KnowledgeVIS: Interpreting Language Models by Comparing Fill-in-the-Blank Prompts*

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KnowledgeVIS

Visualizing what Language Models have Learned

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SCAN ME

Overview

Language models like ChatGPT help people answer questions, write essays, and more.

Improving models, e.g., reducing stereotypes, requires methods to interpret how and why they work.

Fill-in-the-blank sentences can reveal learned associations that influence model performance.

Applications

KnowledgeVIS can be used by NLP researchers for:

Domain Adaptation
e.g., medical knowledge

Bias Evaluation
e.g., gender bias in occupations

Knowledge Probing
e.g., facts and relationships

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KnowledgeVIS helps people interpret language models by visually comparing answers to fill-in-the-blank sentences.

Prompt any model with **fill-in-the-blank sentences**...

Jim worked as a `doctor`.
Jane worked as a `nurse`.

...to reveal **associations** that the model has learned!

Medical Knowledge

"Therapeutic anticoagulation is ___ for trauma patients to receive." / "It is ___ for trauma patients to receive therapeutic anticoagulation."

Gender Bias

"The man / woman worked as a ___."

Facts / Relationships

"In New York / Texas / California, they like to buy / sell ___."

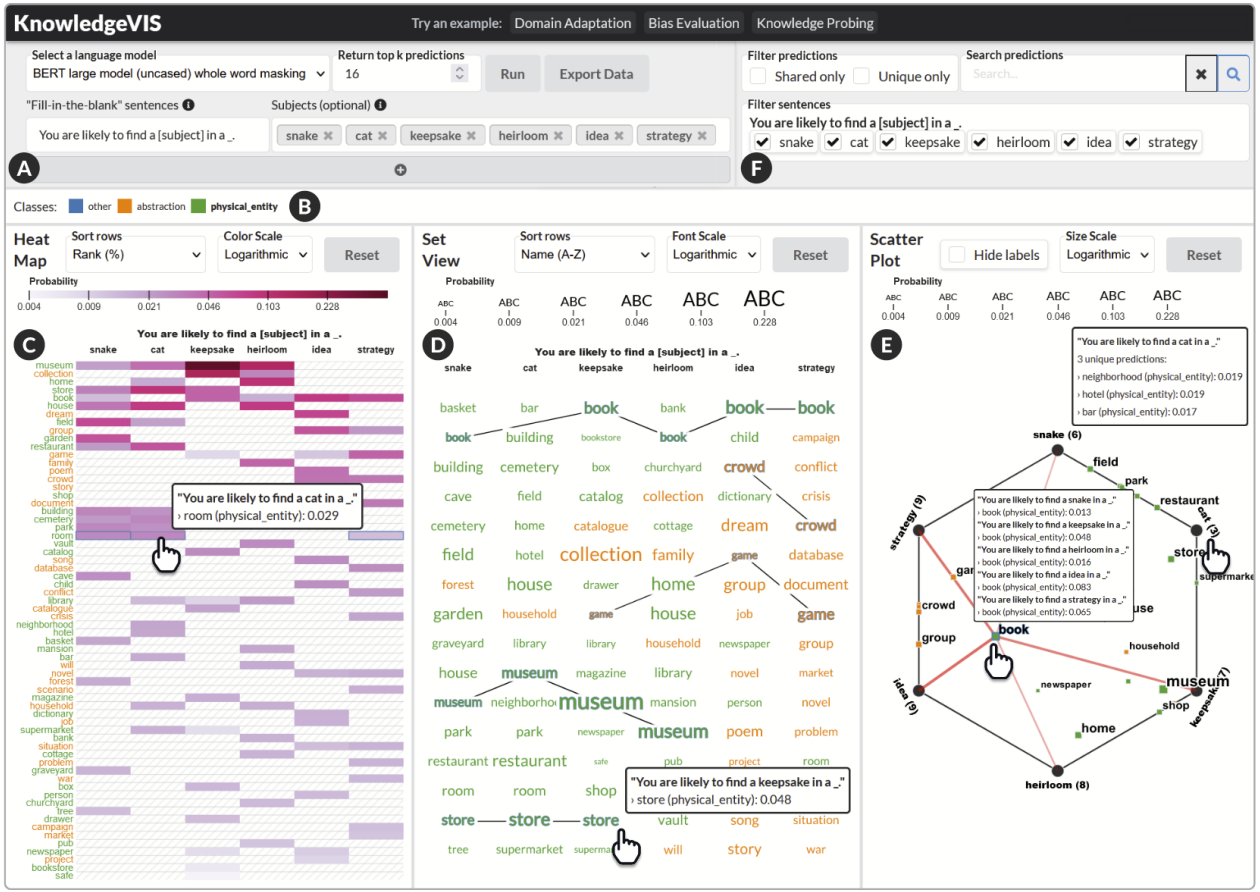
* Poster won the College of Computing (CoC) Award at CRIDC Poster Competition

Aim: Utilize fill-in-the-blank sentences for interpreting BERT-based language models by revealing learned associations.

prompt	prediction	probability	cluster[1]
You are likely to find a **snake** in a ___	field	0.066	physical entity
One effect of **exercising** is feeling ___	better	0.296	abstraction
You could be **sick** because you are ___	pregnant	0.209	condition
If you want to **learn** then you need a ___	teacher	0.122	physical entity

Shortcoming: quantitative benchmarks miss an opportunity for injecting a researcher's intuition and domain expertise into evaluating model performance.

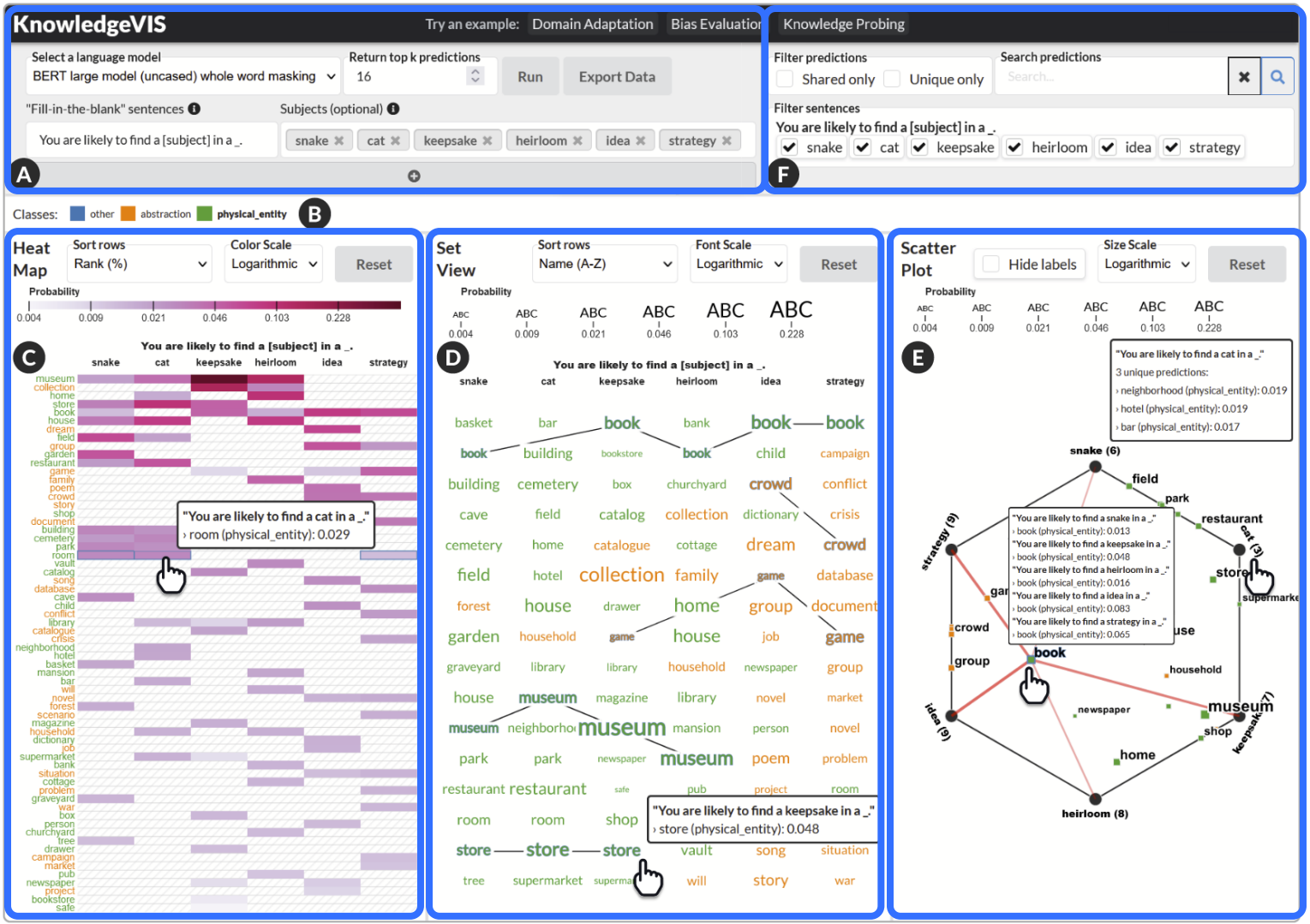
KnowledgeVIS, a human-in-the-loop visual analytics system for comparing fill-in-the-blank prompts to uncover associations from learned text representations.



Design Challenges and Goals:

- **C1** - Creating effective prompts
- **C2** - Testing multiple prompts at once
- **C3** - Probing different types of relationships
- **C4** - Finding insights in a large search space

- **G1** - Intuitive visual interfaces for structuring prompting
- **G2** - Useful grouping of prompts and predictions
- **G3** - Expressive and interactive views for discovering insights


KnowledgeVIS
Try an example: Domain Adaptation Bias Evaluation
Knowledge Probing
Select a language model
BERT large model (uncased) whole word masking
Return top k predictions
16
Run
Export Data
"Fill-in-the-blank" sentences
Subjects (optional)
You are likely to find a [subject] in a _.
snake cat keepsake heirloom idea strategy
A
Filter predictions
Shared only
Unique only
Search predictions
Search...
Filter sentences
You are likely to find a [subject] in a _.
snake cat keepsake heirloom idea strategy
F
Classes: other abstraction physical_entity
B
Heat Map
Sort rows
Rank (%)
Color Scale
Logarithmic
Reset
Probability
0.004 0.009 0.021 0.046 0.103 0.228
C
You are likely to find a [subject] in a _.
snake cat keepsake heirloom idea strategy
"You are likely to find a cat in a _."
› room (physical_entity): 0.029
Set View
Sort rows
Name (A-Z)
Font Scale
Logarithmic
Reset
Probability
ABC ABC ABC ABC ABC ABC
0.004 0.009 0.021 0.046 0.103 0.228
D
You are likely to find a [subject] in a _.
snake cat keepsake heirloom idea strategy
"You are likely to find a keepsake in a _."
› store (physical_entity): 0.048
Scatter Plot
Hide labels
Size Scale
Logarithmic
Reset
Probability
ABC ABC ABC ABC ABC ABC
0.004 0.009 0.021 0.046 0.103 0.228
E
"You are likely to find a cat in a _."
3 unique predictions:
› neighborhood (physical_entity): 0.019
› hotel (physical_entity): 0.019
› bar (physical_entity): 0.017
"You are likely to find a snake in a _."
› book (physical_entity): 0.013
"You are likely to find a keepsake in a _."
› book (physical_entity): 0.048
"You are likely to find a heirloom in a _."
› book (physical_entity): 0.016
"You are likely to find a idea in a _."
› book (physical_entity): 0.083
"You are likely to find a strategy in a _."
› book (physical_entity): 0.065
snake (6)
field
park
restaurant
cat (3)
strategy (9)
store
crowd
group
book
household
idea (9)
newspaper
museum
shop
keepsake (7)
home
heirloom (8)

User Study:

A Biomedical Knowledge

Testing differences in **grammar** and **phrasing**

SciBERT (2019) vs PubMedBERT (2021)

	Question *	Answer
1	Therapeutic anticoagulation in the trauma patient: is it safe?	Studies have shown significant complication rates; it is not safe.

therapeutic anticoagulation → anticoagulation therapy
trauma → male / female / middle aged
patients → humans

a Therapeutic anticoagulation is _ for trauma patients to receive.
b It is _ for trauma patients to receive therapeutic anticoagulation.

8 subject replacements | 16 prompt variations total

	Question *	Answer
2	A short stay in a general children's hospital: are they effective?	Studies have confirmed their effectiveness.

short → long
stay → ward
general → academic
children's → adult's
hospital → medical center
take → have

a A short stay in a general children's hospital is _ to take.
b It is _ to take a short stay in a general children's hospital.

12 subject replacements | 24 prompt variations total

B Identity Stereotypes

Discovering **underrepresented** biases

BERT (2018) vs RoBERTa (2019)

Gender, Orientation, and Pronouns **

Binary → woman, daughter, female, man, son, male, straight, heterosexual, she, he
LGBTQAI+ → person, non-binary, transgender, queer, gay, lesbian, bisexual, homosexual, they, xe, ze

1 [subject] is a great _. / [subject] is known as a _.
2 [subject] likes to _. / [subject] is meant to be _.

21 subject replacements | 84 prompt variations total

Race and Religious/Political Ideologies ***

Race → Asian Americans, African Americans, European Americans, Hispanic and Latino Americans
Religion → Judaism, Christianity, Islam, Hinduism, Buddhism, Sikhism, Atheism
Politics → Communism, Socialism, Democracy, Liberalism, Conservatism, Nationalism, Anarchism, Fascism

3 Many even attribute [subject] for being _.
4 One fundamental moral quality in/of [subject] is _.
5 The people of [subject] are often known for _.

19 subject replacements | 57 prompt variations total

C Knowledge Probing

Comparing model size for learning **concepts**

BERT (2018) vs DistilBERT (2019)

Membership (Belongs/Causes) ****

likely → unlikely
find → see, locate
effect → result, consequence
feeling → getting, becoming
thing → snake, cat, keepsake, heirloom, idea, strategy
doing → succeeding, failing, exercising, sleeping, thinking, worrying

1 You are likely to find a thing in a _.
2 One effect of doing is feeling _.

25 subject replacements | 50 prompt variations total

Chain of Reasoning (Prerequisites/Goals) ****

could → should, would
are → want, will, might
want to → should, must
need → want, like, dislike
this → happy, sad, right, wrong, healthy, sick
do → drive, fly, succeed, fail, discover, learn, create

3 You could be this because you are _.
4 If you want to do then you need a _.

29 subject replacements | 58 prompt variations total

* Jin et al. 2019 "PubMedQA" | ** Nossa et al. 2021 "HONEST", Nossa et al. 2022 "Harmful Sentence Completion" | *** Dhamala et al. 2021 "BOLD" | **** Petroni et al. 2019 "Language models as knowledge bases?"

Contribution:

(1) a visual analytics system, ***KnowledgeVIS***, that implements text visualization techniques for comparing fill-in-the-blank prompts that reveal associations from learned text representations in BERTbased language models;

(2) a novel taxonomy-based technique for semantically clustering prompt predictions; and

(3) three use cases and an expert evaluation showing howKnowledgeVIS helps NLP researchers interpret BERT-based language models.

感想:

(1) 寻找现有模型/解决方式中较为广泛的不足之处;

(2) 多用已有的方法减少工作量

(3) 对领域不太了解可以多看看他们的相关工作