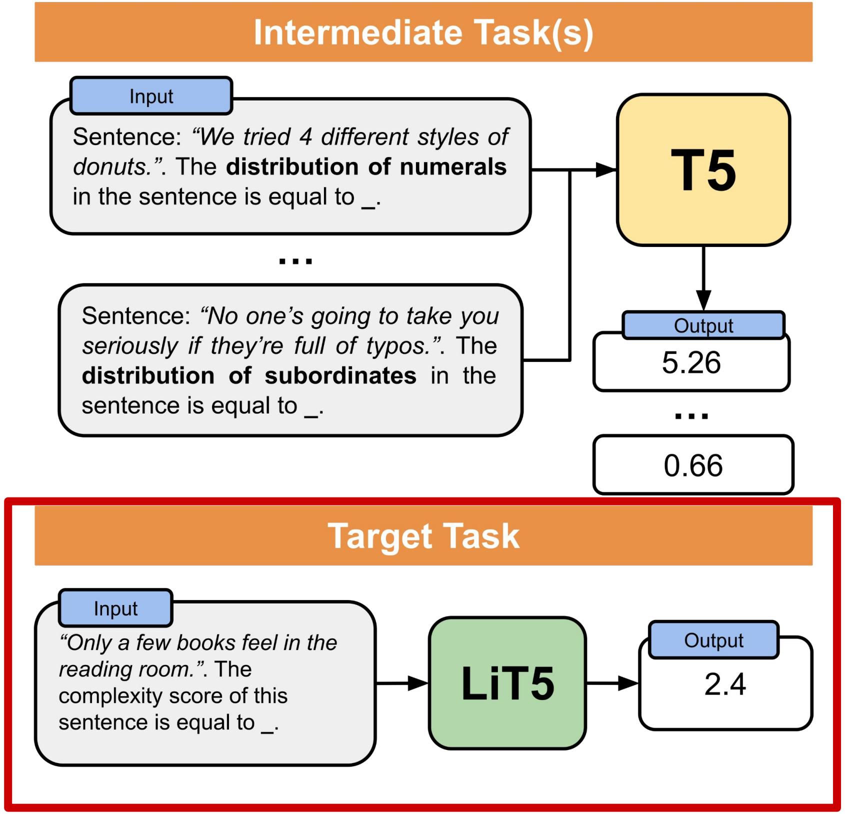

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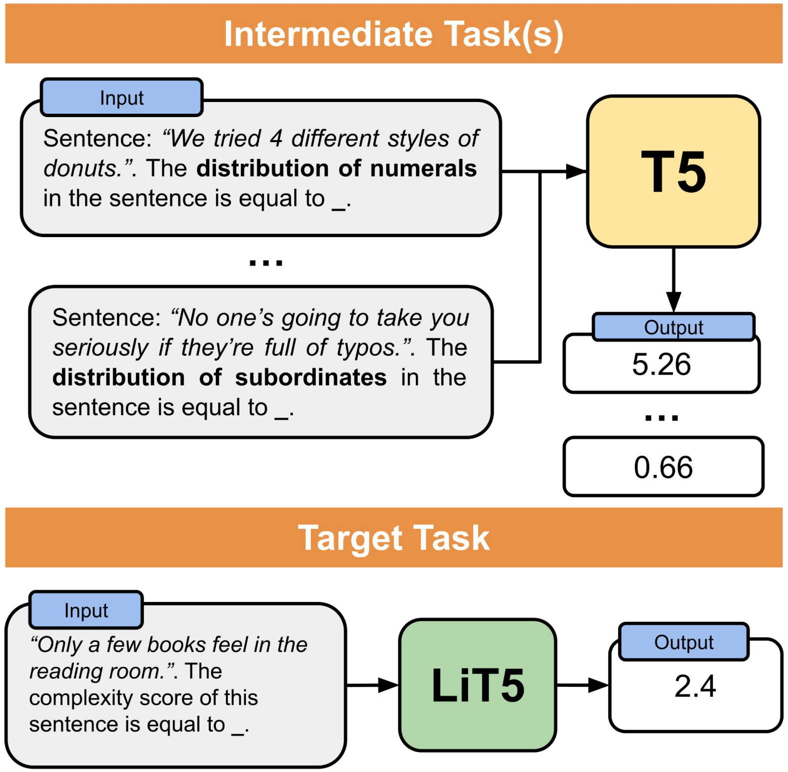
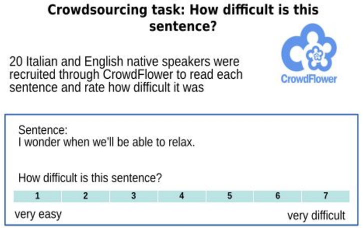


Data

- Intermediate tasks:
  - 10 morpho- and syntactic characteristics of a sentence
    - selected on the degree of correlation between sentence-level complexity judgments and their values

Profiling-UD: extraction of feature values from ITA e ENG UD treebank

Features Italian	Corr	Features English	Corr
char_per_tok	0.28	upos_dist_NUM	0.35
upos_dist_ADJ	0.21	dep_dist_nummod	0.31
upos_dist_NUM	0.19	upos_dist_SYM	0.27
lexical_density	0.17	upos_dist_AUX	0.25
dep_dist_aux	0.17	dep_dist_compound	0.25
dep_dist_mark	0.16	upos_dist_PRON	0.24
aux_mood_dist_Ind	0.14	upos_dist_DET	0.23
obj_post	0.14	subord_prop_dist	0.17
upos_dist_PUNCT	0.13	aux_form_dist_Fin	0.16
subord_prop_dist	0.12	aux_mood_dist_Ind	0.14



  - Prediction of their distribution in the Italian and English versions of the Universal Dependency Treebanks extracted with Profiling-UD

- Target task:
  - corpus of 1,440 Italian and 2,400 English sentences manually rated by 20 crowdsourced workers for the level of perceived complexity on 1-7 Likert scale (Brunato et al., EMNLP 2018)

Models and Evaluation

Models:

Language	Model	Parameters
English	t5-small	60M
	t5-base	220M
	t5-large	770M
Italian	it5-small	60M
	it5-base	220M
	it5-large	738M

Evaluation:

- We used Spearman correlation score as evaluation metric:
  - **Intermediate tasks**: Correlation between the gold value of each feature in the Italian or English treebank and the predicted value of the models for the intermediate tasks.
  - **Target task**: Correlation between average judgments of complexity and the complexity scores obtained with the fine-tuned LiT5 models.

Enhancing T5 with Linguistic Features

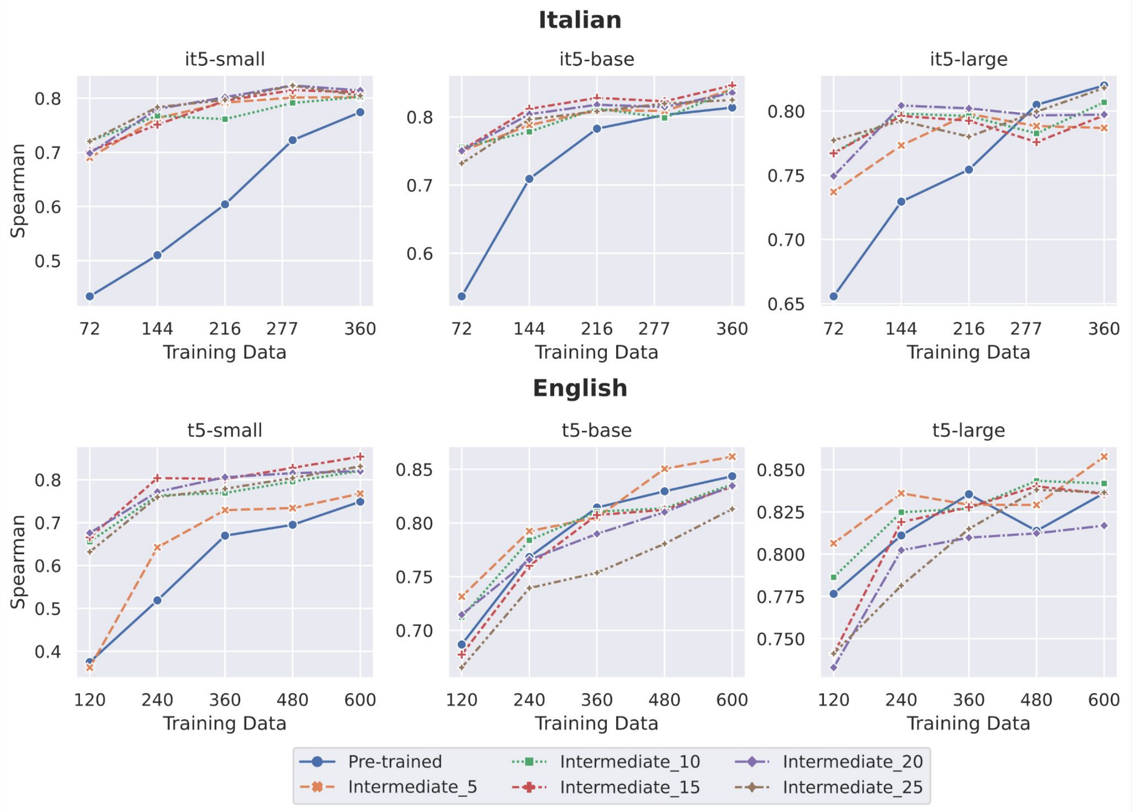
Italian

	it5-small					it5-base					it5-large				
	5	10	15	20	25	5	10	15	20	25	5	10	15	20	25
All	0.41	0.49	0.53	0.55	0.56	0.53	0.64	0.73	0.76	0.77	0.6	0.72	0.75	0.81	0.83
aux_mood_dist_Ind	0.17	0.31	0.34	0.38	0.4	0.36	0.73	0.81	0.86	0.87	0.59	0.81	0.87	0.89	0.9
char_per_tok	0.0056	-0.046	0.06	0.061	0.13	0.15	0.28	0.36	0.48	0.53	0.15	0.31	0.42	0.6	0.63
dep_dist_aux	0	0	0	0.14	0.17	0	0.12	0.68	0.81	0.85	0.074	0.59	0.71	0.81	0.8
dep_dist_mark	0	0	0.091	0.21	0.23	0	0.38	0.59	0.65	0.74	0.021	0.44	0.76	0.77	0.82
lexical_density	0.0054	0.14	0.15	0.2	0.17	0.21	0.22	0.22	0.25	0.29	0.18	0.18	0.17	0.2	0.19
obj_post	0.18	0.31	0.38	0.41	0.41	0.35	0.38	0.42	0.46	0.5	0.46	0.54	0.59	0.68	0.69
subord_prop_dist	0.51	0.52	0.58	0.63	0.64	0.63	0.68	0.77	0.8	0.79	0.59	0.7	0.71	0.75	0.77
upos_dist_ADJ	0.14	0.18	0.22	0.18	0.22	0.26	0.39	0.44	0.44	0.45	0.24	0.29	0.39	0.53	0.58
upos_dist_NUM	0	0	0	0	0	0	0.34	0.93	0.94	0.94	-0.024	0.91	0.9	0.92	0.92
upos_dist_PUNCT	-0.15	0.13	0.22	0.21	0.25	0.17	0.3	0.41	0.51	0.54	0.2	0.24	0.38	0.61	0.76

English

	t5-small					t5-base					t5-large				
	5	10	15	20	25	5	10	15	20	25	5	10	15	20	25
All	0.45	0.51	0.66	0.79	0.87	0.54	0.78	0.88	0.89	0.9	0.89	0.92	0.93	0.93	0.93
aux_form_dist_Fin	0.55	0.66	0.76	0.84	0.85	0.69	0.74	0.9	0.91	0.94	0.9	0.92	0.94	0.95	0.95
aux_mood_dist_Ind	0.46	0.63	0.79	0.86	0.89	0.72	0.72	0.86	0.9	0.9	0.92	0.93	0.93	0.95	0.94
dep_dist_compound	0	0	0.14	0.35	0.52	0	0.16	0.57	0.57	0.61	0.53	0.62	0.64	0.63	0.68
dep_dist_nummod	0	0	0	0.5	0.7	0	0.65	0.8	0.8	0.81	0.73	0.74	0.83	0.8	0.81
subord_prop_dist	0.67	0.72	0.75	0.81	0.85	0.64	0.78	0.87	0.87	0.85	0.86	0.9	0.89	0.89	0.88
upos_dist_AUX	0	0	0.57	0.84	0.89	0.17	0.77	0.9	0.93	0.94	0.9	0.96	0.94	0.97	0.96
upos_dist_DET	0	-0.011	0.33	0.62	0.81	0.14	0.74	0.84	0.84	0.88	0.75	0.87	0.92	0.89	0.93
upos_dist_NUM	0	0	0.19	0.76	0.9	0.23	0.85	0.92	0.91	0.91	0.89	0.92	0.93	0.94	0.94
upos_dist_PRON	0	0.11	0.53	0.66	0.83	0.26	0.84	0.9	0.92	0.92	0.89	0.93	0.95	0.95	0.94
upos_dist_SYM	0	0	0	0	0.53	0	0.27	0.37	0.38	0.65	0.27	0.71	0.8	0.75	0.75

Predicting Complexity with LI Models



Selected Findings

- Informing models linguistically over several epochs allows them to progressively improve their degree of language proficiency.

- The method of linguistic enhancement is particularly effective, especially when applied to smaller models and in scenarios with limited availability of target training data.

- Small models, refined through intermediate fine-tuning, can frequently surpass the performance of larger models that have not undergone this intermediate refinement process.

Thanks for the attention!