Human-readable labels of structured data allow LMs to **generalize to new domains.**

Mind the Labels: Describing Relations in Knowledge Graphs With Pretrained Models

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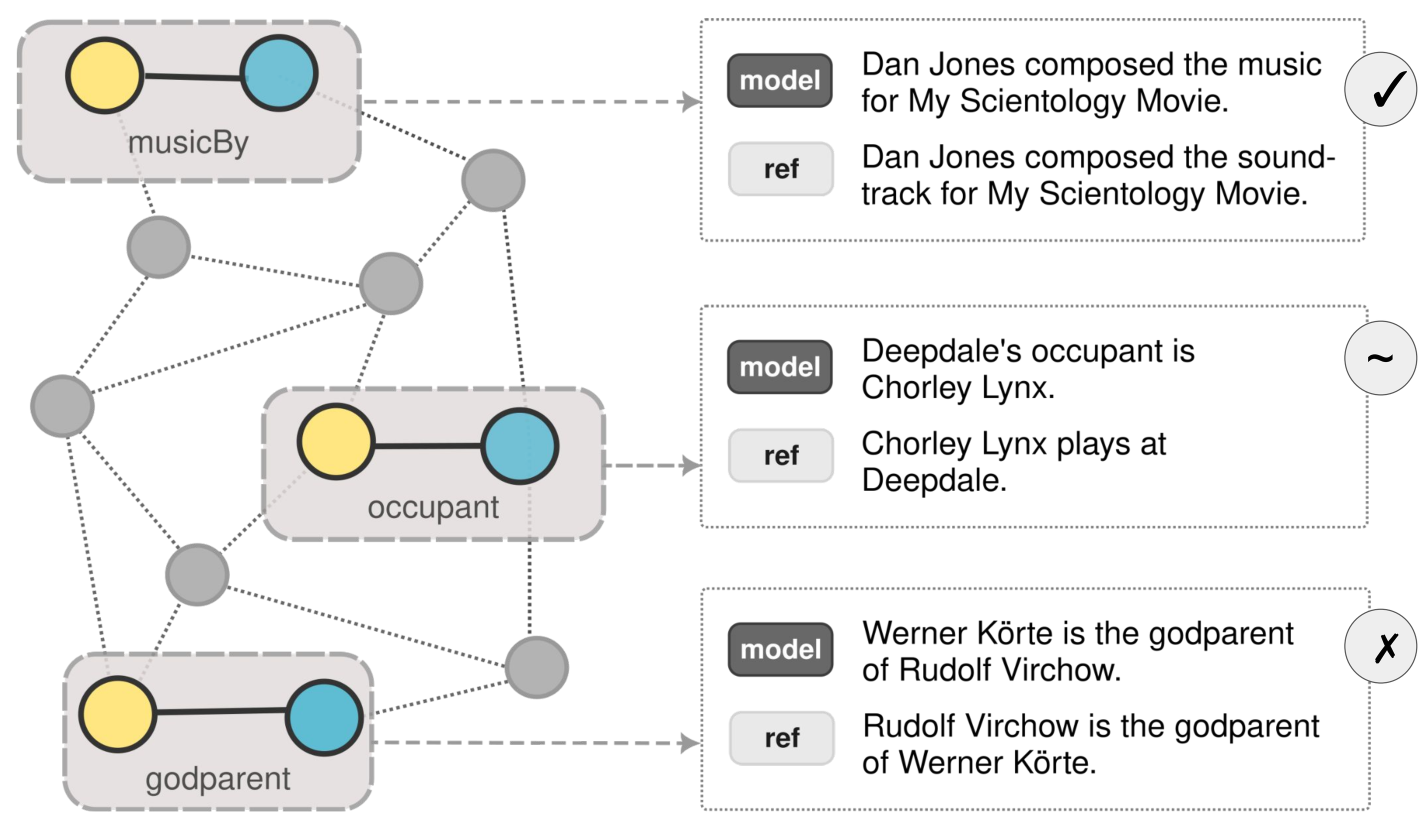
Data-to-text generation models do not generalize well to new domains.

Data = **labels** ← ***verbalized***
`values` ← ***copied***

Does it help to use human-readable and unambiguous data labels?

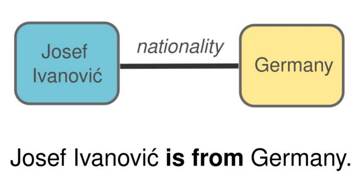


Rel2Text Dataset

1. We scraped 7,334 single triples *(subject, relation, object)* from 3 large-scale open KGs.

WIKIDATA DBpedia yago

2. We collected their verbalizations on Prolific, resulting in **4,097 examples** with **1,522 unique relations**.



3. For the test set, we used relations with <90 % semantic similarity to the relations in the training data.

Experiments

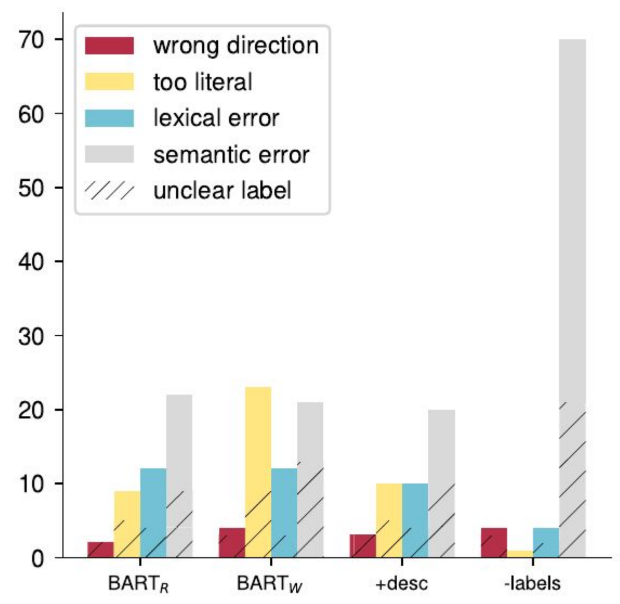
Finetuning BART (Rel2Text train / WebNLG / KeLM)
↓
evalutating on **Rel2Text test set**

Setups:
- original data
- few-shot (25, 50, 100, 200)
- masked rel. labels (test, train, all)
- relation descriptions (replaced, concatenated)

Downstream tasks
(w/ BART-Rel2Text):
- representing tables for tabular reasoning
- zero-shot data-to-text generation

Results & Takeaways

Rel2Text	BLEU	% Log. Entail	PPL↓ (GPT-2)
Human	-	-	5.88
Copy baseline	29.04	91.21	7.55
BART-WebNLG	41.99	89.39	5.65
BART-Rel2Text	52.54	91.85	5.89
+rel. desc.	53.07	91.88	5.92
-rel. labels	42.53	57.26	5.66



Models trained on original train sets are highly successful with unseen relations **(up to 91% entailment prob.)**. Better lex. & sem. similarity with Rel2Text train.

Common sources of errors: semantic **ambiguity** (→*"vehicle"*), unclear relation **direction** (→*"parent"*). Masked relations guessed incorrectly in 78/100 cases.

Using **descriptions** gives only slight improvements → better methods needed.

Similar or better results on **downstream tasks** compared to using manual templates w/ no handcrafting efffforts.

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https://github.com/kasnerz/rel2text/

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