## Phrase Retrieval Learns Passage Retrieval, Too

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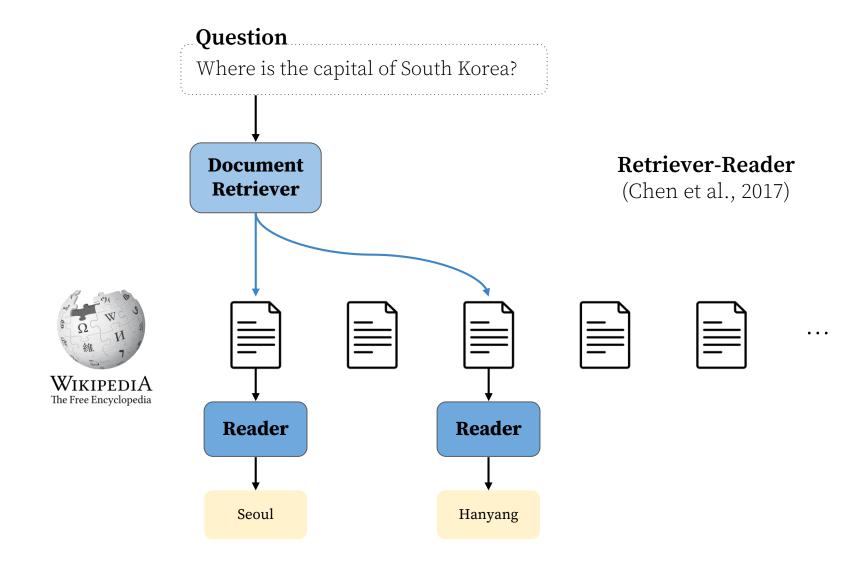
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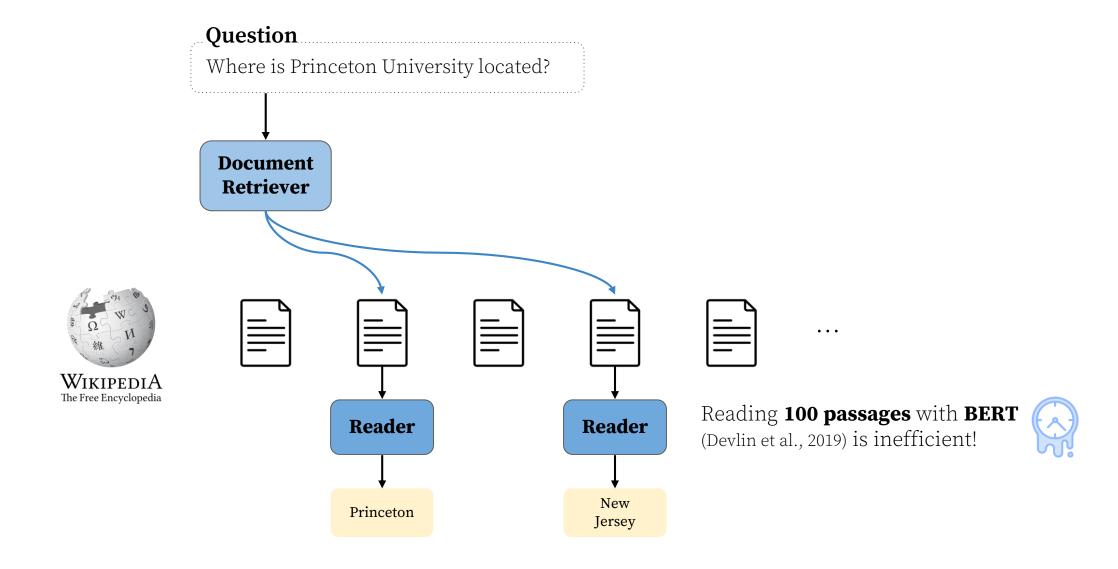


# 01 Background

### Open-Domain Question Answering



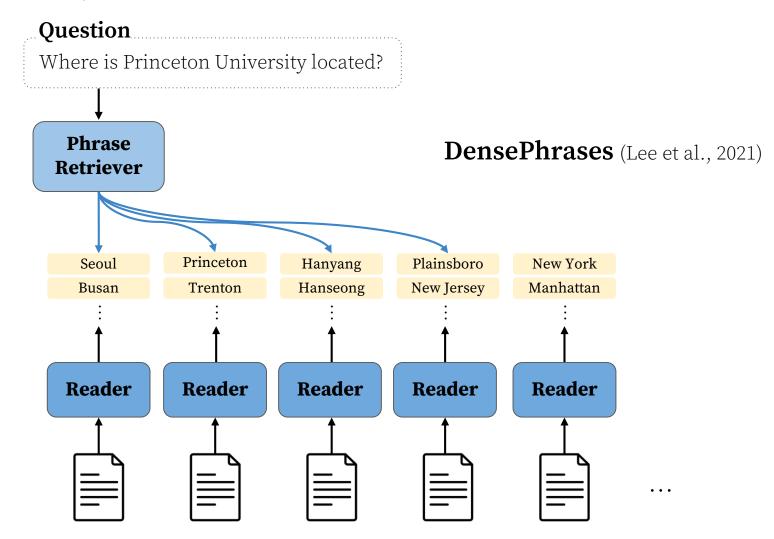
### Open-Domain Question Answering



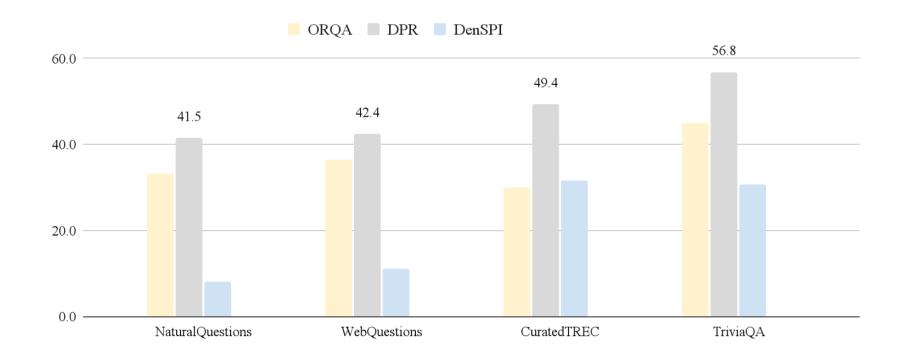
The Free Encyclopedia

### Phrase Retrieval for Open-Domain QA

Phrase = any contiguous segment of text up to L words (Seo et al., 2019)

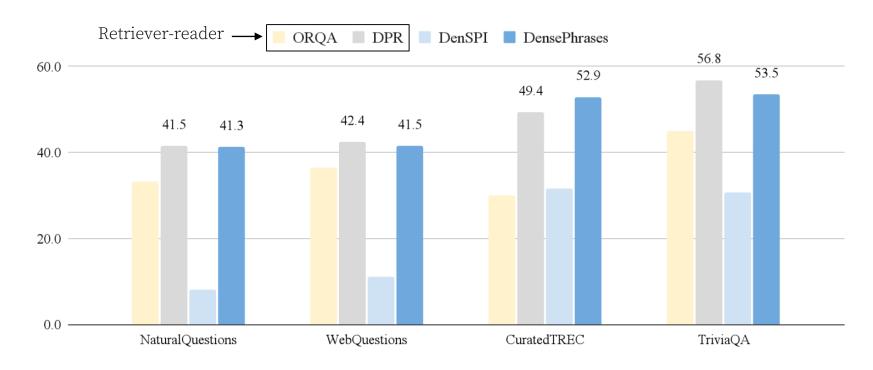


## Phrase Retrieval is Accurate and Fast





## Phrase Retrieval is Accurate and Fast



Without any reader model, phrase retrieval is competitive with retriever-reader approaches.

Dense phrase retrieval makes open-domain QA fast and simple!

# 02 Research Motivation

### Fixed Granularity for Text Retrieval

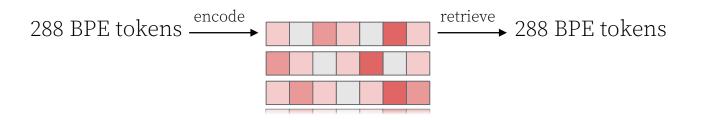
#### Sentence Retrieval

SBERT (Reimers et a., 2019), SimCSE (Gao et al., 2021): 1 sentence

### Passage Retrieval

ORQA (Lee et al., 2019): 288 BPE tokens for a passage

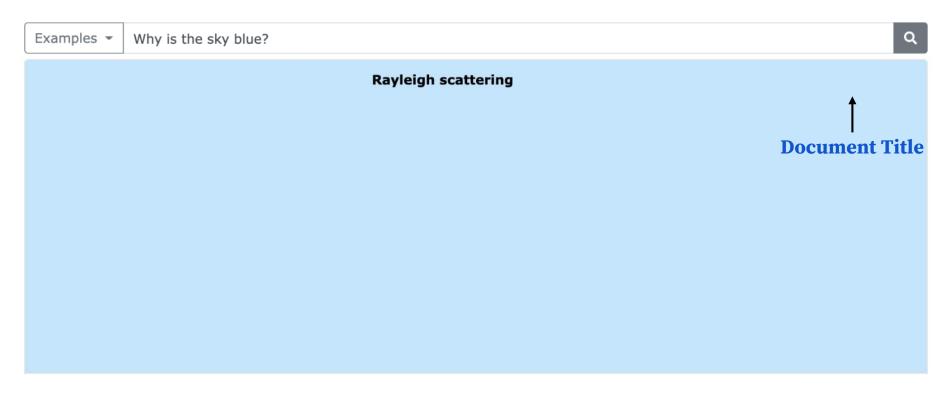
DPR (Karpukhin et al., 2020): 100 words for a passage



**Different** index for **different** granularity?



## Phrases as a Basic Retrieval Unit



Retrieving Phrases  $\Rightarrow$  Sentences  $\Rightarrow$  Passages  $\Rightarrow$  Documents  $\Rightarrow$  ...

**Single** index for **multi** granularity!





Q1: Is this **better** than passage retrievers?

Experiment #1: Passage Retrieval / Experiment #2: Open-domain QA



Q2: Why does this work?

Analysis / Experiment #3: Entity Linking & Dialogue

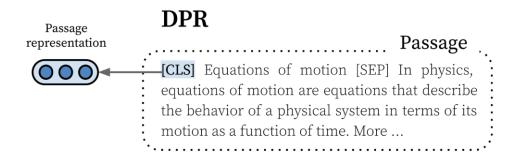


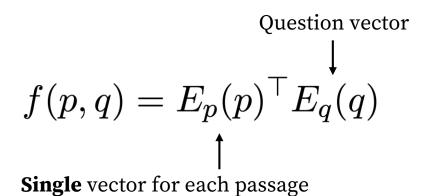
Q3: How **efficient** is this?

Phrase Filtering & Quantization-aware Fine-tuning

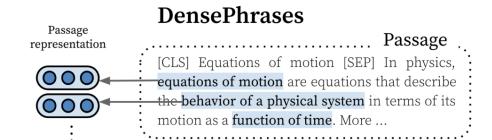
# O3 Formulation / Experiments #1, #2

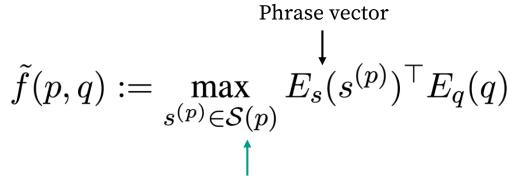
### Passage Retrieval





### **Phrase-based** Passage Retrieval

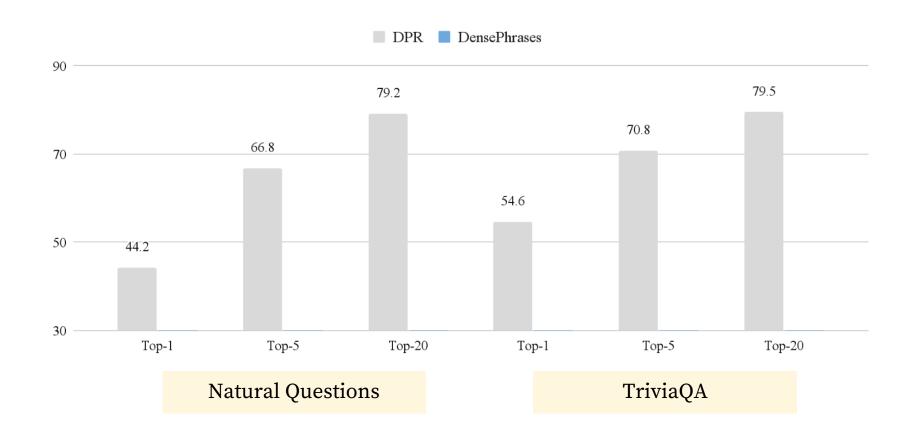




Multiple (phrase) vectors for each passage

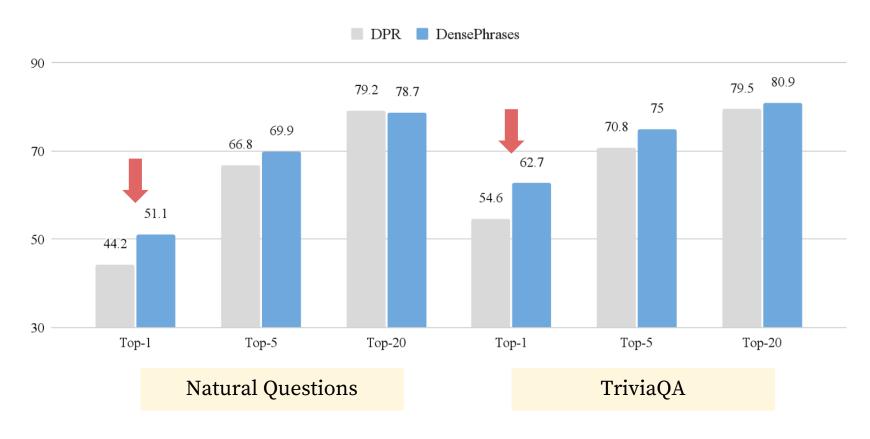


### Passage Retrieval: DPR vs DensePhrases





### Passage Retrieval: DPR vs DensePhrases

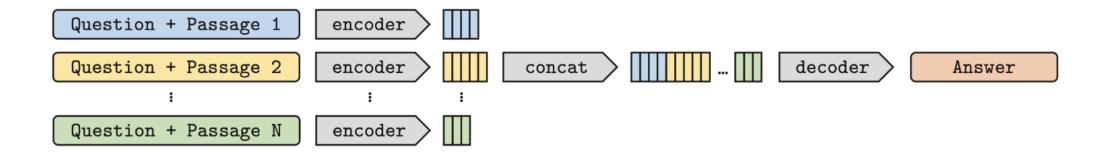


Without any re-training, **DensePhrases outperforms DPR** on passage retrieval!

Larger gains when k is small.

### Fusion-in-Decoder for Open-domain QA

Izacard and Grave, 2021



Feeds top-k passages from **DPR** to **T5** (Raffel et al., 2020) to generate answers.

**FiD** achieves state-of-the-art performance when k is large (e.g., k=100).

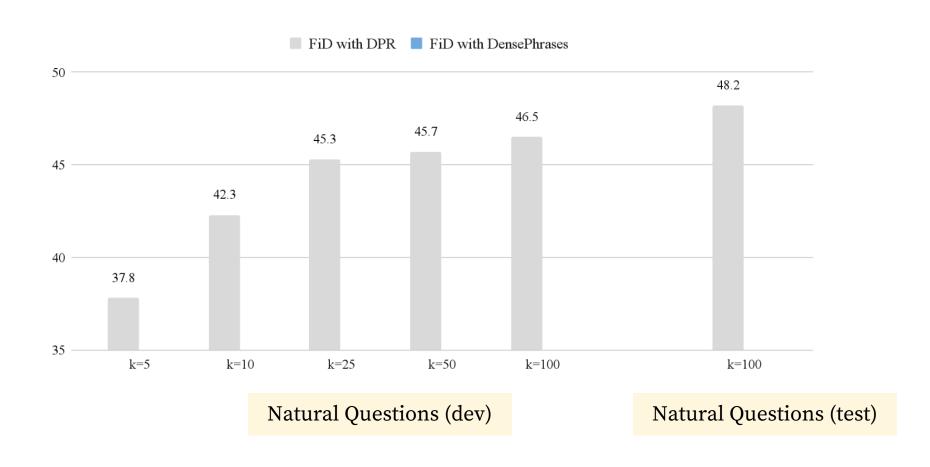
Requires 64 **32GB** V100 GPUs for training!



Feed top-k passages from **DensePhrases** to T5 to generate answers?

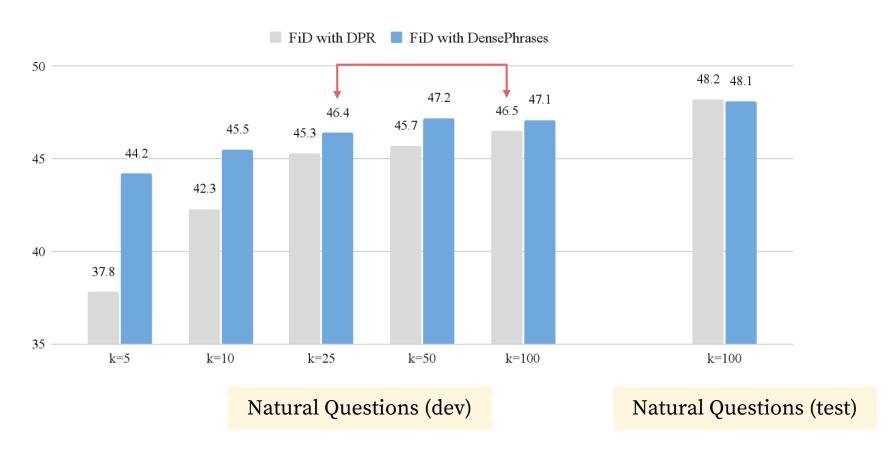


### Open-domain QA: DPR vs DensePhrases





### Open-domain QA: DPR vs DensePhrases



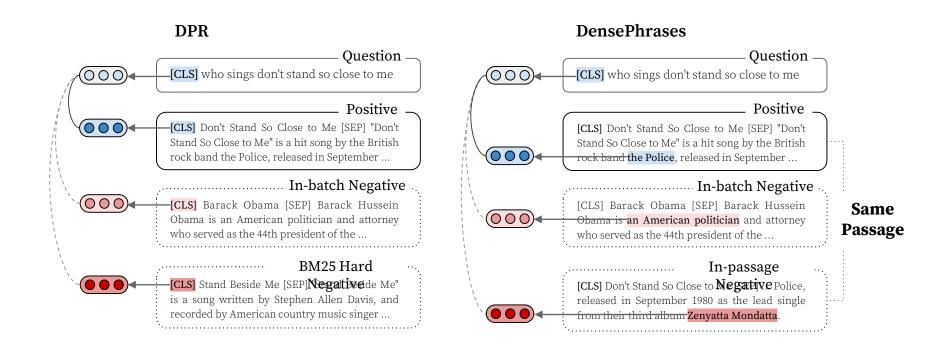
**DensePhrases outperforms DPR** on open-domain QA (+6.4 EM when k=5).

**k=25~50 is enough** for good performance ( $k \le 50$  fits in **24GB**)

# O4 Analysis / Experiments #3



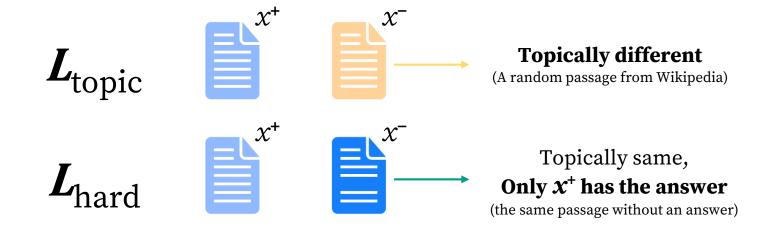
### Why DensePhrases > DPR on Passage Retrieval?



**In-passage negatives** in DensePhrases work similar to **BM25 hard negatives** in DPR!

# 04 Analysis

Analysis With  $L_{
m topic}$  and  $L_{
m hard}$ 



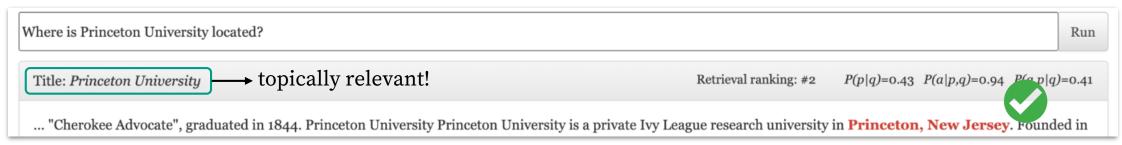
For both metrics, lower numbers are better.

**DPR** has good  $L_{\mathrm{topic}}$  while **DensePhrases** has good  $L_{\mathrm{hard}}$ .



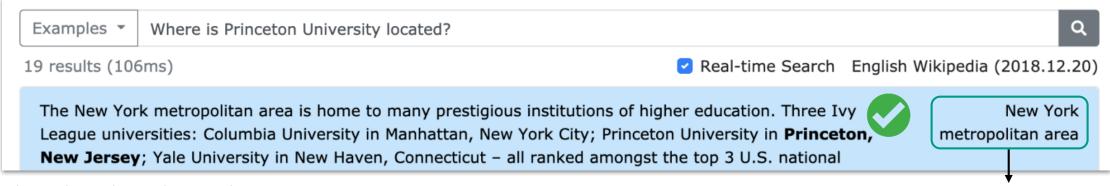
### $L_{\text{topic}}$ and $L_{\text{hard}}$ : What Do They Really Mean?

**DPR** (Karpukhin et al., 2020)



http://qa.cs.washington.edu:2020/

#### DensePhrases (Lee et al., 2021)



http://densephrases.korea.ac.kr

Good  $L_{hard}$  can give correct answer even when the passage is less relevant.

topically less relevant, but still correct answer!





For many coarse-granularity retrieval, we need good  $L_{\text{topic}}$ !

### **Entity Linking**

[START\_ENT] **Security Council** [END\_ENT] members expressed concern on Thursday.



United Nations Security Council

### **Knowledge-grounded Dialogue**

Have you heard of Yamaha? They started as a piano manufacturer in 1887!

Yamaha Corporation



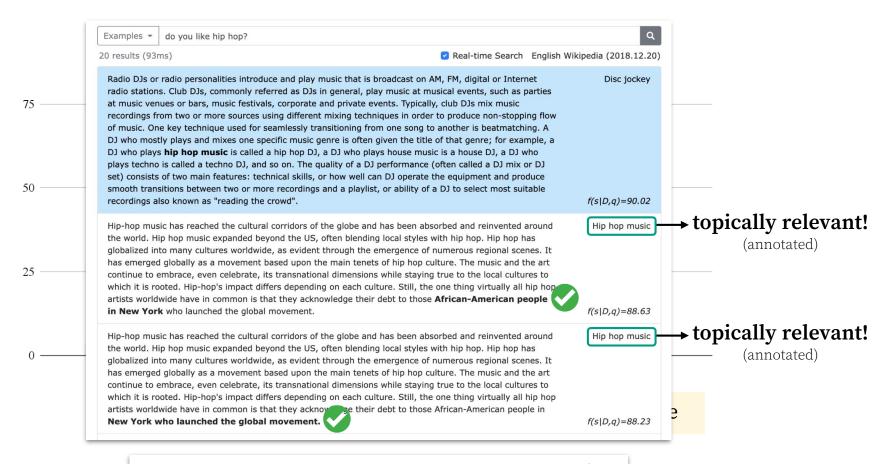
Only **one document** is relevant (annotated) for each query! (KILT; Petroni et al., 2021)

## Retrieval for Entity Linking & Dialogue





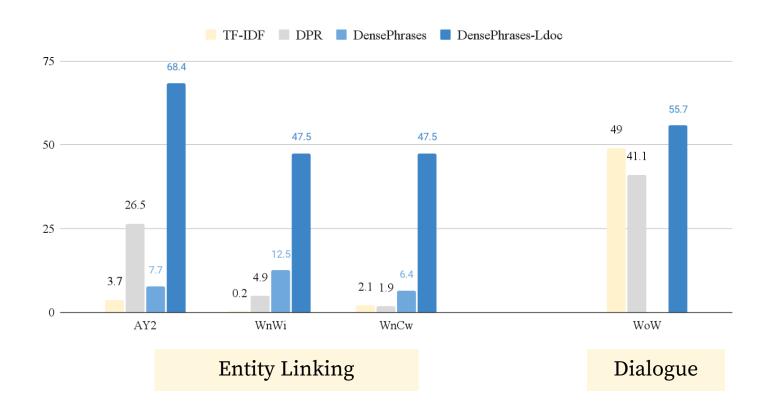
### Retrieval for Entity Linking & Dialogue



Maximize the marginal probability of any phrases in the relevant document



## Retrieval for Entity Linking & Dialogue

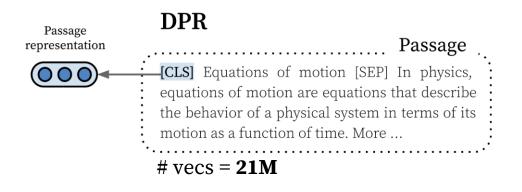


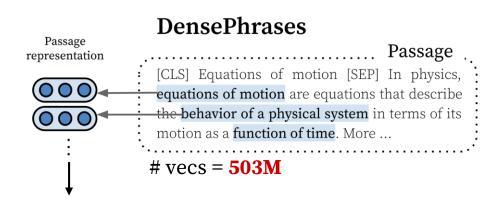
DensePhrases can be adapted to **retrieve topically relevant documents**!

# 05 Complexity Analysis



## Problem of Multi-vector Encoding Luan et al., 2021; Khattab and Zaharia, 2020





More vectors, **more space!** 



Phrase indexes are **heavy!** 











**1.2TB** (Seo et al., 2019)

**1.5TB** (Lee et al., 2020)

**320GB** (Lee et al., 2021)



### Reducing the Size of Phrase Index

"The New York metropolitan area is home to many prestigious institutions of higher education."

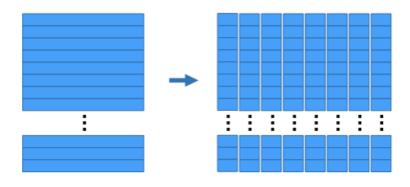


"The New York metropolitan area"

"prestigious institutions"

"higher education"

...



#### **Optimized Product Quantization**

(Ge et al., 2013)

 $\vdash$ 

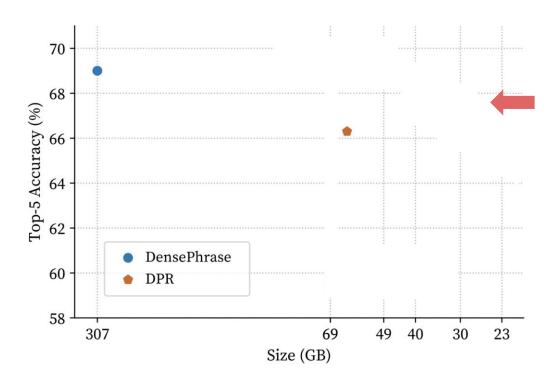
**Query-side Fine-tuning** 

(Lee et al., 2021)

=

**Quantization-aware Fine-tuning** 

### Reducing the Size of Phrase Index



We can safely reduce the size down to **23GB!** (DPR = 69GB)

DensePhrases with # vector/passage = 8.8 is similar to DPR.

# 06 Conclusion

# 06 Conclusion



Q1: Is this **better** than passage retrievers?

Yes! **DensePhrases > DPR** on passage retrieval and open-domain QA!



Q2: **Why** does this work?

Better at fine-grained entailment, can be used for coarse retrieval.



Q3: How **efficient** is this?

Can safely reduce the index size from **307GB to 23GB!** 

Paper: https://arxiv.org/abs/2109.08133

Code & Models: https://github.com/princeton-nlp/DensePhrases

**Demo**: http://densephrases.korea.ac.kr/

E-mail: jinhyuklee@cs.princeton.edu

## 감사합니다

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