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An open-source search engine with Large Language Models in Julia programming language

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Rhenium

The search. Reinvented.



...but we have search already!

Scopus
PubMed
Google Scholar
Semantic Scholar...

existing solutions are...

not accessible • narrow • limited resource usage • basic functionality • closed source • frozen • not intelligent

Time for upgrade.

modern search engine:

- intelligent
- customizable
- open



algorithm for semantic search

> transform documents to vector embeddings

while True:

- ... wait for search query from the user
- > transform the query to vector embedding o display documents with similar vectors

sample vector embedding

«A quick brown fox jumped over the lazy dog»

0.3323966 0.6897468 -0.41367245 0.9050691 0.278994140.3591251 0.06844619 -0.068081394 0.6580575 0.13972706-1.0214432 0.21378978 -0.26289803 -0.52735114 -0.36524937 -0.29600602 0.15361847 -0.13564132 -1.0625327 -0.3357952 -1.1116723 0.46550542 -1.0217727 -0.54985404 -0.1699316 -0.033429492 -1.2249262 0.86744684 0.13178378 0.20464417 -0.07231642 -0.40423 -0.9075301 0.014228986 -0.6959451 0.17448542 -0.187875 -0.97408384 -0.30829257 -0.4895594 0.009005581 0.7310476-0.58808756 0.32100388 -0.58030295 0.12345423 -0.32376578 0.080631174 0.42329445 -0.76645315 -0.17619115 -0.09561391 -1.2635218 0.06686572 0.24867119 0.7882624 0.15952975 0.66556424 0.3575984 -0.4402481-0.56573486 -0.15152067 0.20452015 0.15044808 0.3790673 0.4046746 0.10349394 -0.74216646 -0.41839486 -0.6980051 -0.25074166 -0.8568389 0.4902732 0.14900629 -1.0337443 -0.3640406 1.2026353 -0.604866 0.75401837 0.7514906 0.9260016 0.7186613 -0.35461208 0.17814498-0.53443074 -0.80356896 0.4195293 -0.21487397 -0.23569633 -0.535494 0.9091784 0.4148689 0.58047 -0.71082586 1.2237266 0.5143566 0.6858553 0.16907518 -1.0889707 -1.0602703 -0.044914458 1.0562452 -0.39917028 0.53946054 0.4968267 0.18140882 -0.5325031 -0.10433626-0.6770337 0.6820697 -0.7788533 -0.82671356 0.161646 0.13410634 0.262196 -0.5227663 0.5709462 0.174716590.055271886 0.42494166 0.26631585 -0.9587653 -0.030337654 0.58339536 1.0953573 0.98313093 -0.10052058 0.38251966 -0.3887956 0.87375206

-0.038645677 0.4431979 0.44748423 -1.1605067 -0.6225495

-0.025457121 0.88639474 -0.52687454 0.42610833

0.016878389 -0.1850919 0.2601459 0.5304479 -1.1237053 -0.22663605 0.9292201 -0.46498993 0.2563679 -1.003673

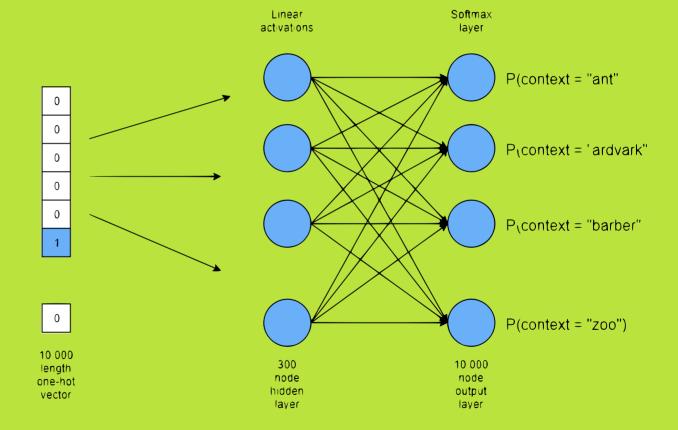
0.3213501 -1.2995219 -1.0151855 -0.32354406 0.6434173 -0.40887073 -0.17340171 0.34564218 0.34115812 -0.6829699

vector embeddings how to get 'em

word2vec

simple feed-forward neural network

Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781.



vector embeddings how to get 'em

BERT

transformer-based neural network

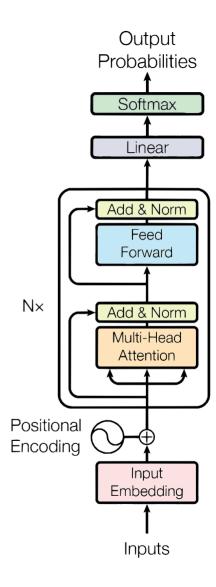
Kenton, J. D. M. W. C., & Toutanova, L. K. (2018). BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of NAACL-HLT (Vol. 1, p. 2)

variants:

DistilBERT ROBERTa DeBERTa

. . .

! cannot be used directly for retrieval



vector embeddings how to get 'em





siamese neural network BERT plus BERT

Reimers, N., & Gurevych, I. (2019). Sentence-BERT: Sentence embeddings using siamese BERT-networks. arXiv preprint arXiv:1908.10084.



> 100 m research papers exist rhenium
10,953,684
articles
indexed

what's inside?

2.5m arXiv : math, physics, computer

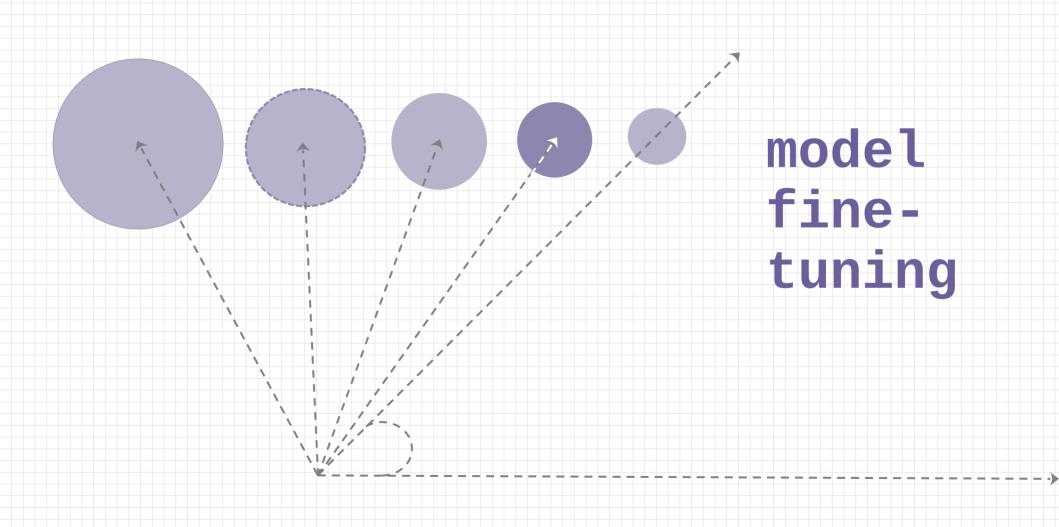
8.5m PubMed : biology and medicine

40k ACL : computational linguistics



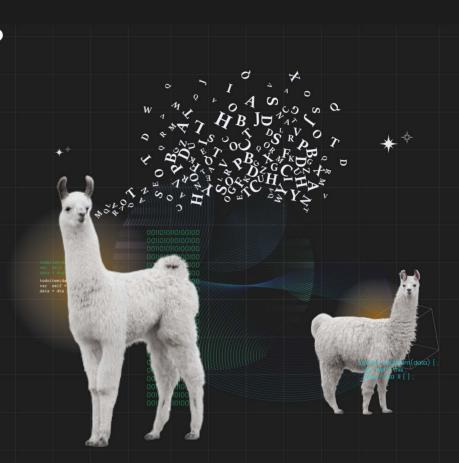
ranking of language models

Rank ▲	Model	Model Size (Million A Parameters)	Memory Usage (GB, fp32)	Average A	ArguAna ▲
2	g <u>te-large-en-v1.5</u>	434	1.62	57.91	72.11
5	voyage-lite-02-instruct	1220	4.54	56.6	70.28
3	GritLM-7B	7242	26.98	57.41	63.24
7	<u>LLM2Vec-Mistral-supervised</u>	7111	26.49	55.99	57.48
12	<u>text-embedding-3-large</u>			55.44	58.05
1	SFR-Embedding-Mistral	7111	26.49	59	67.17
18	<u>LLM2Vec-Llama-supervised</u>	6607	24.61	54.6	56.53
13	GritLM-8x7B	46703	173.98	55.09	59.49
21	g <u>te-base-en-v1.5</u>	137	0.51	54.09	63.49
4	e5-mistral-7b-instruct	7111	26.49	56.89	61.88
42	g <u>te-base</u>	109	0.41	51.14	57.12



why fine-tuning?

- special terms
- results tailored to the field of research
- expert knowledge



biology medicine



use BioBERT!
available on

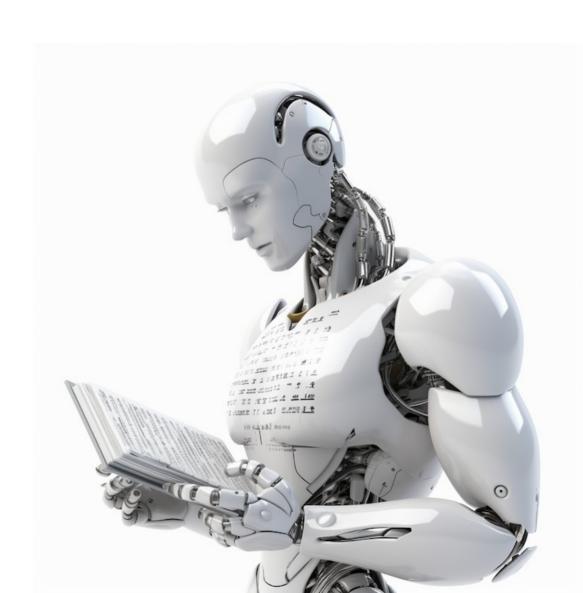
pritamdeka/BioBERT-mnli-snliscinli-scitail-mednli-stsb



fine-tuning for the AI domain

dataset

1 million articles relevant to «artificial intelligence»



AI-ROBERTa

base model: DistilRoBERT

a

training :

1.unsupervised
MLM on a
corpus of AI
texts

2.supervised training on NLI datasets

training :

time 8-9 hours

AI-BERT-GPL

base model: **DistilBERT**

training stages

- 1.generating queries from texts in the corpus
- 2.retrieve negative passages
- 3.calculate similarity scores
- 4. <u>supervised training on</u> resulting dataset

training :

> 40 hours

^{*} MLM — Masked Language Modeling

^{*} NLI — Natural Language Inference

^{*} GPL — Generative Pseudo Labeling



	gte-large	BioBERT	AI-RoBERTa	AI-BERT-GPL
MRR@10	0.99283333	0.91068095	0.90570238	0.93495714
NDCG@10	0.95424540	0.77984771	0.78139278	0.80093784
MAP	0.92281592	0.71697288	0.71533471	0.74431640
cosine distance accuracy	0.94180943	0.85071644	0.86098910	0.79142114
processes	gte-large	BioBERT	AI-RoBERTa	AI-BERT-GPL
1	4857	12485	16456	17123
2	8266	17947	27651	28721
4	9015	22072	35919	37423
6	8513	22601	39599	40988
7	8339	22183	40656	41260
8	8261	21986	40462	41776
max. query per second	150	377	677	696



future work

: index 100m research articles

: support for many research fields

: improve performance of existing models

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