

Language Models as Context-sensitive Word Search Engines



**Matti
Wiegmann**



Michael
Völske



Martin
Potthast



Benno
Stein

¹Bauhaus-Universität Weimar ²Leipzig University

Language Models as Context-sensitive Word Search Engines

Motivation

Context-sensitive word search engines retrieve words that match a given context.

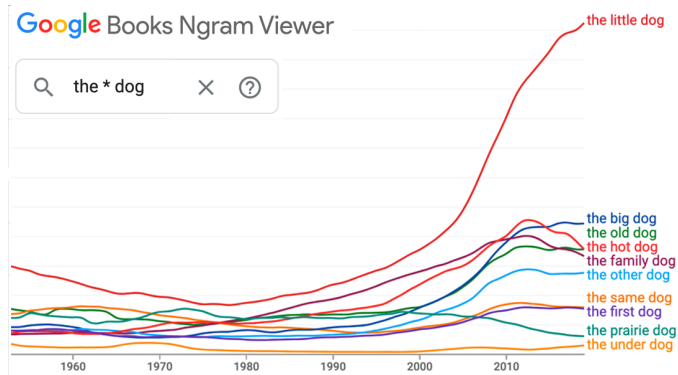
- Trivially: Thesauri, idiom collections, ...

Language Models as Context-sensitive Word Search Engines

Motivation

Context-sensitive word search engines retrieve words that match a given context.

- Trivially: Thesauri, idiom collections, ...

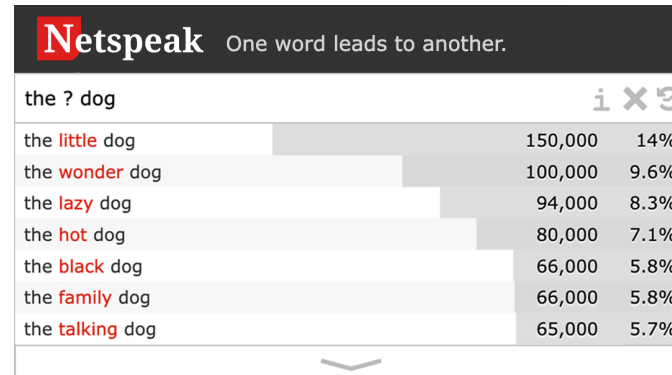
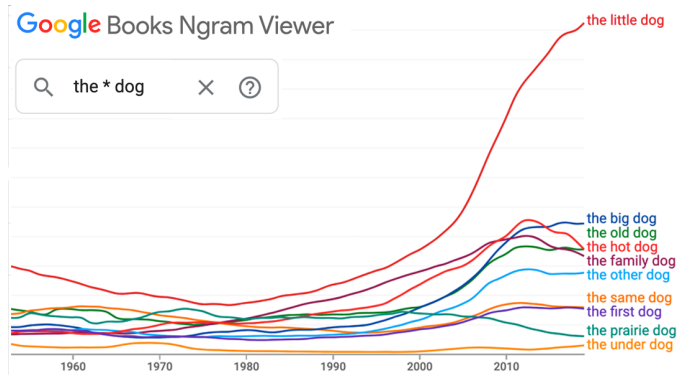


Language Models as Context-sensitive Word Search Engines

Motivation

Context-sensitive word search engines retrieve words that match a given context.

- Trivially: Thesauri, idiom collections, ...
- Context allows wildcard queries $q = q_l ? q_r$ and ranking.

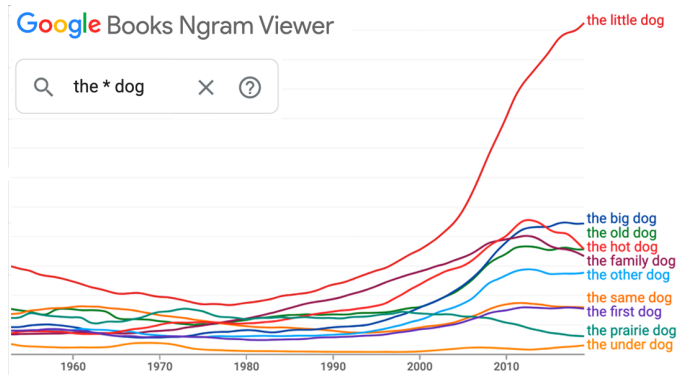


Language Models as Context-sensitive Word Search Engines

Motivation

Context-sensitive word search engines retrieve words that match a given context.

- Trivially: Thesauri, idiom collections, ...
- Context allows wildcard queries $q = q_l ? q_r$ and ranking.
- Counting frequencies beats predictions and smoothing for word search.



Netspeak One word leads to another.

the ? dog

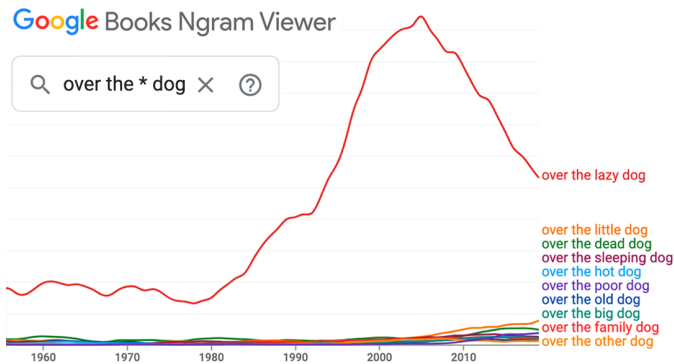
| | | |
|------------------------|---------|------|
| the little dog | 150,000 | 14% |
| the wonder dog | 100,000 | 9.6% |
| the lazy dog | 94,000 | 8.3% |
| the hot dog | 80,000 | 7.1% |
| the black dog | 66,000 | 5.8% |
| the family dog | 66,000 | 5.8% |
| the talking dog | 65,000 | 5.7% |

Language Models as Context-sensitive Word Search Engines

Motivation

Context-sensitive word search engines retrieve words that match a given context.

- Trivially: Thesauri, idiom collections, ...
- Context allows wildcard queries $q = q_l ? q_r$ and ranking.
- Counting frequencies beats predictions and smoothing for word search.
 - Context-sensitive word search engines are build on n -gram collections.



Netspeak One word leads to another.

the ? dog

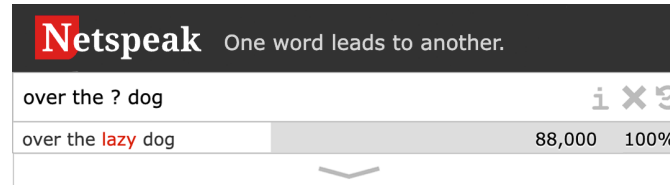
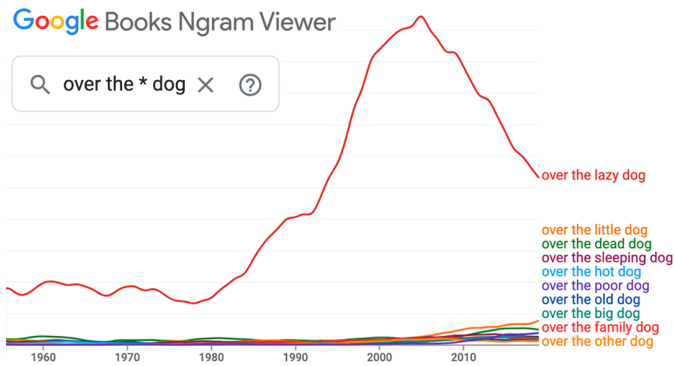
| | | |
|------------------------|---------|------|
| the little dog | 150,000 | 14% |
| the wonder dog | 100,000 | 9.6% |
| the lazy dog | 94,000 | 8.3% |
| the hot dog | 80,000 | 7.1% |
| the black dog | 66,000 | 5.8% |
| the family dog | 66,000 | 5.8% |
| the talking dog | 65,000 | 5.7% |

Language Models as Context-sensitive Word Search Engines

Motivation

Problem: Increasing n requires exponential observations; We're limited to $n \leq 5$.

→ Infer the answers to wildcard queries and their probabilities from a (large) language model.



Language Models as Context-sensitive Word Search Engines

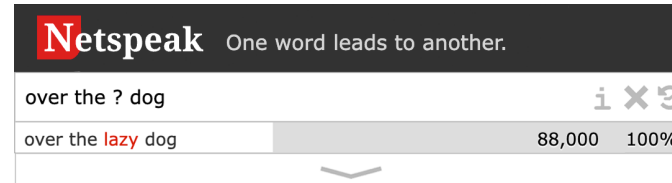
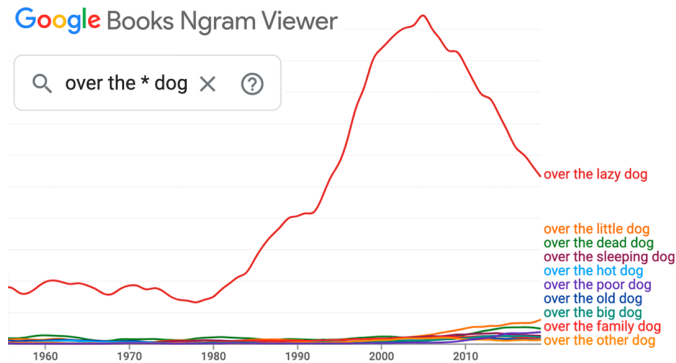
Motivation

Problem: Increasing n requires exponential observations; We're limited to $n \leq 5$.

→ Infer the answers to wildcard queries and their probabilities from a (large) language model.

Contributions:

- Tune large language models to n -grams while preserving corpus characteristics and idioms.
- Predict the ranking with frequency.



Language Models as Context-sensitive Word Search Engines

Language Modeling for Word Search

Solving wildcard queries $q = q_l ? q_r$ with:

1. Masked

Language Modeling

We used `DistillBERT`

2. Conditional

Language Modeling

We used `BART`

Language Models as Context-sensitive Word Search Engines

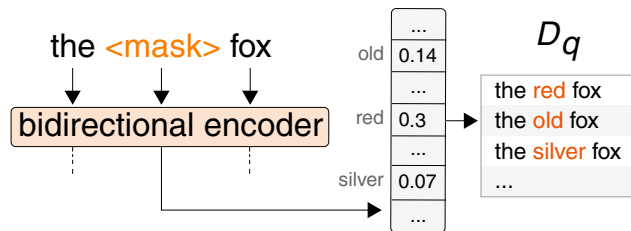
Language Modeling for Word Search

Solving wildcard queries $q = q_l ? q_r$ with:

1. Masked

Language Modeling

We used DistillBERT



Pretrain and Predict

2. Conditional

Language Modeling

We used BART

Language Models as Context-sensitive Word Search Engines

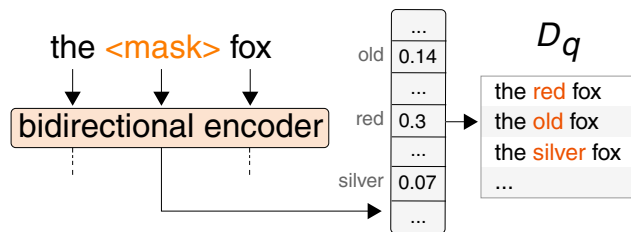
Language Modeling for Word Search

Solving wildcard queries $q = q_l ? q_r$ with:

1. Masked

Language Modeling

We used DistillBERT

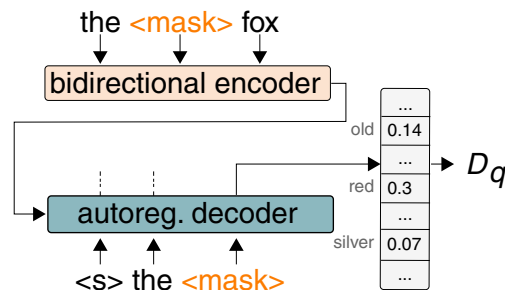


Pretrain and Predict

2. Conditional

Language Modeling

We used BART



Pretrain and Predict

Language Models as Context-sensitive Word Search Engines

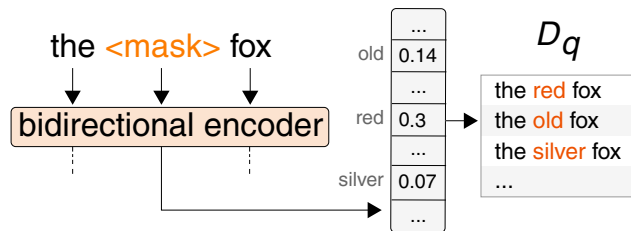
Language Modeling for Word Search

Solving wildcard queries $q = q_l ? q_r$ with:

1. Masked

Language Modeling

We used DistillBERT

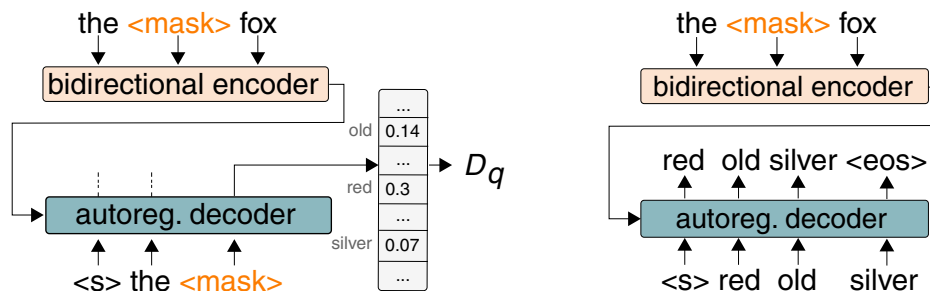


Pretrain and Predict

2. Conditional

Language Modeling

We used BART



Pretrain and Predict

Finetune

Language Models as Context-sensitive Word Search Engines

Experimental Evaluation

- ❑ **Data:** 3 and 5-grams from Wikitext and CLOTH.
- ❑ **Models:** DistillBERT, BART, DistillBERT_{ft}, BART_{ft}, Netspeak.
- ❑ Experiment 1: Predict masked word; Measure position in the result set via MRR.
- ❑ Experiment 2: Predict the observable ranking. Measure nDCG. High frequency results have a higher relevance.

Language Models as Context-sensitive Word Search Engines

Experimental Evaluation

- **Data:** 3 and 5-grams from Wikitext and CLOTH.
- **Models:** DistillBERT, BART, DistillBERT_{ft}, BART_{ft}, Netspeak.
- **Experiment 1:** Predict masked word; Measure position in the result set via MRR.
- Experiment 2: Predict the observable ranking. Measure nDCG. High frequency results have a higher relevance.

the lazy dog → the <mask> dog → $\frac{1}{2}$

the little dog
the lazy dog
the wonder dog

Language Models as Context-sensitive Word Search Engines

Experimental Evaluation

- **Data:** 3 and 5-grams from Wikitext and CLOTH.
- **Models:** DistillBERT, BART, DistillBERT_{ft}, BART_{ft}, Netspeak.
- **Experiment 1:** Predict masked word; Measure position in the result set via MRR.
- **Experiment 2:** Predict the observable ranking. Measure nDCG. High frequency results have a higher relevance.



Language Models as Context-sensitive Word Search Engines

Results

Core Results:

- Finetuned models within 5 p.p. of Netspeak for queries with observable answers.
- Finetuning doubles MRR and nDCG, depending on word class and wildcard position. No substantial difference between model types.
- 80% of 5-gram queries have no observable results:
 - Language models can answer, Netspeak can not;
 - Average MRR loss of 7 p.p.
- Runtime per Query: 5ms for BERT and Netspeak, 11 ms for BART

Language Models as Context-sensitive Word Search Engines

Results

Core Results:

- Finetuned models within 5 p.p. of Netspeak for queries with observable answers.
- Finetuning doubles MRR and nDCG, depending on word class and wildcard position. No substantial difference between model types.
- 80% of 5-gram queries have no observable results:
 - Language models can answer, Netspeak can not;
 - Average MRR loss of 7 p.p.
- Runtime per Query: 5ms for BERT and Netspeak, 11 ms for BART

Language Models as Context-sensitive Word Search Engines

Results

Core Results:

- ❑ Finetuned models within 5 p.p. of Netspeak for queries with observable answers.
- ❑ Finetuning doubles MRR and nDCG, depending on word class and wildcard position. No substantial difference between model types.
- ❑ 80% of 5-gram queries have no observable results:
 - Language models can answer, Netspeak can not;
 - Average MRR loss of 7 p.p.
- ❑ Runtime per Query: 5ms for BERT and Netspeak, 11 ms for BART

Language Models as Context-sensitive Word Search Engines

Results

Core Results:

- ❑ Finetuned models within 5 p.p. of Netspeak for queries with observable answers.
- ❑ Finetuning doubles MRR and nDCG, depending on word class and wildcard position. No substantial difference between model types.
- ❑ 80% of 5-gram queries have no observable results:
 - Language models can answer, Netspeak can not;
 - Average MRR loss of 7 p.p.
- ❑ Runtime per Query: 5ms for BERT and Netspeak, 11 ms for BART

www.netspeak.org/demo