A Unified Model for Reverse Dictionary and Definition Modelling

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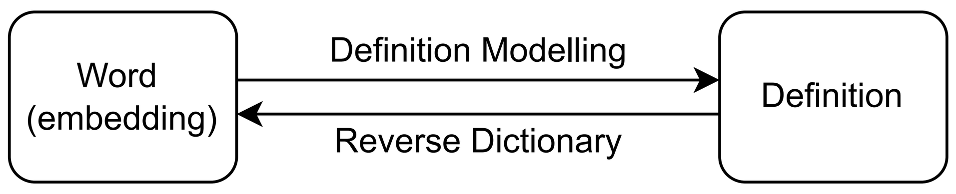
Main Contributions



We present a unified model for two reciprocal tasks: reverse dictionary and definition modelling. The model achieves strong automatic and human evaluation results without relying on external human-annotated data.

The Unified Model

The model learns to encode definitions and words using a shared layer, and then generates both forms via multi-tasking to accomplish reverse dictionary and definition modelling separately. Such a trained system resembles a dual-way neural dictionary.

Unification enabled 1) extra learning objectives like reconstruction and embedding similarity; 2) shared encoder and decoder embeddings.

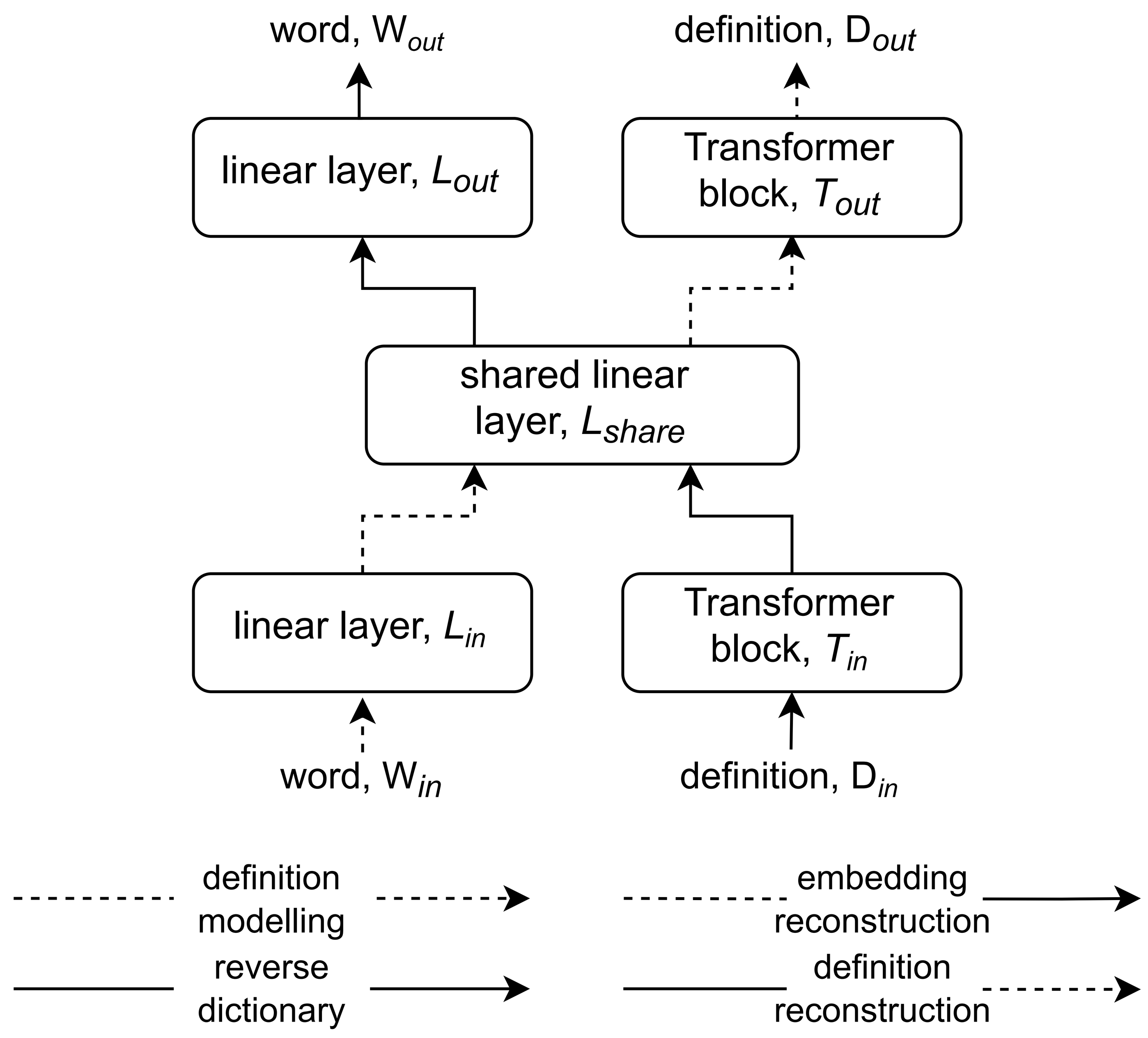


Figure 1. The unified model architecture.

Definition Human Evaluation

Our model notably outperforms a Transformer baseline in both types of human evaluation on definition generation:

1. reference-less: pick the preferred output based on the query word.
2. reference-based: pick the preferred output based on the reference.

	reference-less	reference-based
Transformer	25 (31%)	32 (40%)
unified	**50 (63%)**	**42 (53%)**

Table 1. Chances a model's output is preferred by human evaluators.

Ablation Training Dynamics

We study training objective ablation with the unified model. 1-task refers to using a single reverse dictionary or definition modelling objective; 3-task refers to disabling reconstruction tasks; 5-task is using all objectives.

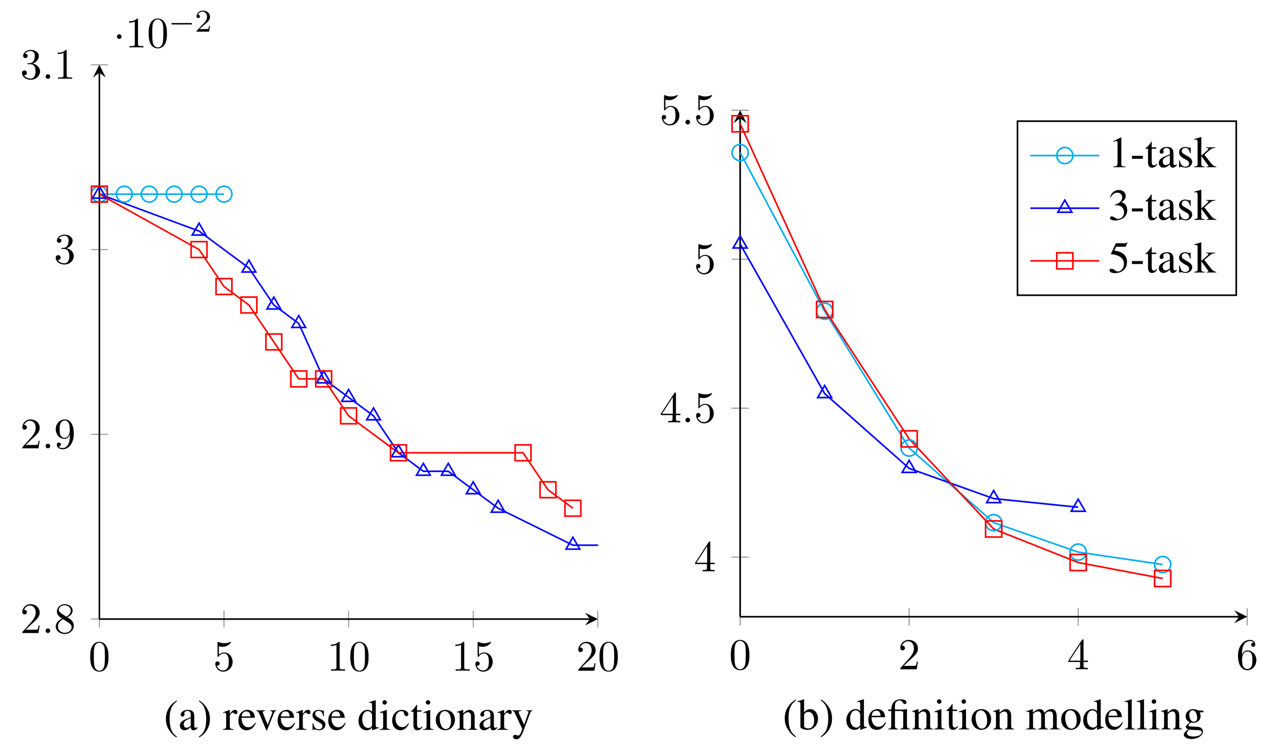


Figure 2. Training losses of the unified model with different objectives

Experiments and Results

	unseen test			human description		
	median rank	acc@ 1/10/100	rank std.	median rank	acc@ 1/10/100	rank std.
OneLook.com	-	-	-	5.5	.33/.54/.76	332
bag-of-words	248	.03/.13/.39	424	22	.13/.41/.69	308
RNN	171	.03/.15/.42	404	17	.14/.40/.73	274
category inference	170	.05/.19/.43	420	16	.14/.41/.74	306
multi-sense	276	.03/.14/.37	426	1000	.01/.04/.18	404
super-sense	465	.02/.11/.31	454	115	.03/.15/.47	396
multi-channel	54	.09/.29/.58	**358**	**2**	**.32**/.64/.88	203
Transformer	79	.01/.14/.59	473	27	.05/.23/.87	332
our unified	**18**	**.13**/**.39**/**.81**	386	4	.22/.64/**.97**	**183**
+ share embed	20	.08/.36/.77	410	4	.23/**.65**/**.97**	**183**

(a) **Reverse dictionary** results on Hill et al.'s data with past results from Zhang et al.

	unseen test	
	BLEU	Rouge-L
RNN	1.7	15.8
xSense	2.0	15.9
Transformer	2.4	17.9
our unified	2.2	18.5
+ share embed	**3.0**	**20.2**

(b) **Definition modelling** results on Chang et al.'s data, with past numbers from Chang & Chen's replicate.

Table 2. Experimental results on reverse dictionary (left) and definition modelling (right).

References

Hill et al., Learning to Understand Phrases by Embedding the Dictionary, TACL 2016
Chang et al., xSense: Learning Sense-Separated Sparse Representations and Textual Definitions for Explainable Word Sense Networks, arXiv 2019
Chang & Chen, What Does This Word Mean? Explaining Contextualized Embeddings with Natural Language Definition, EMNLP 2019
Zhang et al., Multi-channel Reverse Dictionary Model, AAAI 2020

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