Towards Efficient Pre-training of Language Models

Danqi Chen

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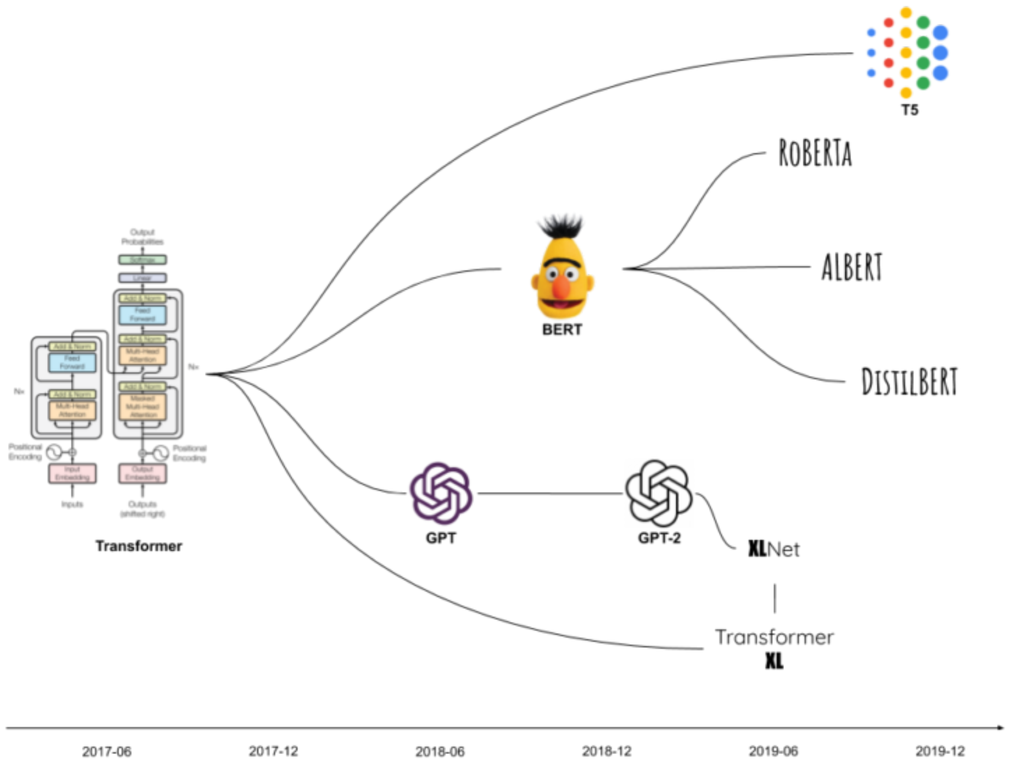
AAAI 2022 Workshop on Self-supervised Learning for Audio and Speech Processing

Pre-trained language models at scale



https://www.factored.ai/2021/09/21/an-intuitive-explanation-of-transformer-based-models/

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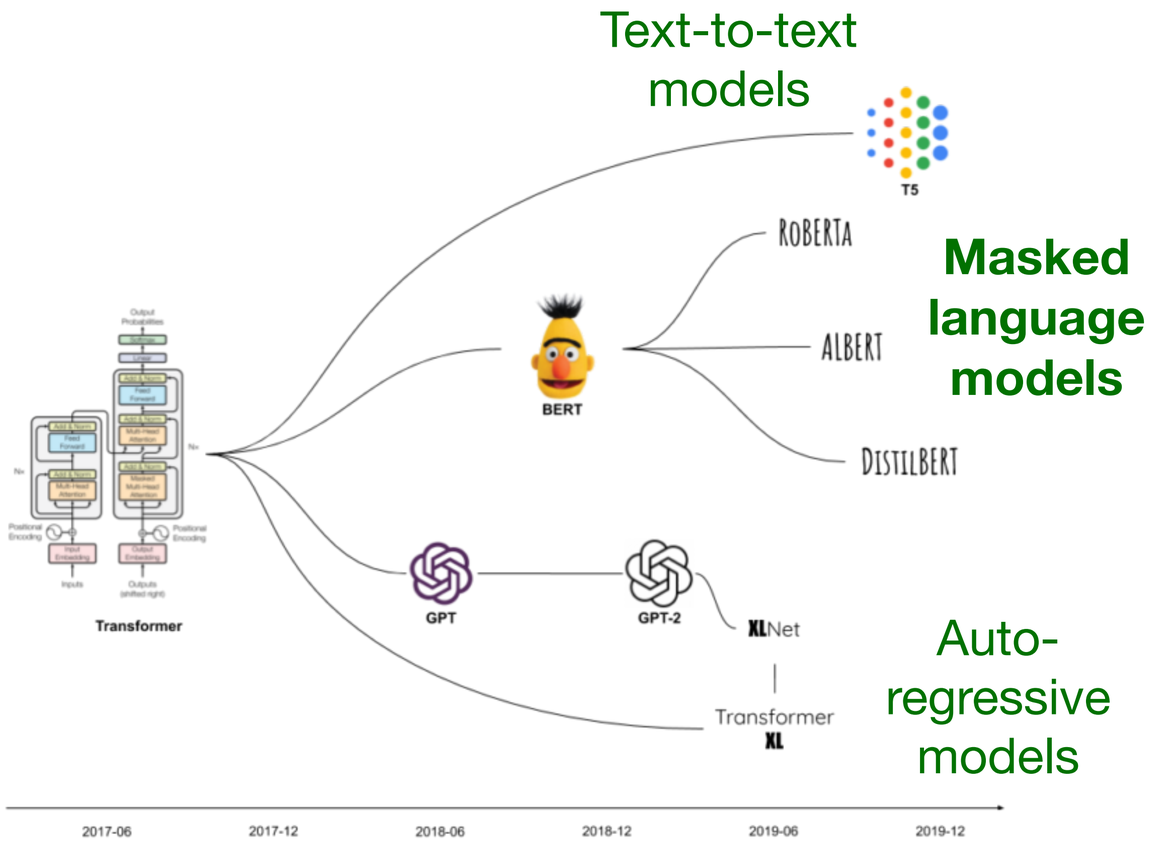

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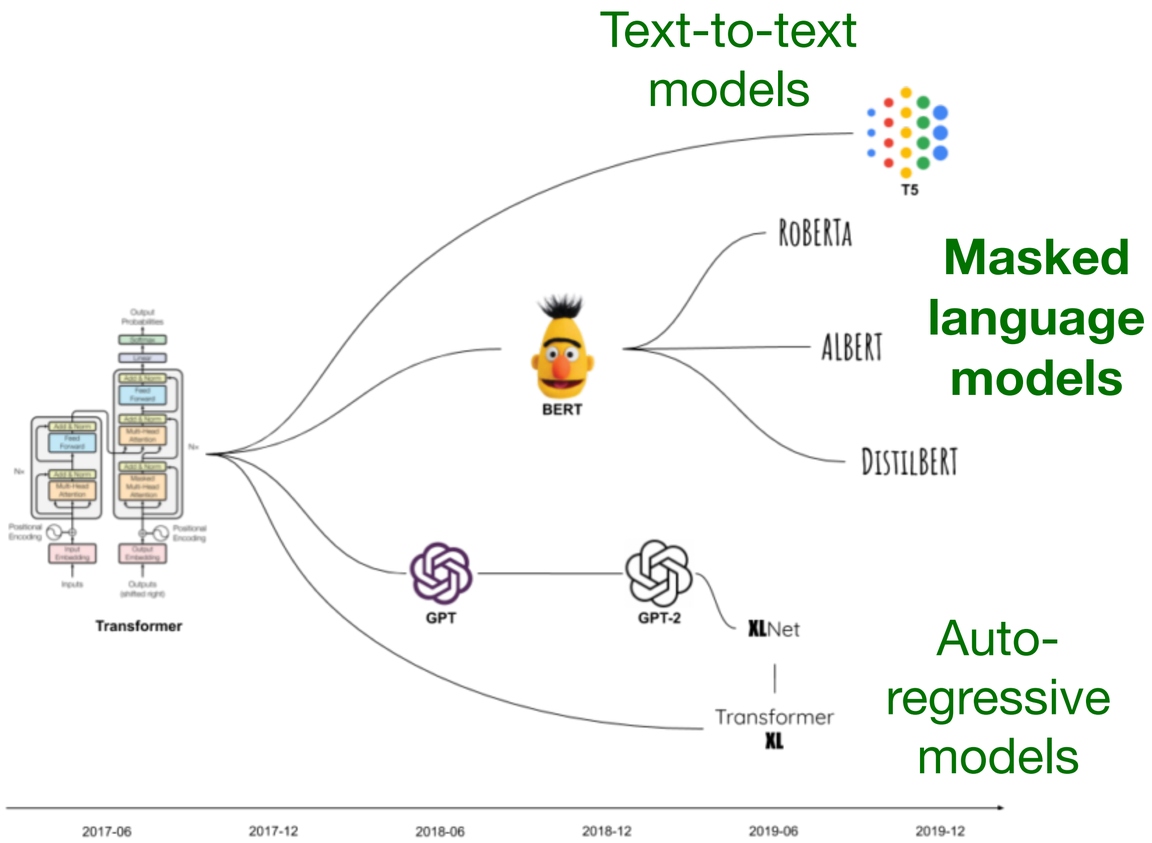

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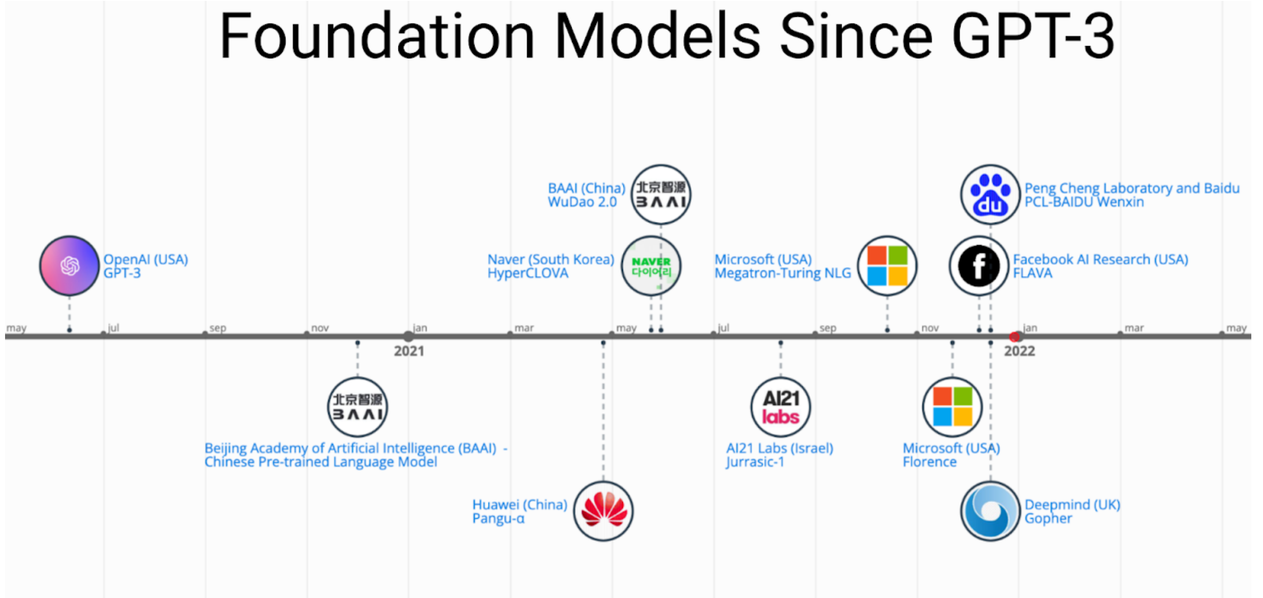

https://lastweekin.ai/p/gpt-3-foundation-models-and-ai-nationalism

Ideas shared across different modalities

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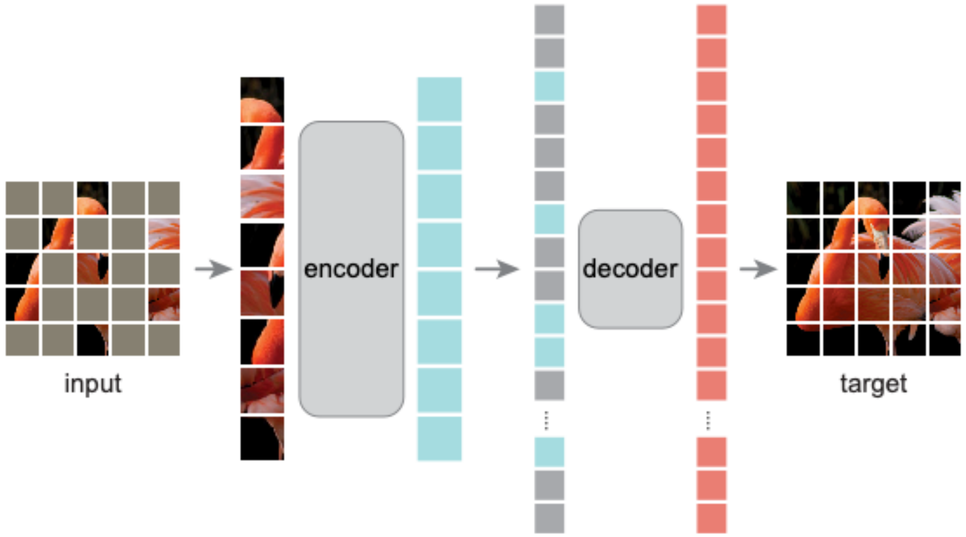

(He et al., 2021)

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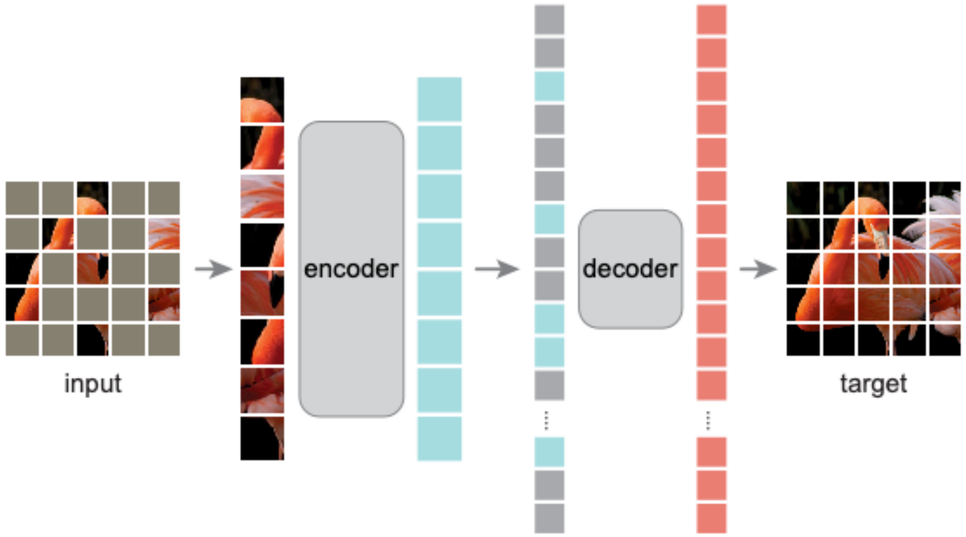

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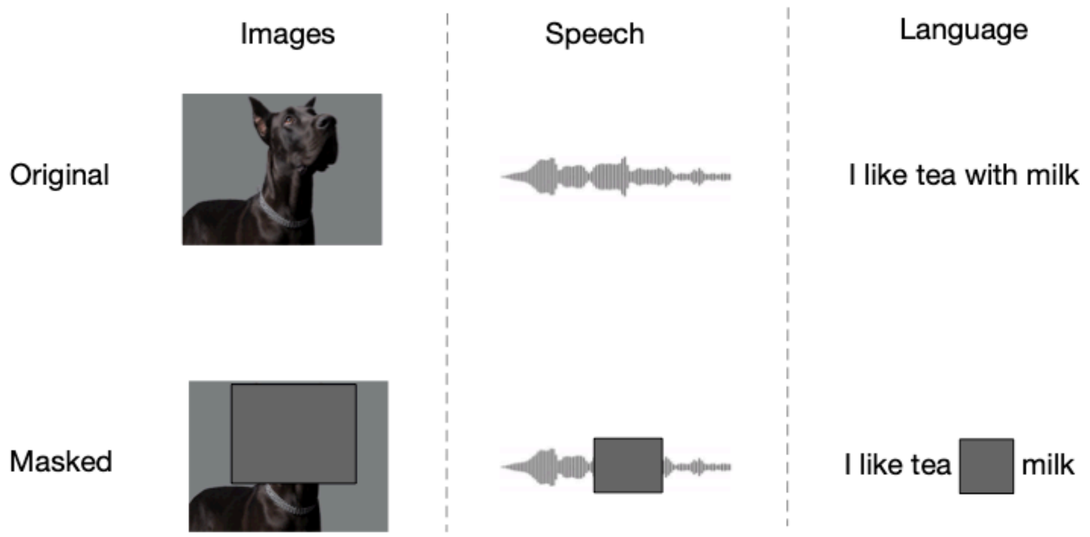
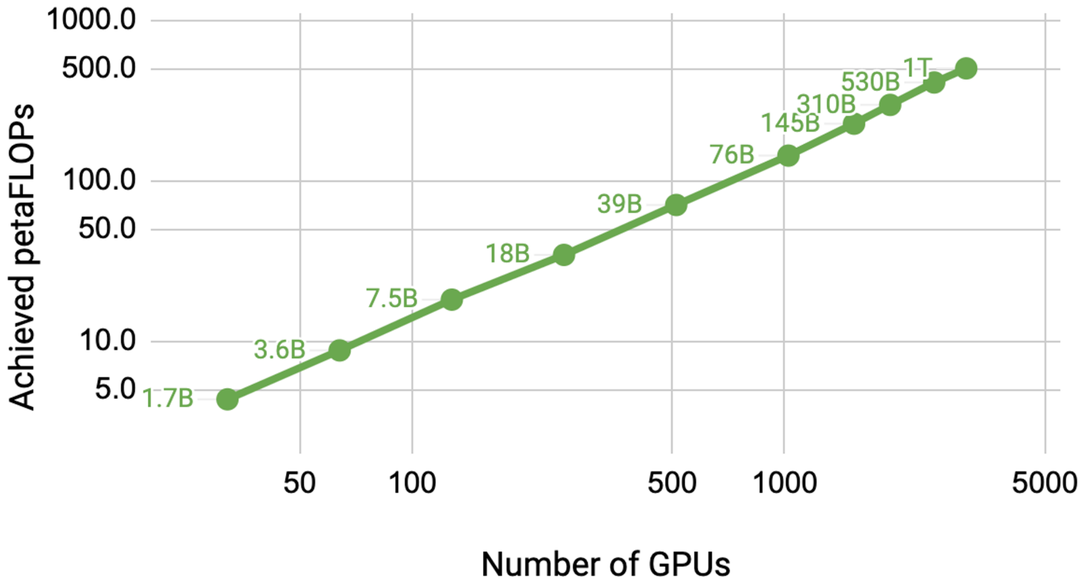


(Baevski et al., 2022)

This talk

As an academic researcher, what can we do in this pre-training era? What if we have at most **8 GPUs** to spare?



Source: Nvidia Blog

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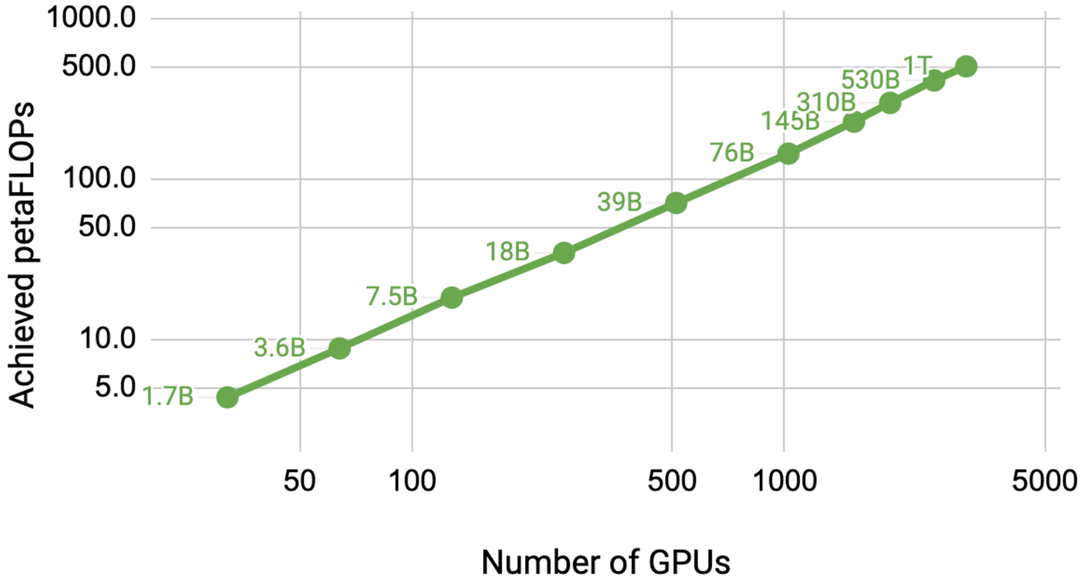
How can we make pre-training more **accessible** and **affordable**?



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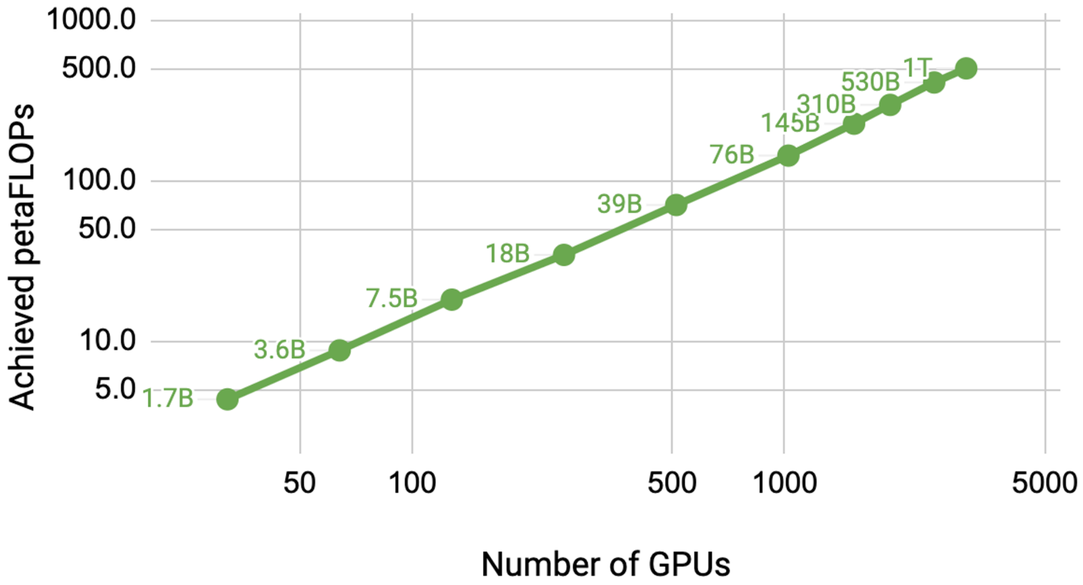

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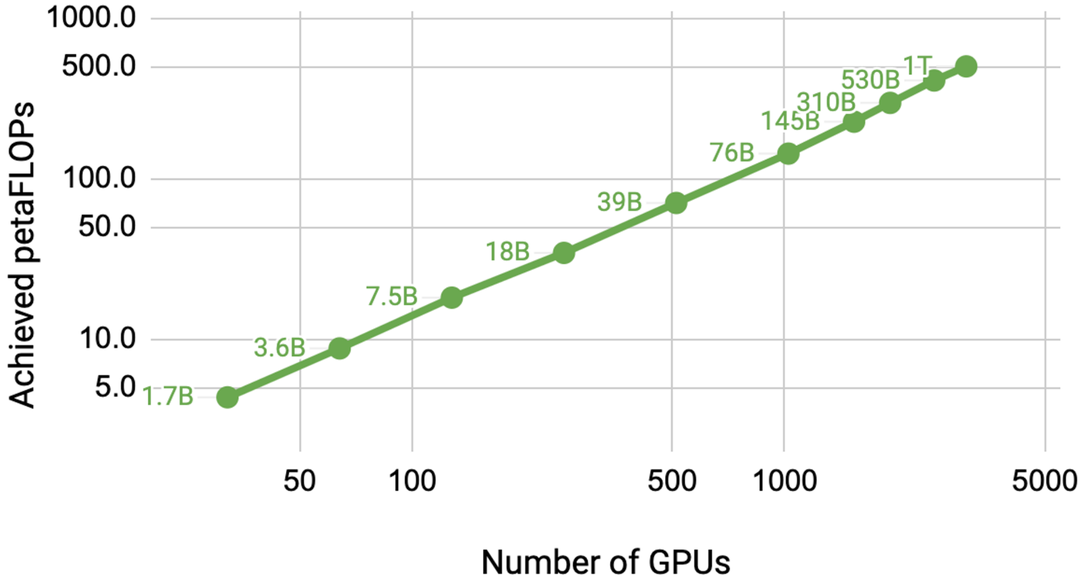

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This talk: two case studies pointing to some promising directions for efficient pre-training

Exploring Optimal Masking Rates and Strategies in Masked Language Models



(Wettig et al., arXiv 2022) Should You Mask 15% in Masked Language Modeling?

BERT pre-training

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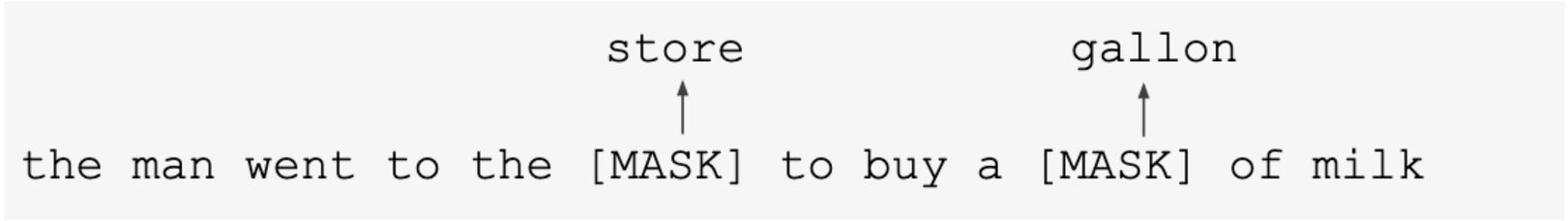
- BERT always masks $k = 15\%$ of input words, and predicts the masked words



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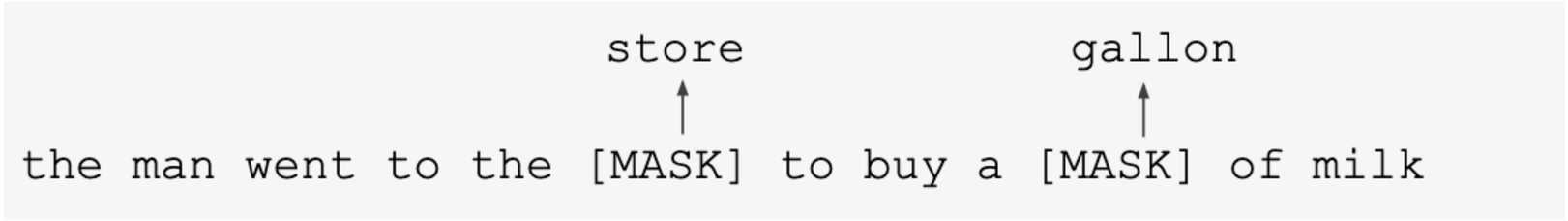

- Common belief:

Too little masking: Too expensive to train
Too much masking: Not enough context

(Credit: Jacob Devlin)

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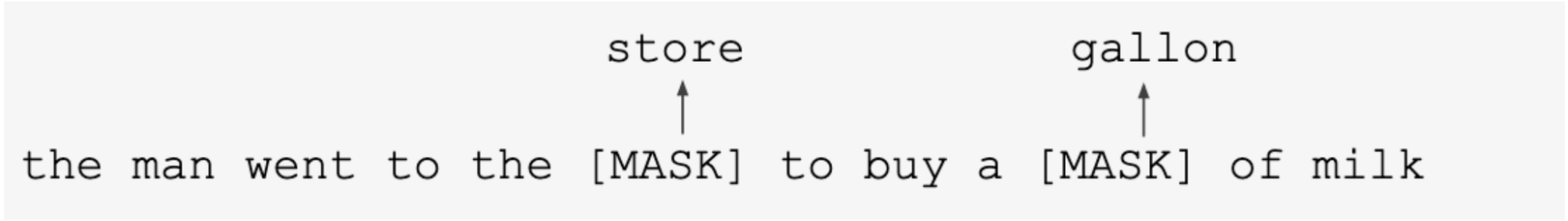

- Common belief:

Too little masking: Too expensive to train

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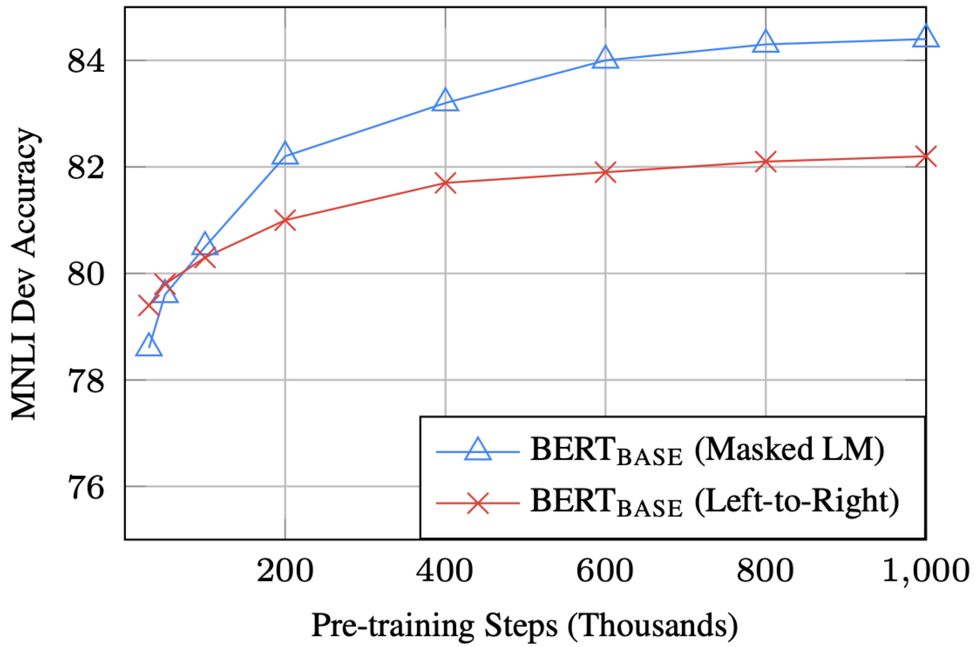
(Credit: Jacob Devlin)

- This 15% masking rate has been used in all the recent MLMs, regardless of **model sizes** and **masking strategies** (span masking, PMI masking)

BERT pre-training

- MLMs are more effective than auto-regressive LMs due to their **bidirectionality**



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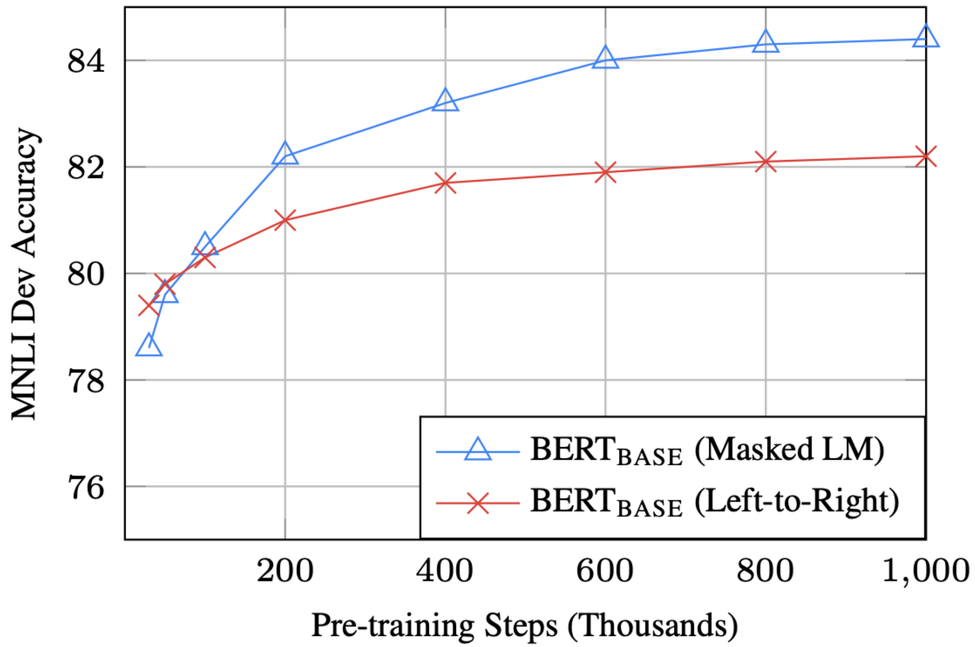

(Devlin et al., 2019)

- However, this k = 15% masking rate has been viewed as a bottleneck for **sample efficiency** because it only learns 15% of tokens per sample

Can we mask more?

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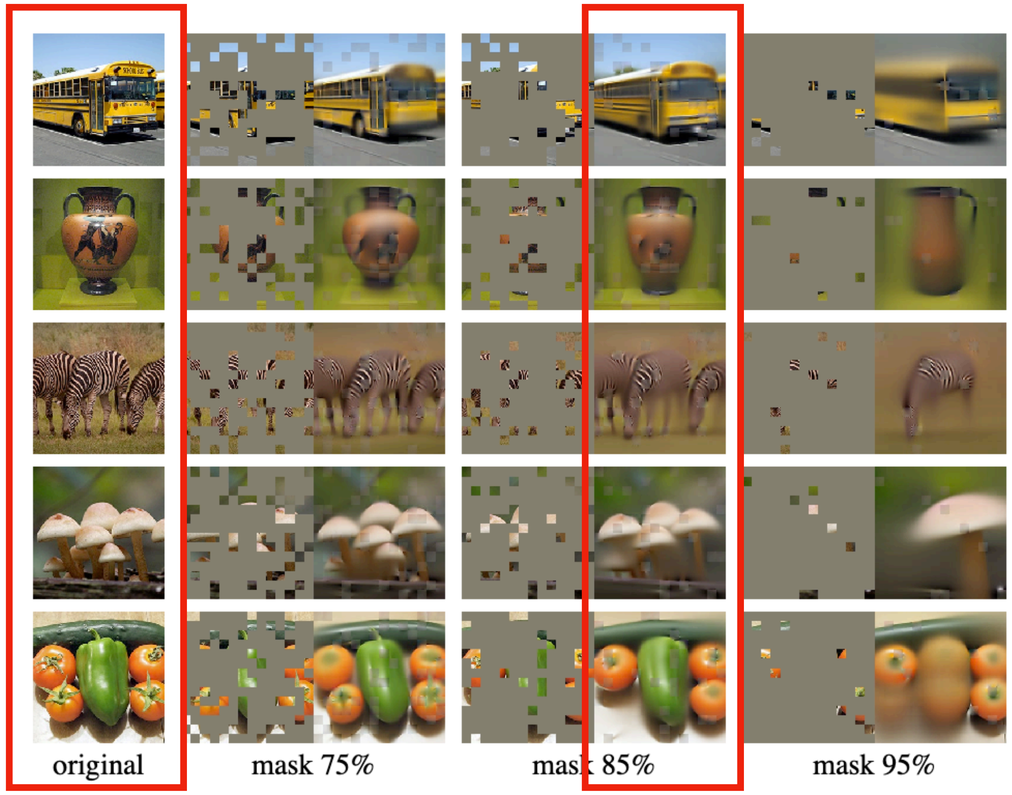

(He et al., 2021)

- In images, we can mask 75% to 95% portion of images and still reconstruct the original input plausibly

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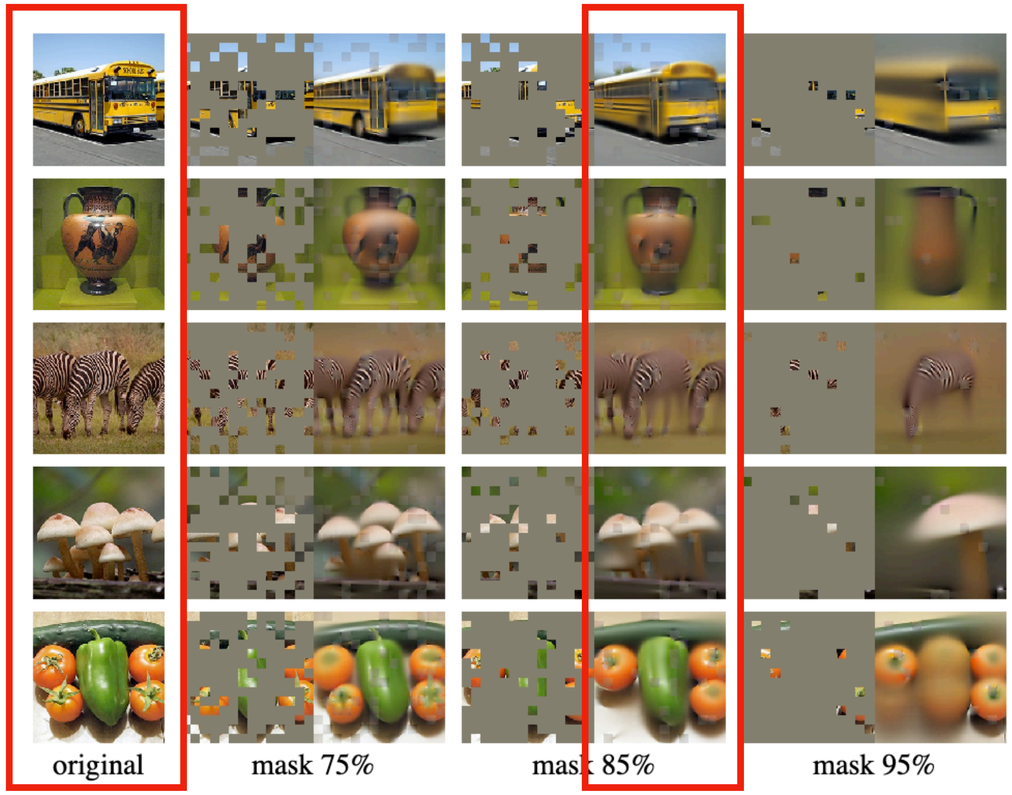

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- In images, we can mask 75% to 95% portion of images and still reconstruct the original input plausibly
- Can we do this for text?

"Information density is different between language and vision."

Can we mask more?

Sentence: We study high mask ing rates in pre-training language models .

	Pre-training	
m	Example	PPL

Wettig et al., 2022. Should You Mask 15% in Masked Language Modeling?

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	Pre-training	
m	Example	PPL
15%	We study high [redacted] ing rates [redacted] pre-training language models .	17.7

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	Pre-training	
m	Example	PPL
40%	We study high [MASK] [MASK] rates [MASK] pre- [MASK] [MASK] models .	69.4
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*: Fine-tuning on downstream tasks

Pre-training			Downstream		
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- These results build on an efficient pre-training recipe (Izsak et al., 2021): training a BERT-large model for 24 hours on 8 RTX 2080 GPUs, performance at least good as BERT-base
- The ability to reconstruct the original inputs may **NOT correlate** with representations for downstream task fine-tuning.

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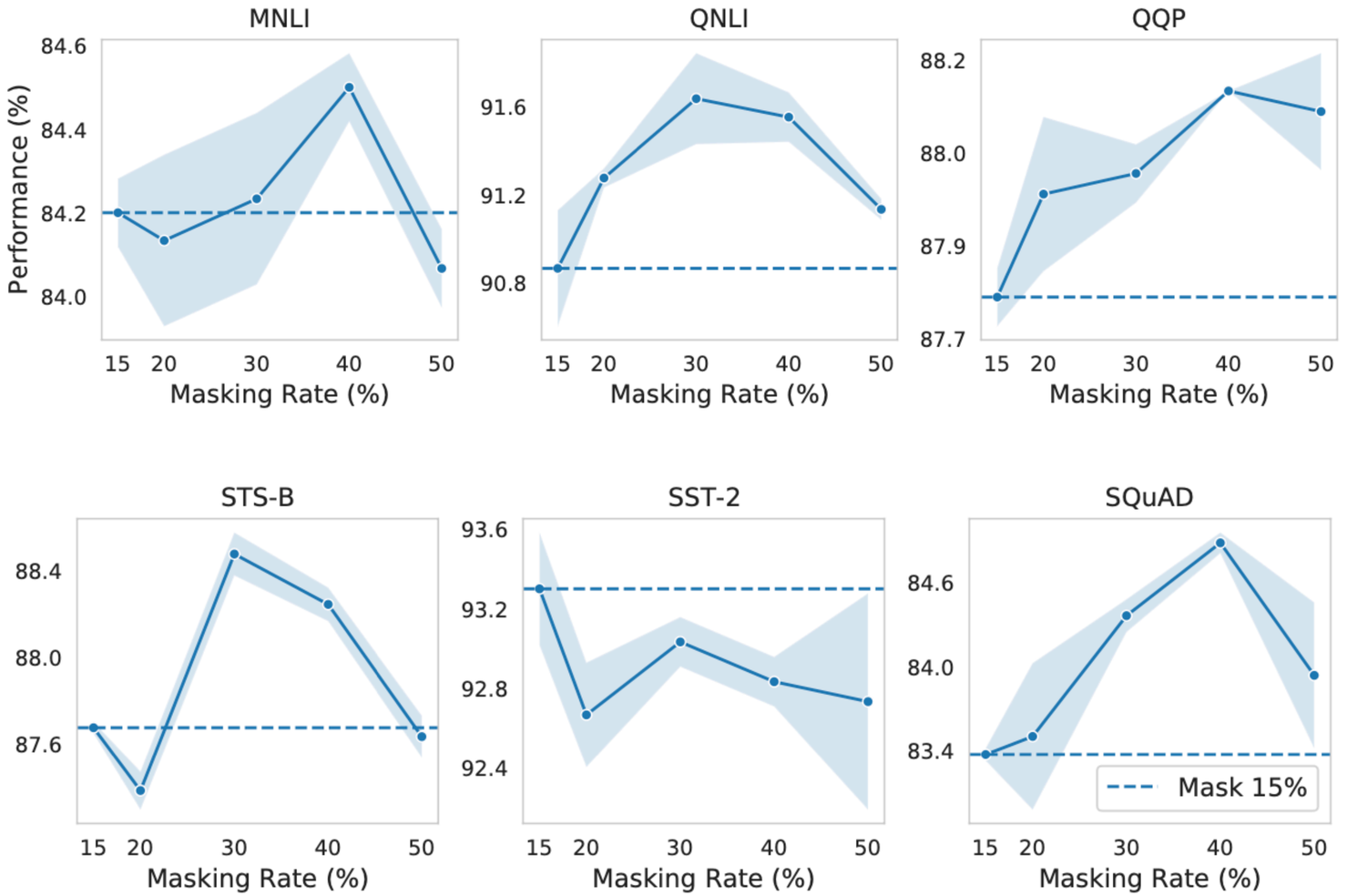
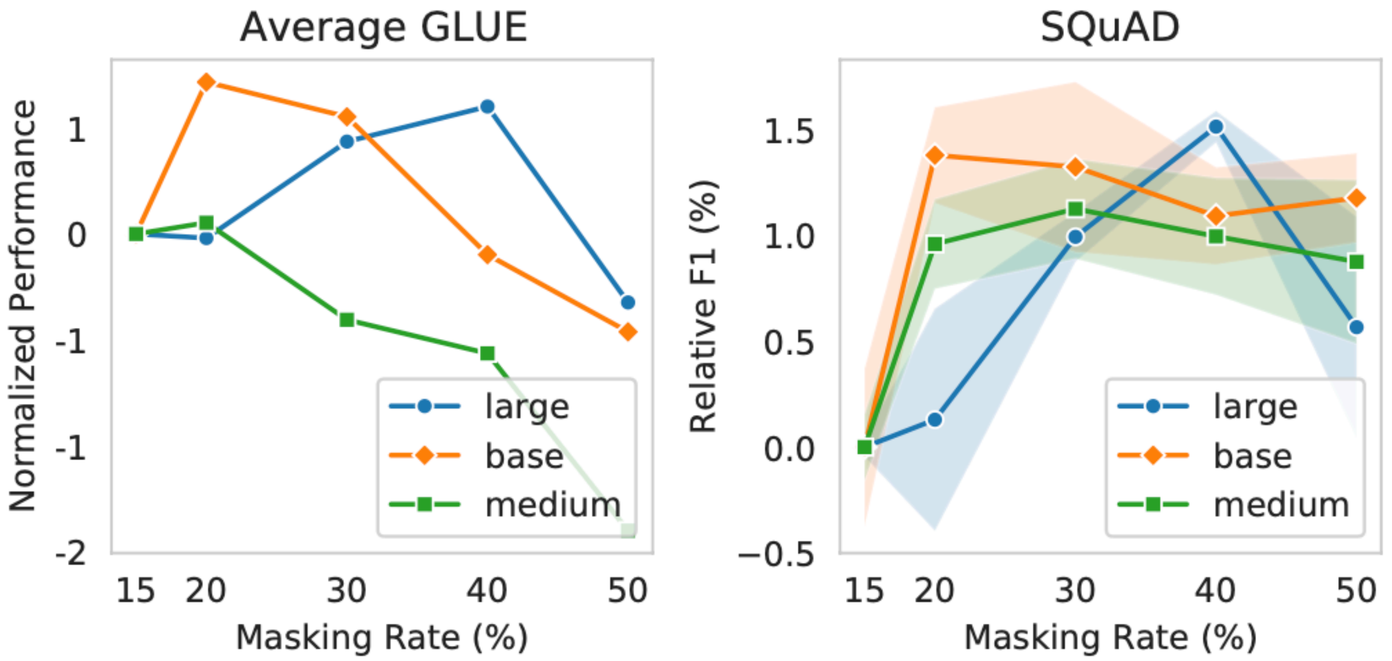


40% masking rate is consistently better than **15%** masking rate

The improvements are even **larger** when combined with **efficient training recipes**

Wettig et al., 2022. Should You Mask 15% in Masked Language Modeling?

Other key findings



Larger models should adopt **larger masking rates**

Wettig et al., 2022. Should You Mask 15% in Masked Language Modeling?

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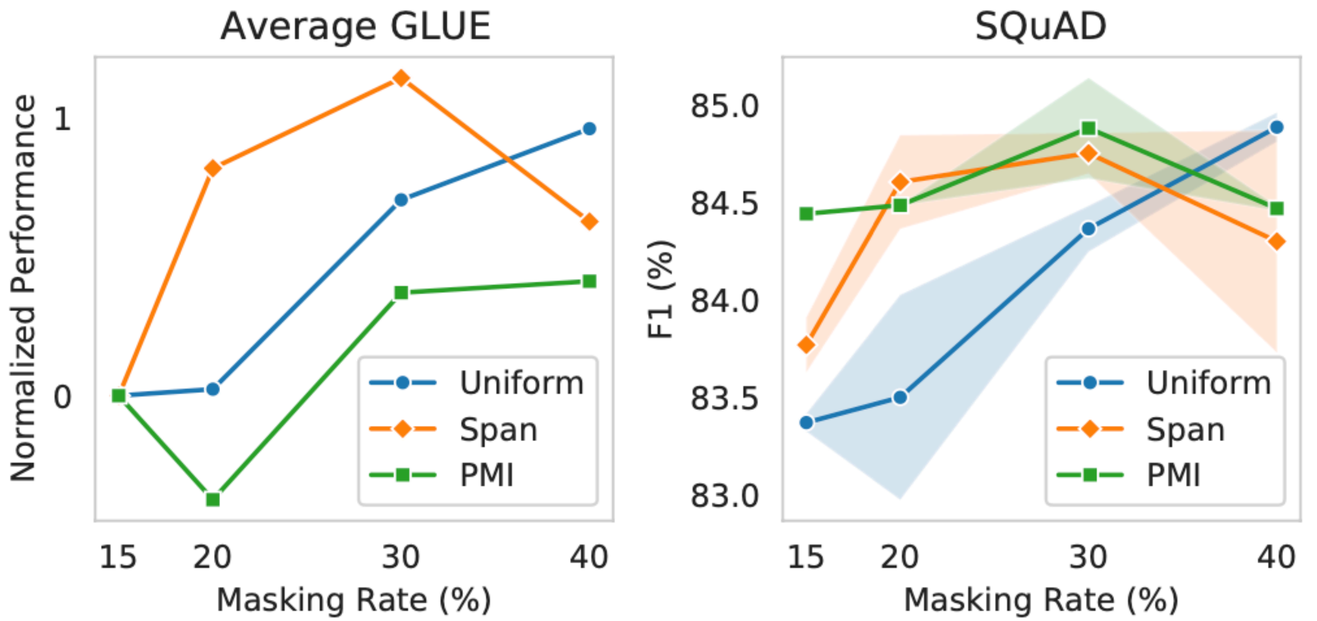

Uniform masking is competitive as **span masking** (Joshi et al., 2020) or **PMI masking** (Levine et al., 2021) with **high masking rates**

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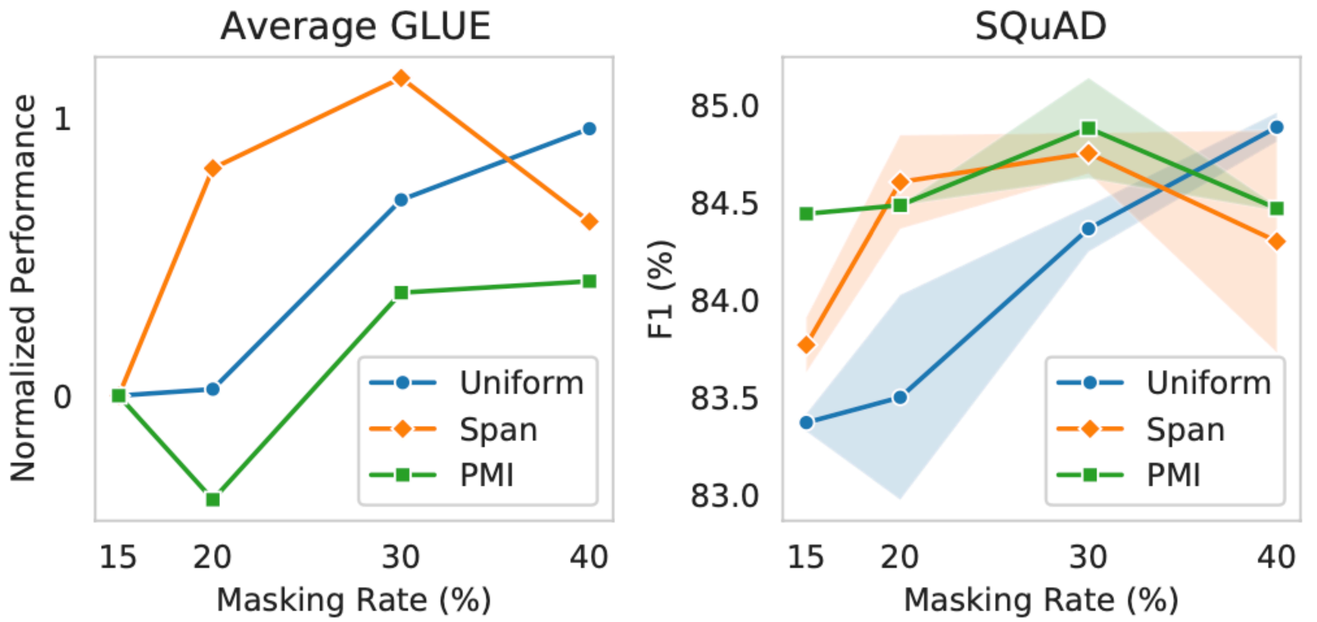

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Bonus: The 80-10-10 corruption strategy may be not important too (see the paper)!

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- The more we **predict**, the better.

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m_{corr}	m_{pred}	MNLI	QNLI	QQP	STS-B	SST-2
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- Why do we want high masking rates?

Q: Can we **only encode** the unmasked (50-60%) tokens to reduce the number of computations?

He et al., 2021 show that they can achieve 4.1x speed-up with 75% input masked

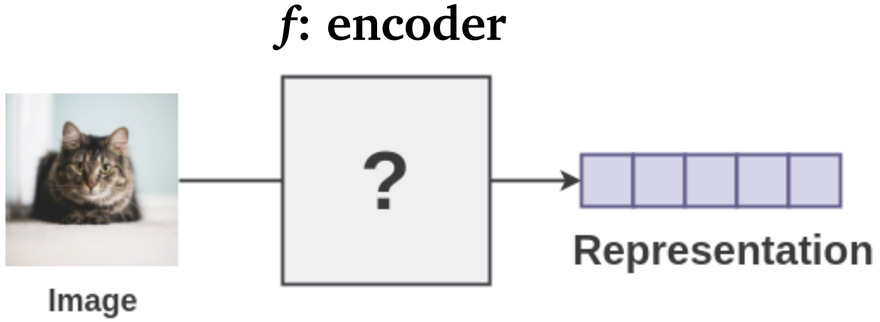
Wettig et al., 2022. Should You Mask 15% in Masked Language Modeling?

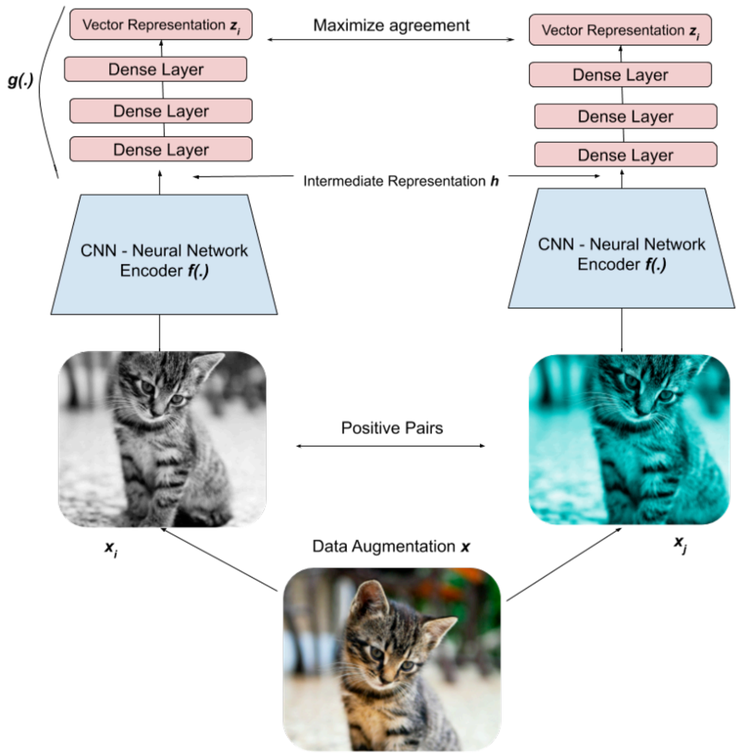
Contrastive Learning Eases the Anisotropy Problem in MLMs

(Gao et al., EMNLP 2021) SimCSE: Simple Contrastive Learning of Sentence Embeddings

Contrastive learning of visual representations

SimCLR (Chen et al., 2020), MoCo (He et al., 2020), SwAV (Caron et al., 2020) and many others





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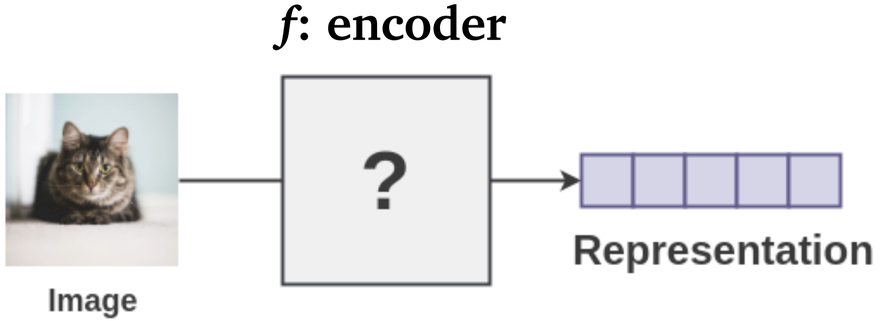
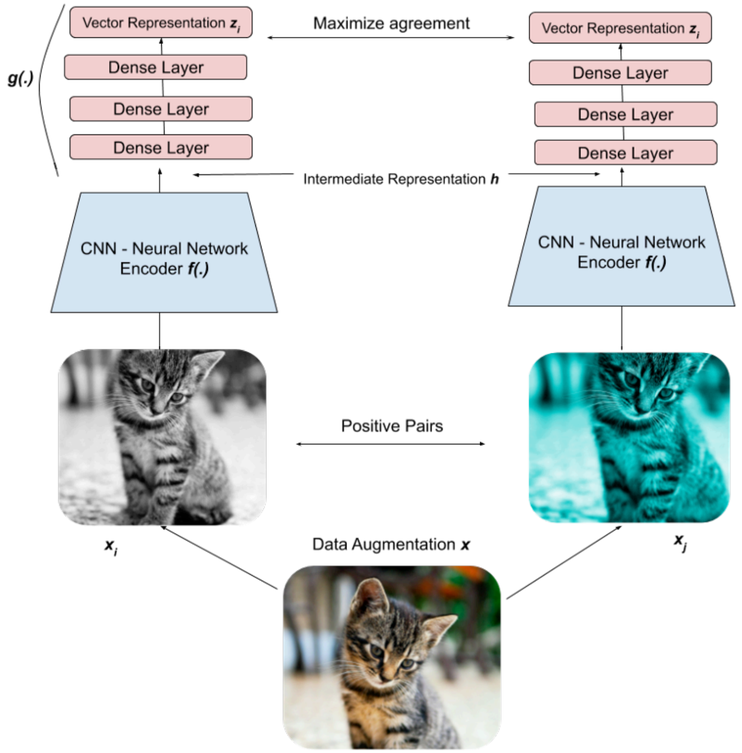


Our goal: learning good sentence representations



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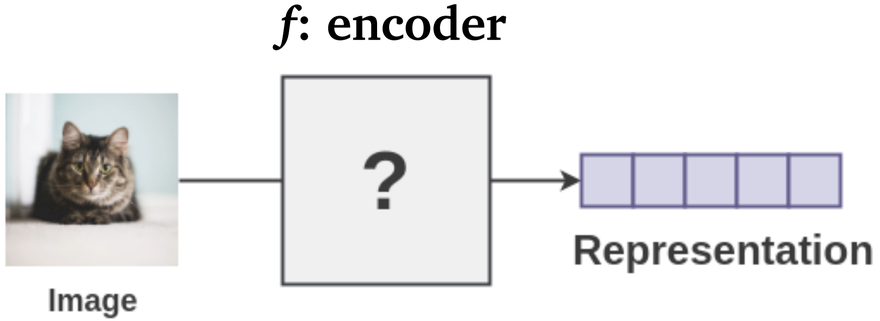
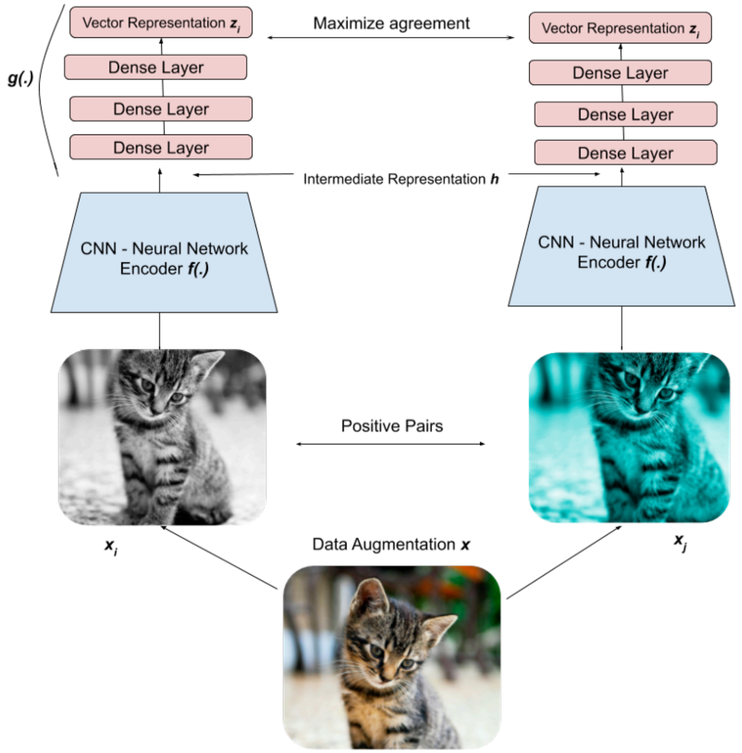
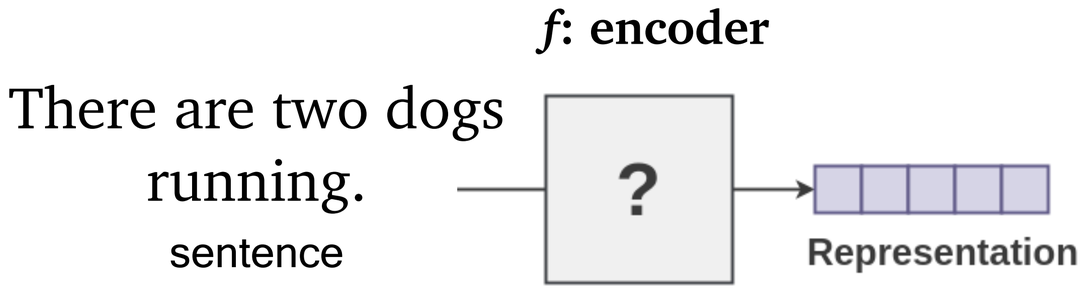




(Chen et al., 2020)

Our goal: learning good sentence representations



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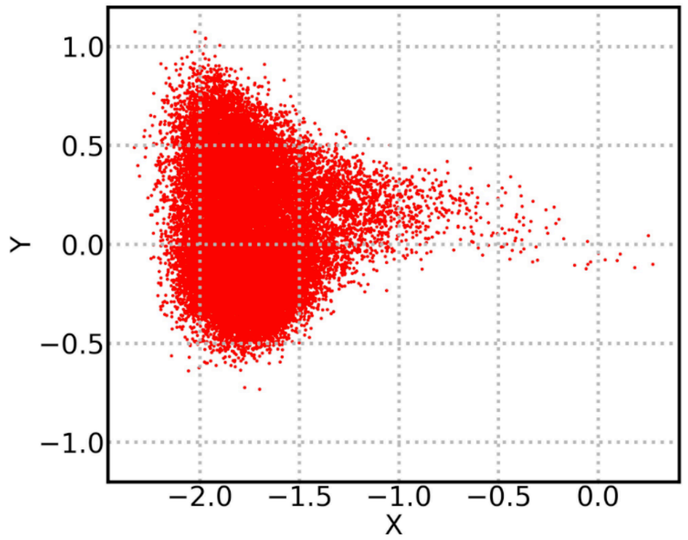
Issue: pre-trained representations are **highly anisotropic** (Gao et al., 2019; Ethayarajh, 2019; Li et al., 2020)



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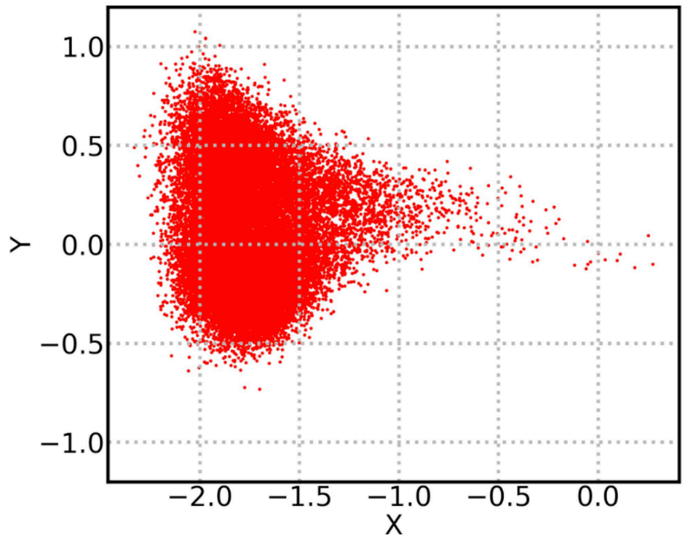

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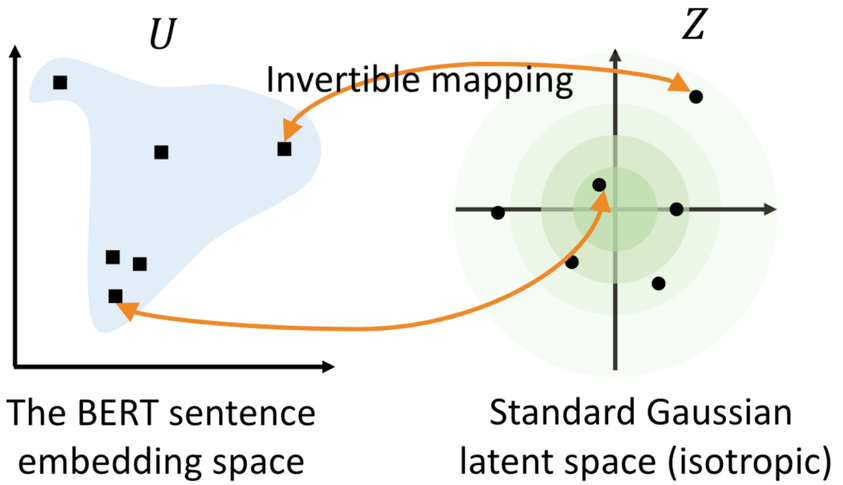
Solution: post-processing and mapping embeddings to an isotropic space



BERT-flow (Li et al., 2020)

BERT-whitening (Su et al., 2021)

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A simple contrastive learning framework for sentence representations:

- **Unsupervised SimCSE: only uses *dropout* as data augmentation**
- See supervised SimCSE in the paper!

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InfoNCE loss (van den Oord et al. 2018)

N: batch size
(in-batch negatives)

$$\mathcal{L}_N = -\mathbb{E}_X \left(\log \frac{\exp(\text{sim}(f(x), f(x^+)))}{\exp(\text{sim}(f(x), f(x^+))) + \sum_{j=1}^{N-1} \exp(\text{sim}(f(x), f(x_j)))} \right)$$

x: a sentence, $f(\cdot)$: BERT encoder "[CLS]" + fine-tuning

Unsupervised SimCSE

Positive pairs: embeddings of the **same sentence** with **different dropout masks**

Negative pairs: embeddings of other sentences (in-batch negatives)

Gao et al., 2021. SimCSE: Simple Contrastive Learning of Sentence Embeddings

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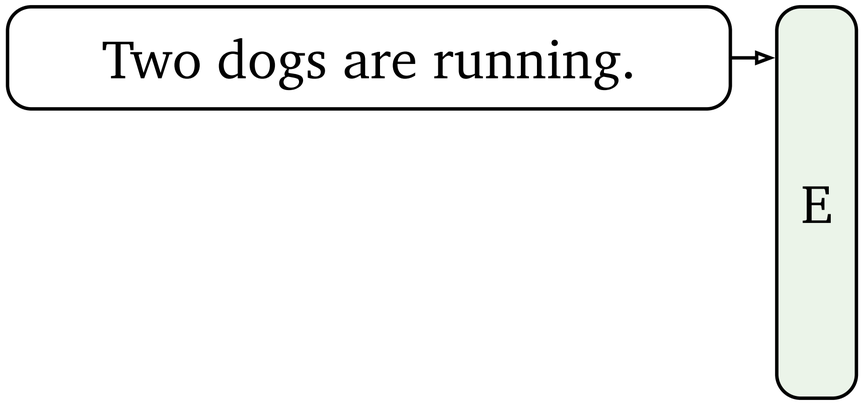

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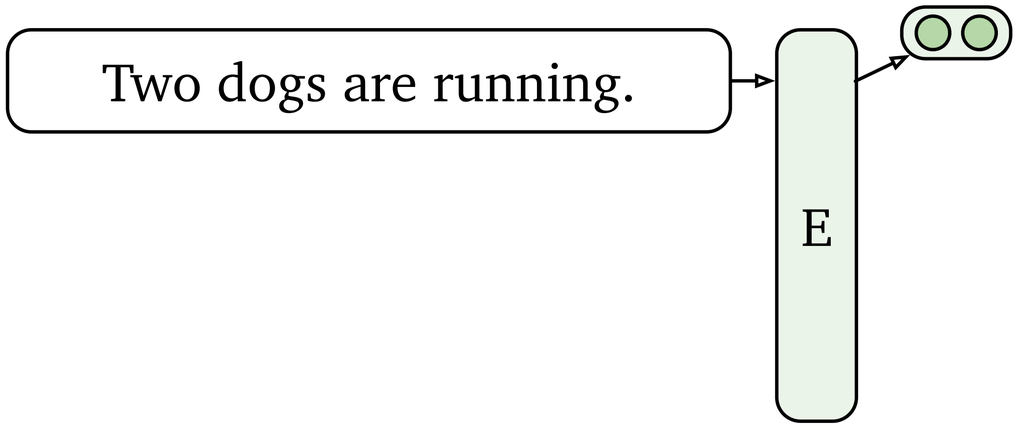

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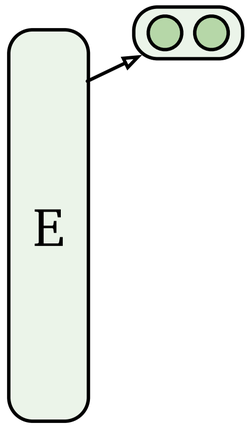

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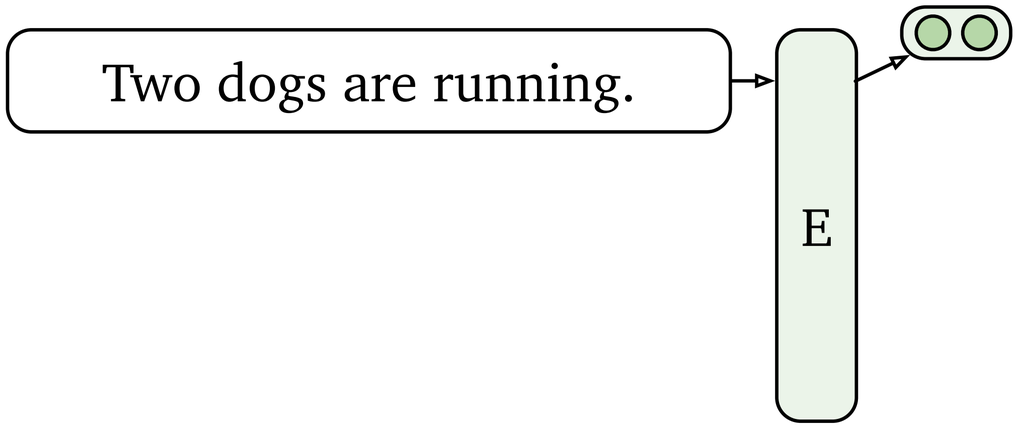

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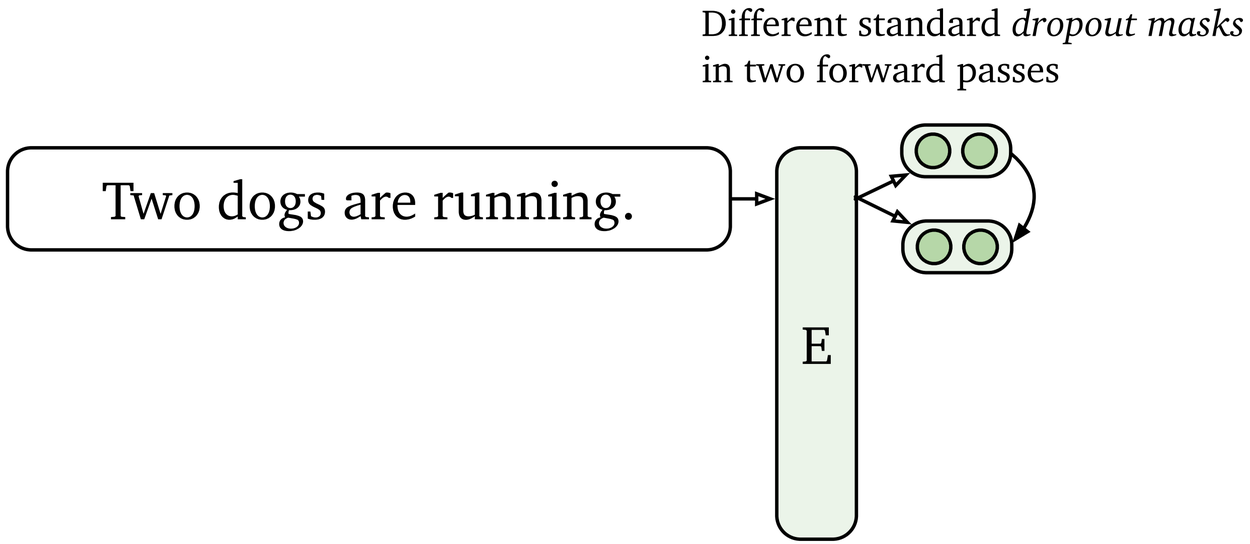

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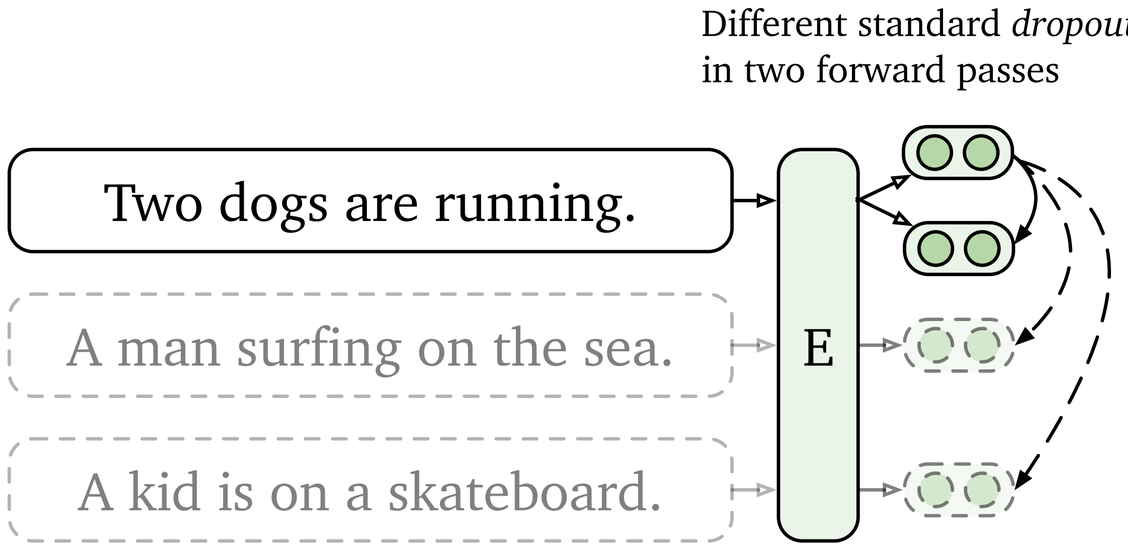

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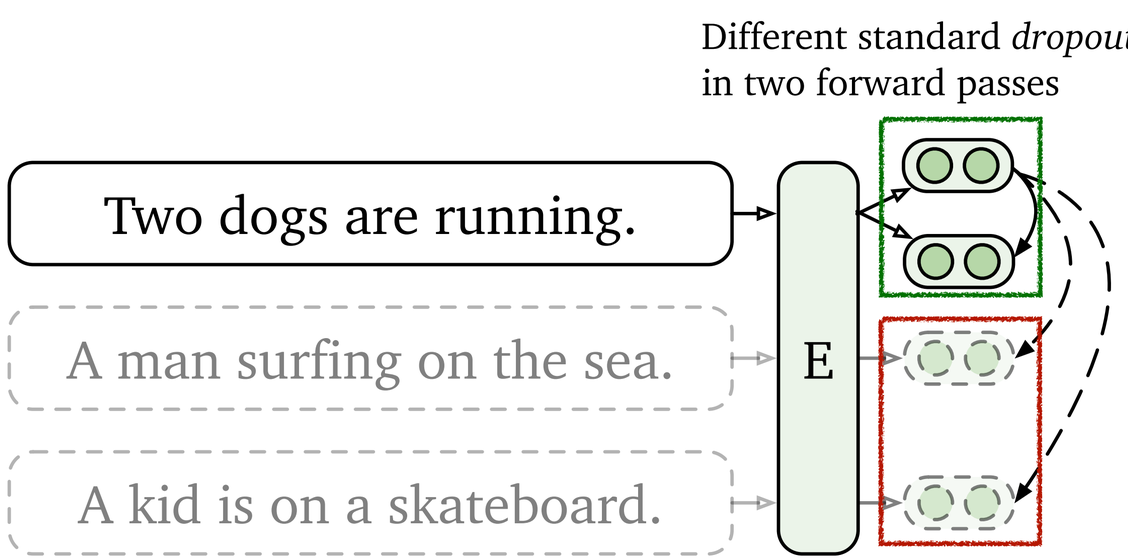


Same sentence with different dropout

$$\ell_i = -\log \frac{e^{\text{sim}(\mathbf{h}_i^{z_i}, \mathbf{h}_i^{z_i'})/\tau}}{\sum_{j=1}^{N} e^{\text{sim}(\mathbf{h}_i^{z_i}, \mathbf{h}_j^{z_j'})/\tau}}$$

sim: cosine similarity

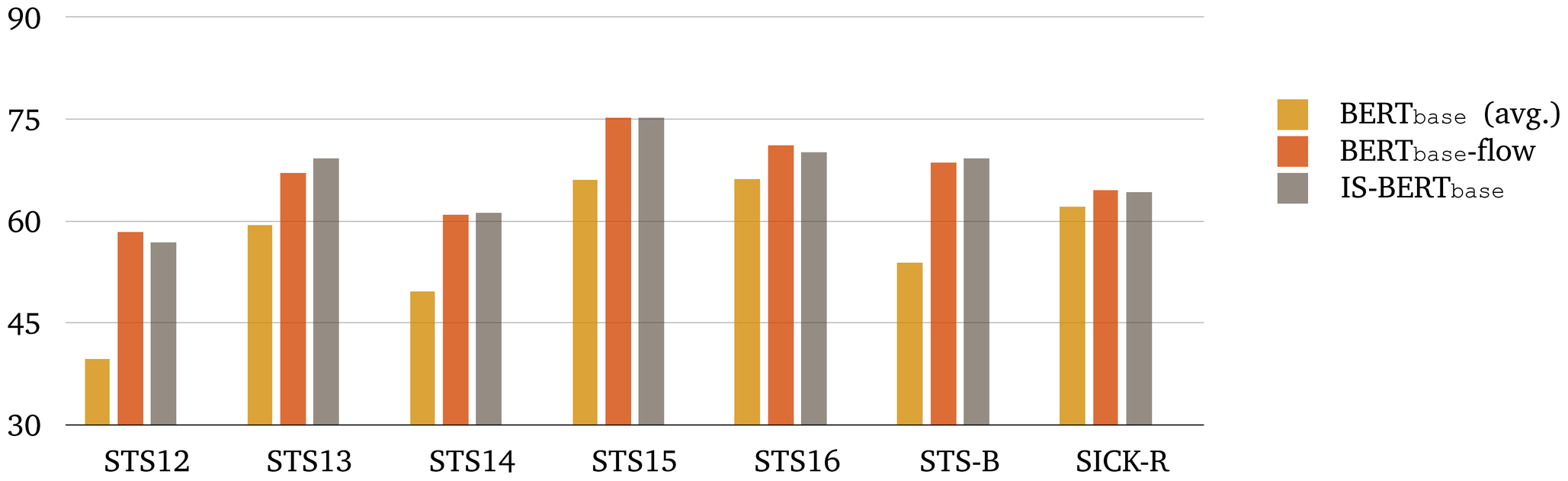
τ: temperature term

In-batch negatives

Gao et al., 2021. SimCSE: Simple Contrastive Learning of Sentence Embeddings

Evaluation on STS tasks

Semantic textual similarity (STS) tasks: Spearman's correlation



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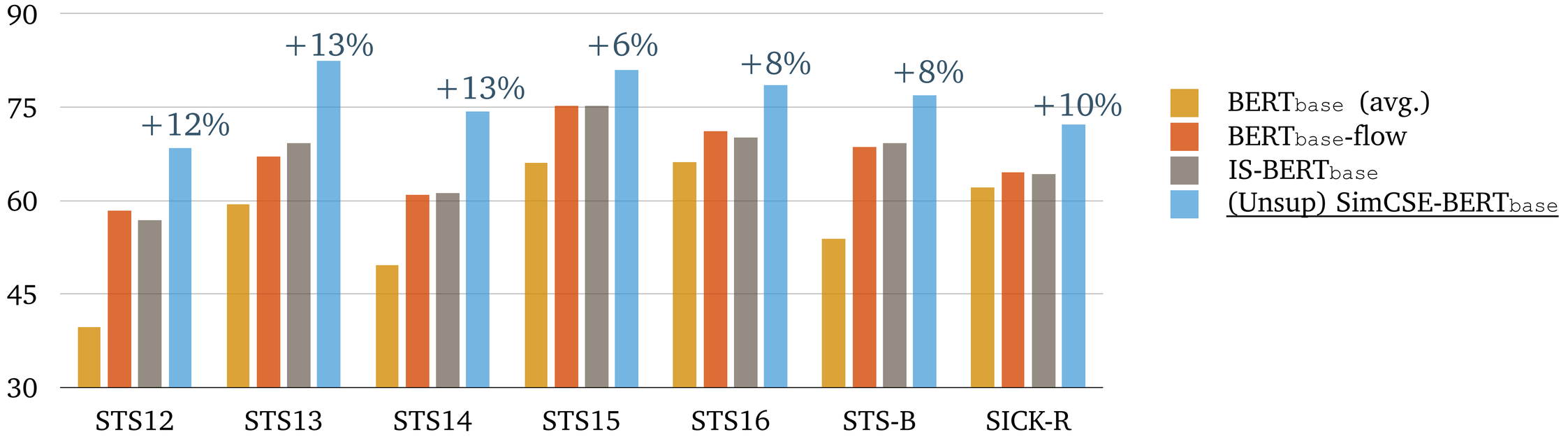

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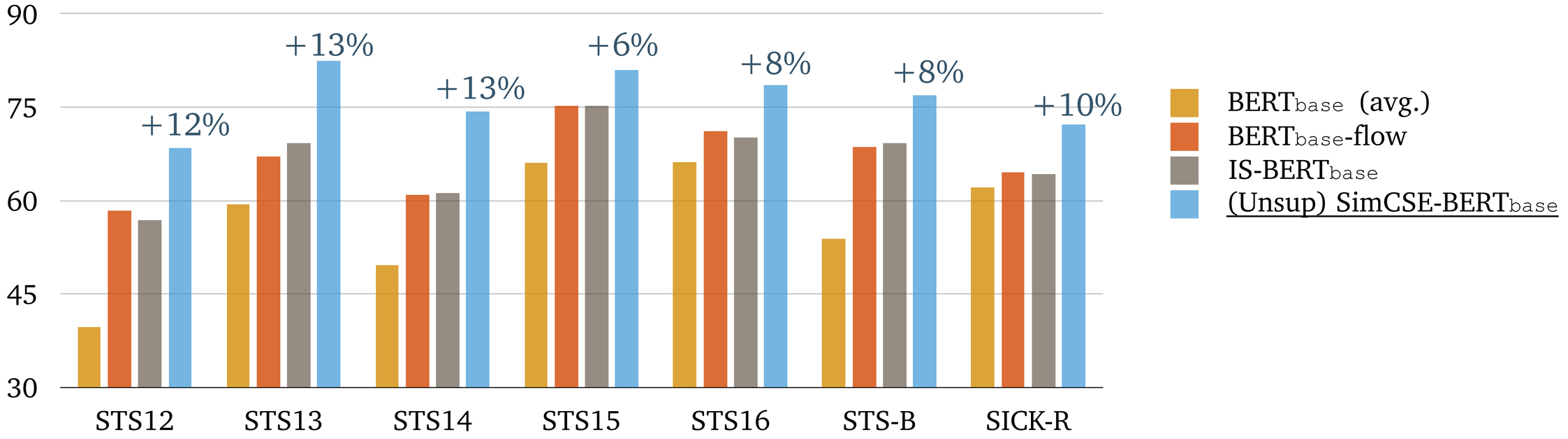

Note: SimCSE is very cheap (batch size = 64, 1 hour on 1 GPU)

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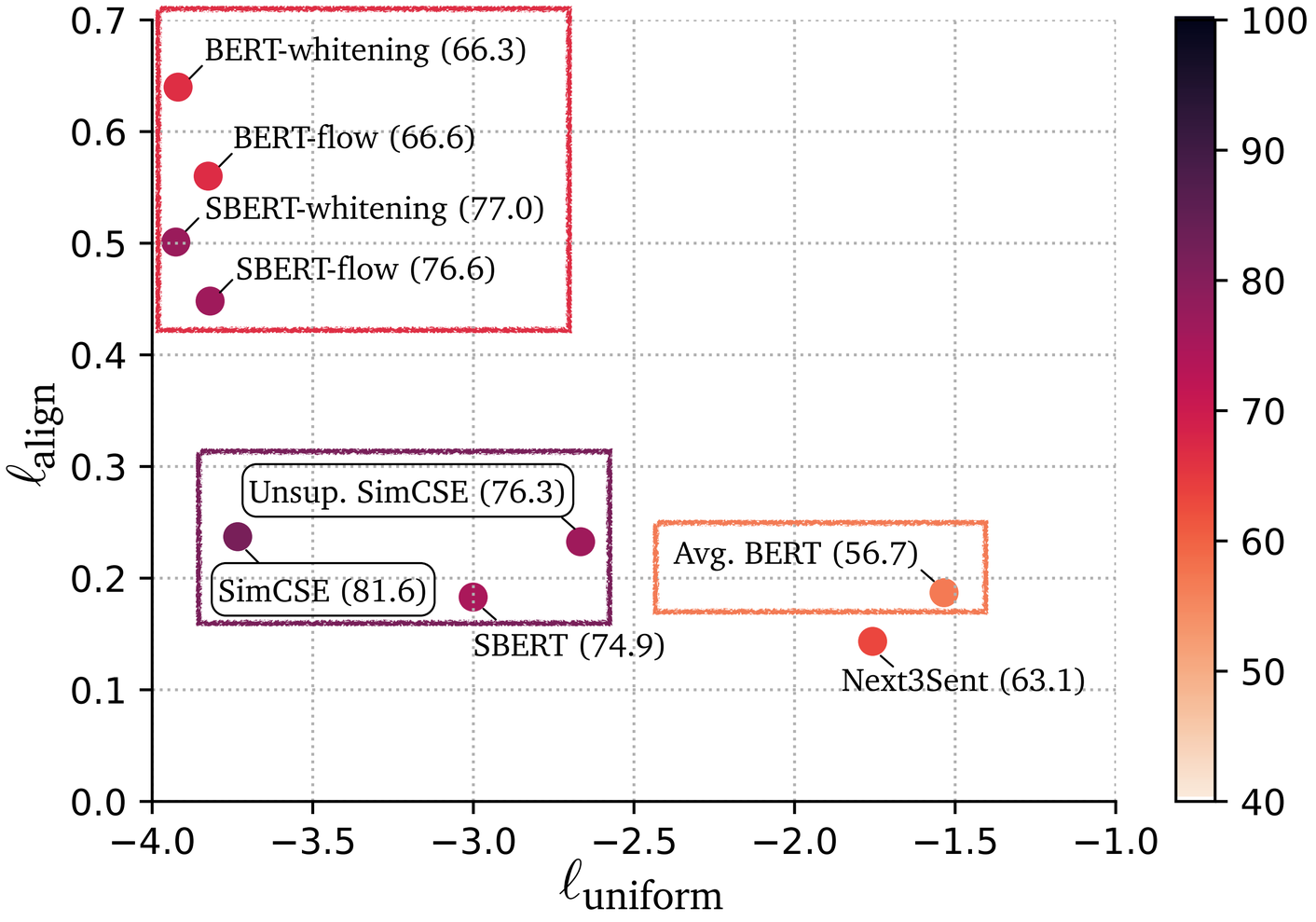
Alignment vs uniformity



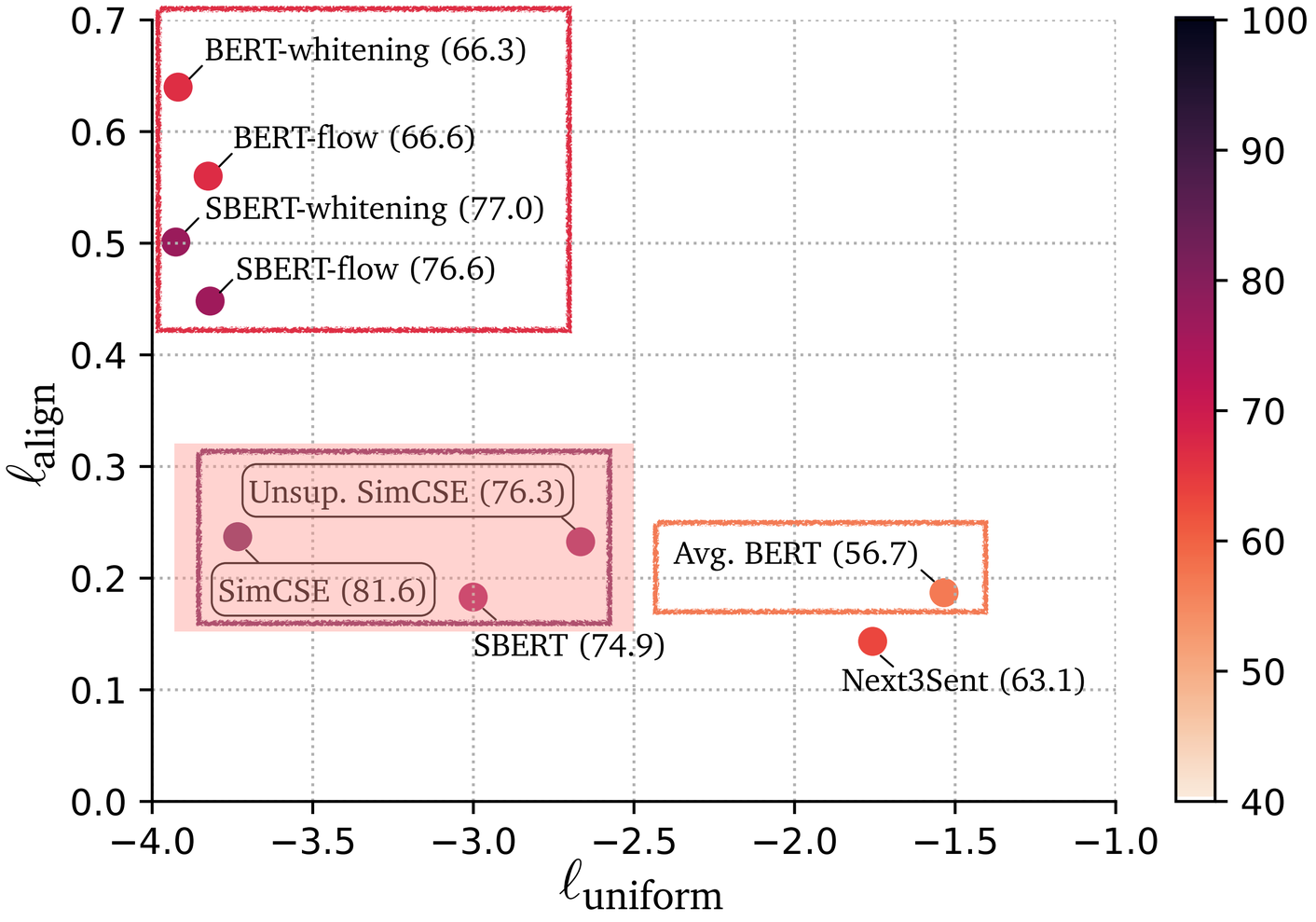
Alignment = how well positive pairs are aligned

Uniformity = how well the embeddings are uniformly distributed

(Wang and Isola, 2020)

$l_{\text{uniform}}, l_{\text{align}}$: the lower, the better

Alignment vs uniformity



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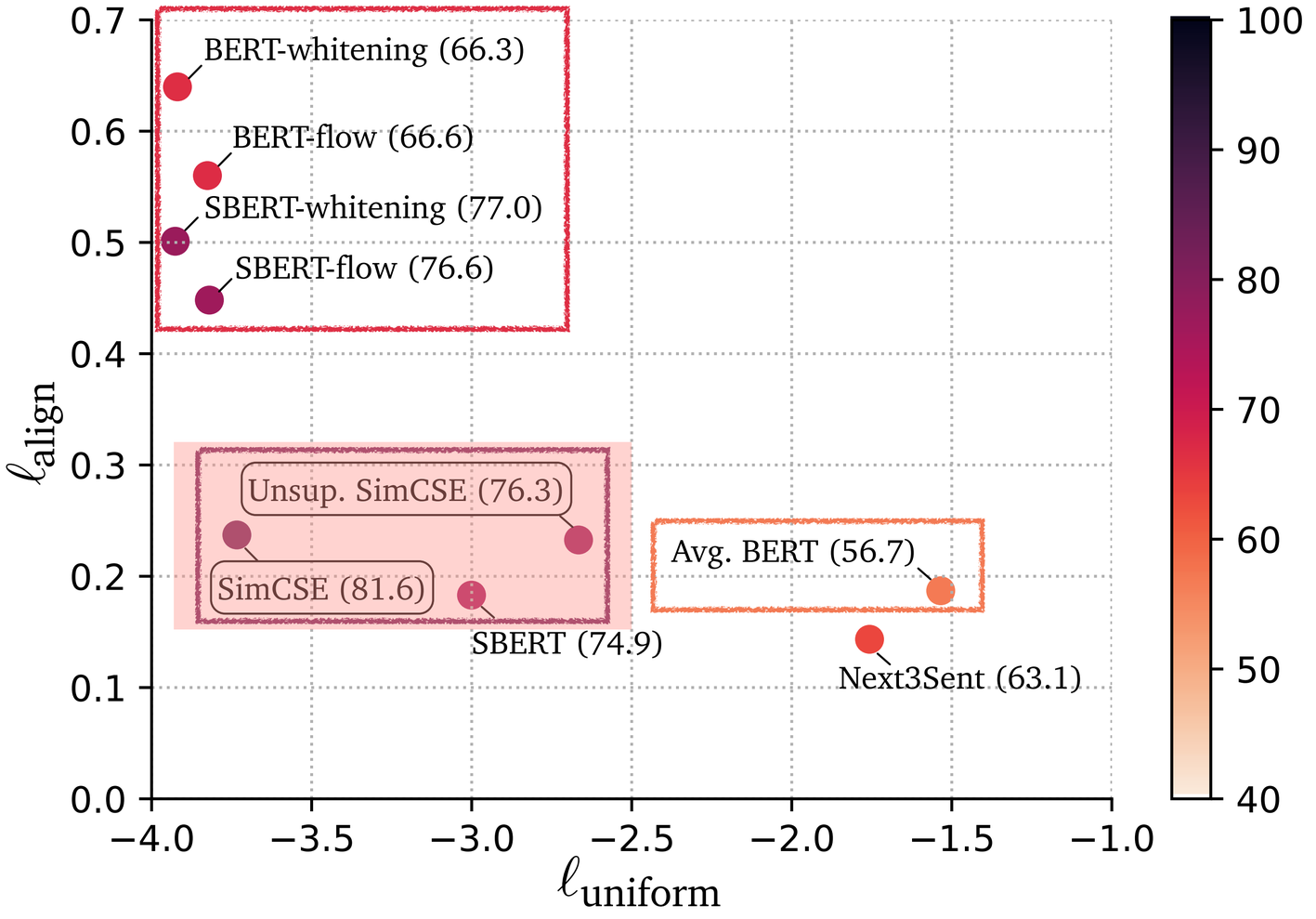

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We also theoretically show that contrastive objective can improve the isotropy by inherently flattening the singular value distribution of the embedding space (see the paper).

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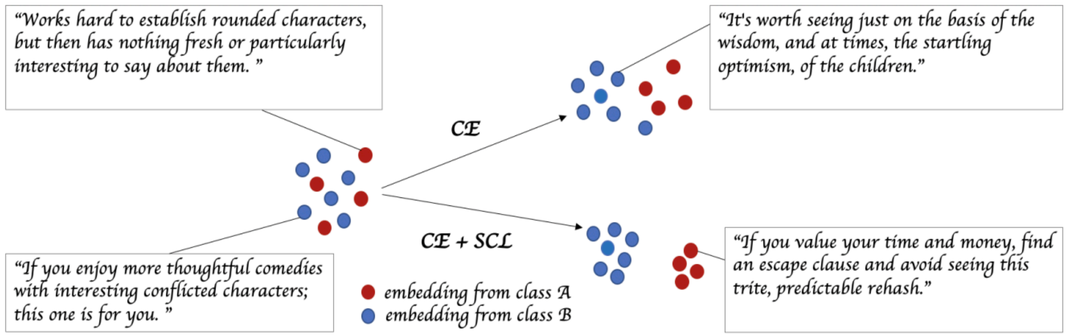
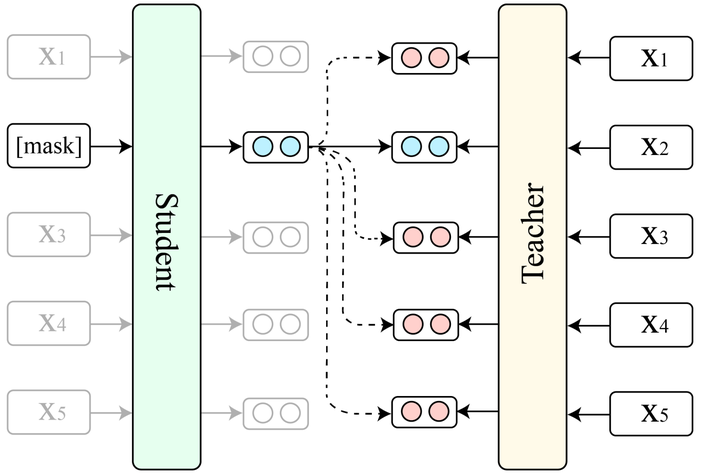


(Gunel et al., 2021): contrastive fine-tuning



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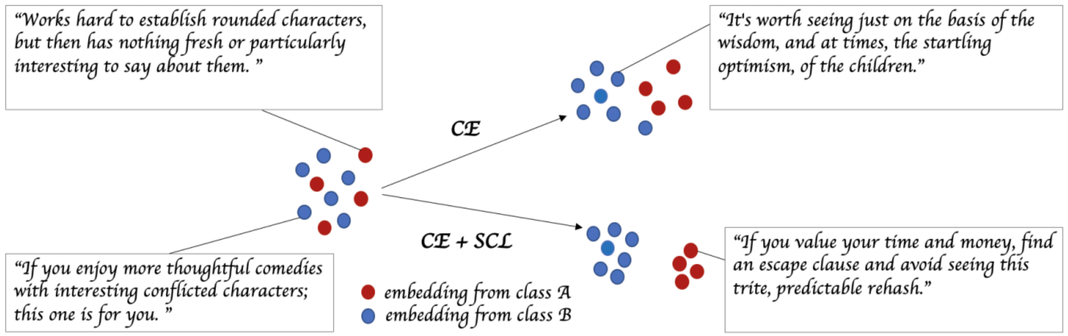

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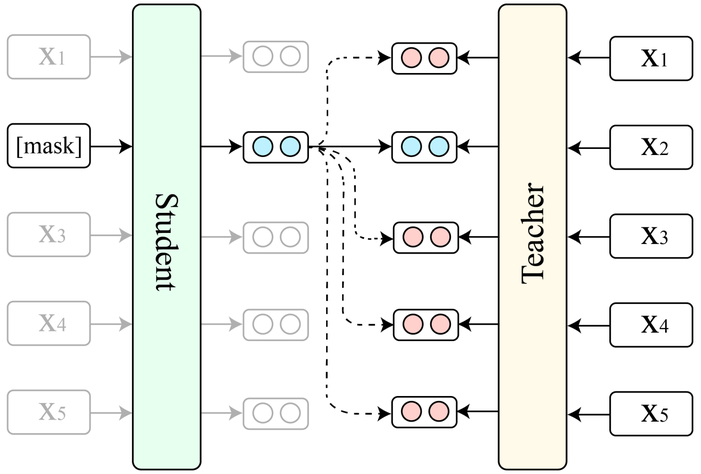

(Su et al., 2021):
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Q: Can we do contrastive pre-training from the scratch?
Would that improve the efficiency of pre-training?

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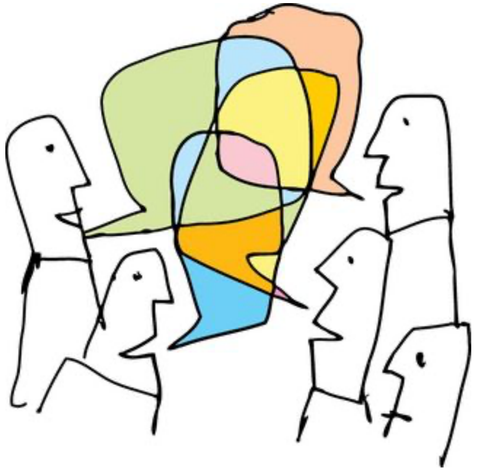

Thanks!

danqic@cs.princeton.edu