

CS224N : Lecture 15 - Add Knowledge to Language Models

What does a LM know?

- Takeaway: predictions generally make sense (e.g. the correct types), but **are not all factually correct**.
- Why might this happen?
 - **Unseen facts**: some facts may not have occurred in the training corpora at all
 - **Rare facts**: LM hasn't seen enough examples during training to memorize the fact
 - **Model sensitivity**: LM may have seen the fact during training, but is sensitive to the phrasing of the prompt
 - Correctly answers "x was made in y" templates but not "x was created in y"
- The **inability to reliably recall knowledge** is a key challenge facing LMs today!
 - Recent works have found LMs can recover *some* knowledge, but have a way to go.

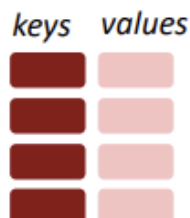
Techniques to add knowledge to LMs

Techniques to add knowledge to LMs



Add pretrained entity embeddings

- ERNIE
- KnowBERT



Use an external memory

- KGLM
- kNN-LM



Modify the training data

- WKLM
- ERNIE (another!), salient span masking

Evaluating knowledge in LMs

Language Model Analysis (LAMA) Probe [\[Petroni et al., EMNLP 2019\]](#)

- How much relational (**commonsense** and **factual**) knowledge is already in off-the-shelf language models?
 - Without any additional training or fine-tuning
- Manually constructed a set of **cloze statements** to assess a model's ability to predict a missing token.

Examples:

The theory of relativity was developed by [MASK].

The native language of Mammootty is [MASK].

Ravens can [MASK].

You are likely to find a overflow in a [MASK].



Language Model Analysis (LAMA) Probe [\[Petroni et al., EMNLP 2019\]](#)

- Generate cloze statements from KG triples and question-answer pairs
- Compare LMs to supervised relation extraction (RE) and question answering systems
- **Goal:** evaluate knowledge present in existing pretrained LMs (this means they may have different pretraining corpora!)

Mean precision at one (P@1)

Corpus	DrQA	RE baseline	fairseq-fconv	Transformer-XL	ELMo	ELMo (5.5B)	BERT-base	BERT-large
Google-RE	-	7.6	2.6	1.6	2.0	3.0	9.8	10.5
T-REx	-	33.8	8.9	18.3	4.7	7.1	31.1	32.2
ConceptNet	-	-	3.6	5.7	6.1	6.2	15.6	19.2
SQuAD	37.5	-	3.6	3.9	1.6	4.3	14.1	17.4

BERT struggles on N-to-M relations

LMs are NOT finetuned!

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Language Model Analysis (LAMA) Probe [Petroni et al.]

You can try out examples to assess knowledge in popular LMs:

<https://github.com/facebookresearch/LAMA>

The cat is on the [MASK].

[1] Example courtesy of the authors at link above.

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```
bert:
| Top10 predictions
0   phone          -2.345
1   floor          -2.630
2   ground         -2.968
3   couch          -3.387
4   move           -3.649
5   roof           -3.651
6   way            -3.718
7   run            -3.757
8   bed            -3.802
9   left           -3.965
```



index	token	log_prob	prediction	log_prob	rank@1000
1	The	-5.547	.	-0.607	14
2	cat	-0.367	cat	-0.367	0
3	is	-0.019	is	-0.019	0
4	on	-0.001	on	-0.001	0
5	the	-0.002	the	-0.002	0
6	[MASK]	-14.321	phone	-2.345	-1
7	.	-0.002	.	-0.002	0

A More Challenging Probe: LAMA-UnHelpful Names (LAMA-UHN)

[Poerner et al., EMNLP 2020]

- Key idea: Remove the examples from LAMA that can be answered **without relational knowledge**
- Observation: BERT may rely on surface forms of entities to make predictions
 - String match between subject and object
 - “Revealing” person name
 - Name can be a (possibly incorrect) prior for native language, place of birth, nationality, etc.
- BERT’s score on LAMA drops ~8% with LAMA-UHN
 - Knowledge-enhanced model E-BERT score drops only <1%

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Native language of French-speaking actors according to BERT

Person Name	BERT
Jean Marais	French
Daniel Ceccaldi	Italian
Orane Demazis	Albanian
Sylvia Lopez	Spanish
Annick Alane	English