2022 AACL-IJCNLP

# Recent Advances in Pre-trained Language Models: Why Do They Work and How to Use Them


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# Recent Advances in **Pre-trained Language Models: Why Do They Work** and How to Use Them

17:00 – 17:10 **Part 1** Introduction

17:10 – 17:40 **Part 2** Why do PLMs work

Link to slides


Hung-yi Lee

**National Taiwan University**


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# Recent Advances in Pre-trained Language Models: Why Do They Work and **How To Use Them**

17:40 – 18:20

**Part 3** How to Use PLMs: Contrastive learning for Pre-trained Language Models

Yung-Sung Chuang
**CSAIL,MIT**

Link to slides

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# Recent Advances in Pre-trained Language Models: Why Do They Work and **How to Use Them**

18:40 – 19:50 **Part 4 + 5** How to Use PLMs: New fine-tuning methods

Cheng-Han Chiang
**National Taiwan University**

Link to slides

# Schedule

| | |
|---|---|
| 17:00 – 17:10 | **Part 1** Introduction [Hung-yi] |
| 17:10 – 17:40 | **Part 2** Why do PLMs work [Hung-yi] |
| 17:40 – 18:20 | **Part 3** How to use PLMs: Contrastive Learning for PLMs [Yung-Sung] |
| 18:20 – 18:30 | Q&A for Part 1+2+3 |
| 18:30 – 18:40 | Break |
| 18:40 – 19:05 | **Part 4** How to use PLMs: Parameter-efficient fine-tuning [Cheng-Han] |
| 19:05 – 19:50 | **Part 5** How to use PLMs: Using PLMs with different amounts of data [Cheng-Han] |
| 19:50 – 20:00 | Conclusion and Future work + Q&A |

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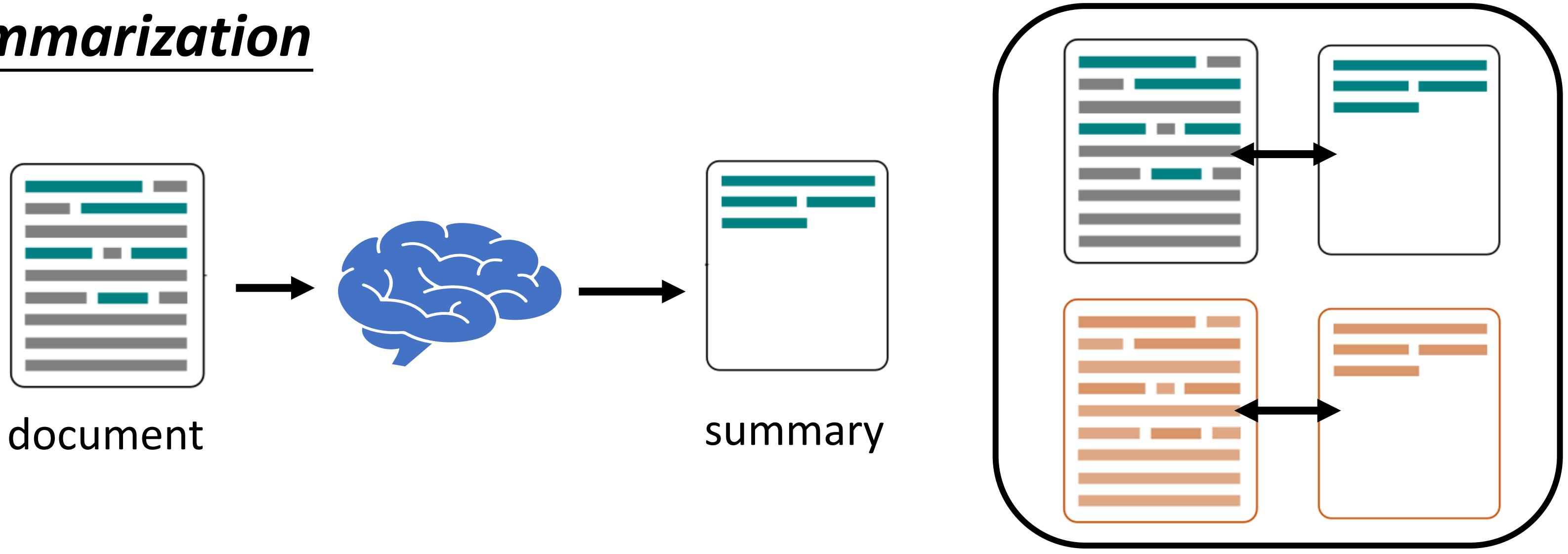
# Part 1:
# Introduction

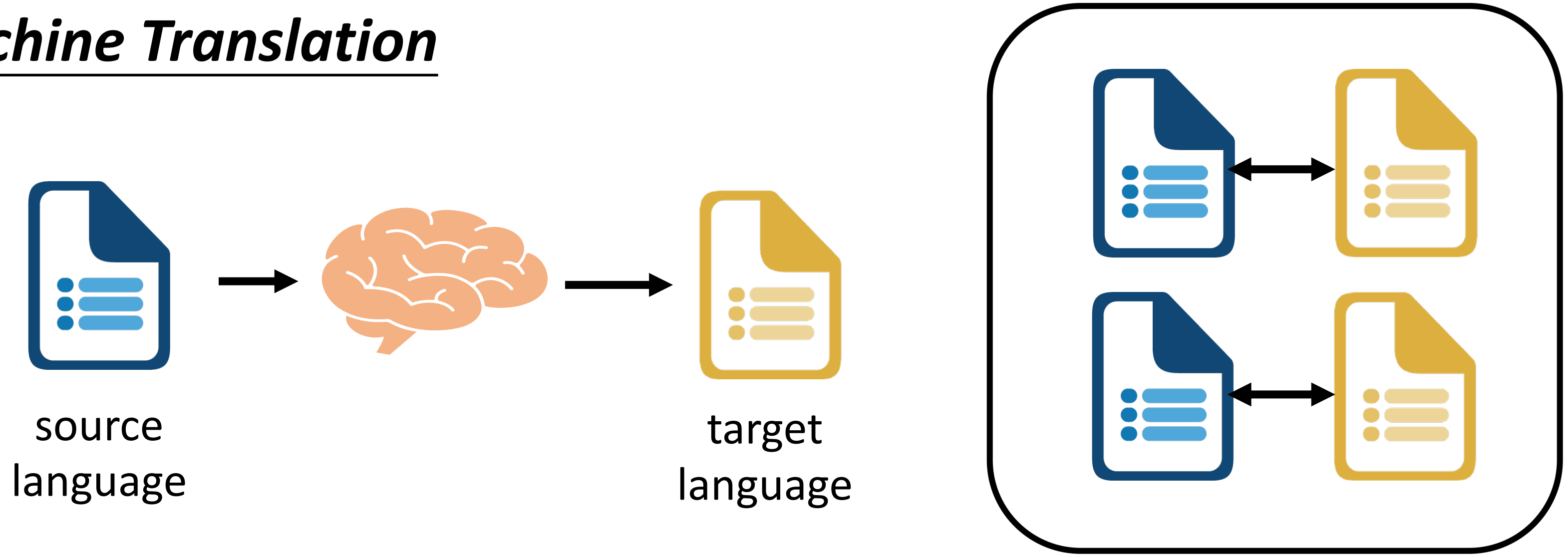
Hung-yi Lee
**National Taiwan University**

# Deep Learning for Human Language Processing

## Summarization




## Machine Translation



# ***So many different tasks ……***

https://youtu.be/tFBrqPPxWzE

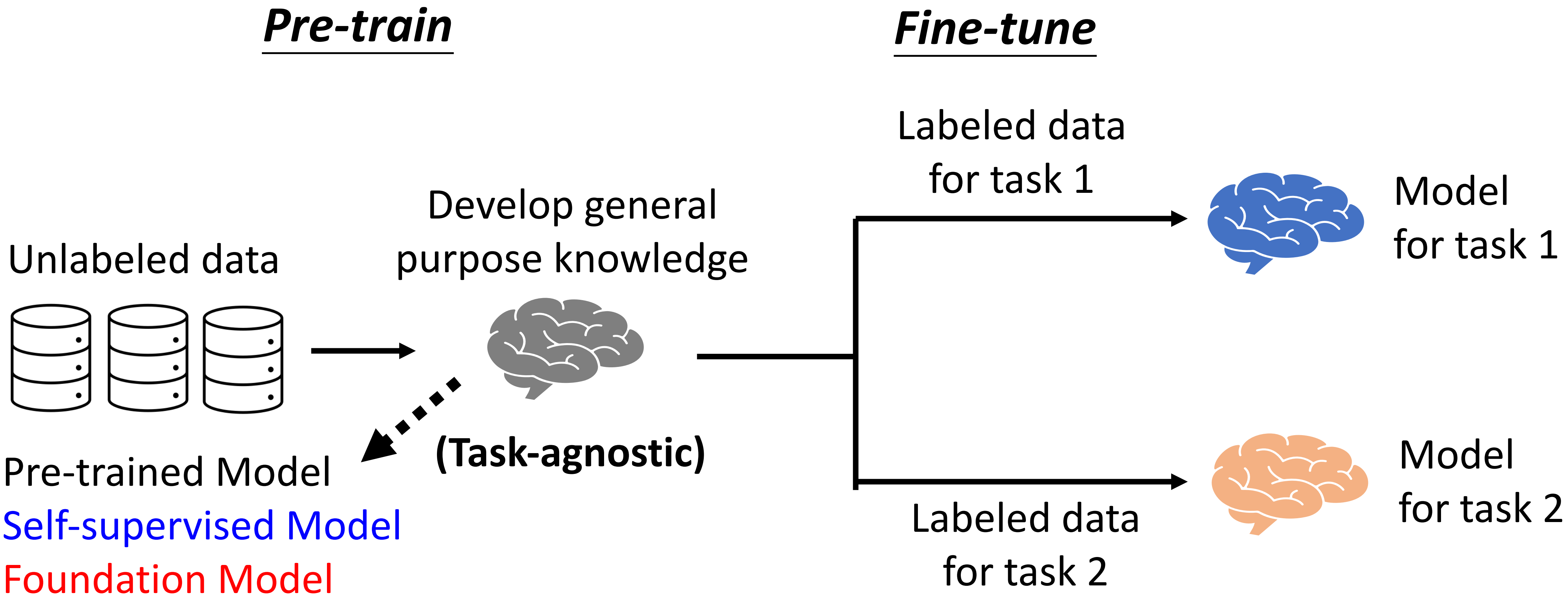
Speech Recognition
Speaker Recognition
Text-to-Speech (TTS)
Denoising
Speech Separation
Voice Conversion (VC)
Spoken Term Detection (STD)
Speech Question Answering
Speech Translation
Spoken Language Understanding
……

Coreference Resolution
Syntactic Parsing
Semantic Parsing
Chatbot
Summarization
Text Style Transfer
Retrieval
Question Answering
Text Translation
Dialogue State Tracking
……

# ***So many languages ……***


There are around 7,000 languages in the world.

# Framework of Pre-training



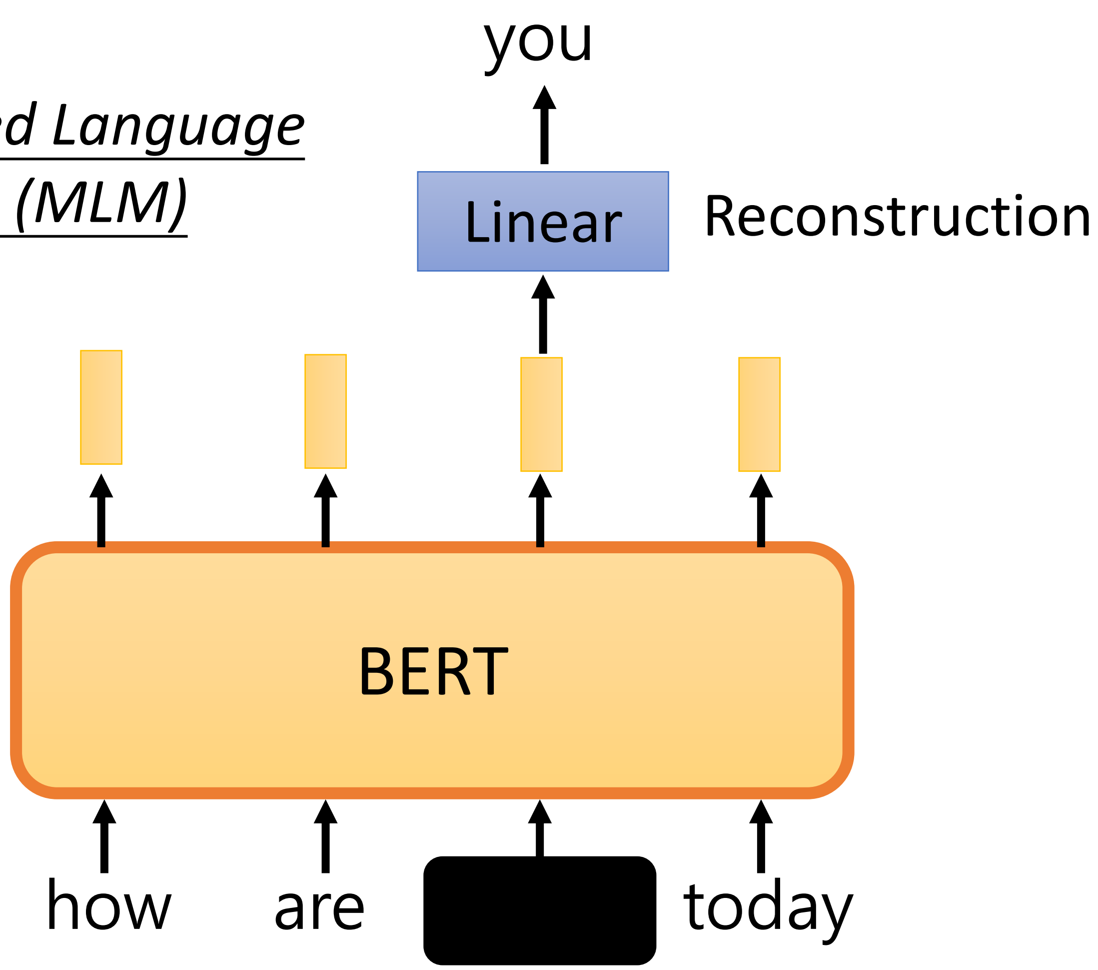
# Pre-training for NLP

***Pre-train***

Unlabeled text data

BERT

*Masked Language Model (MLM)*



# This is not a complete survey!

**Pre-train, Prompt, and Predict: A Systematic Survey of Prompting Methods in Natural Language Processing**

Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, Graham Neubig

https://arxiv.org/abs/2107.13586

**A Primer in BERTology: What we know about how BERT works**

Anna Rogers, Olga Kovaleva, Anna Rumshisky

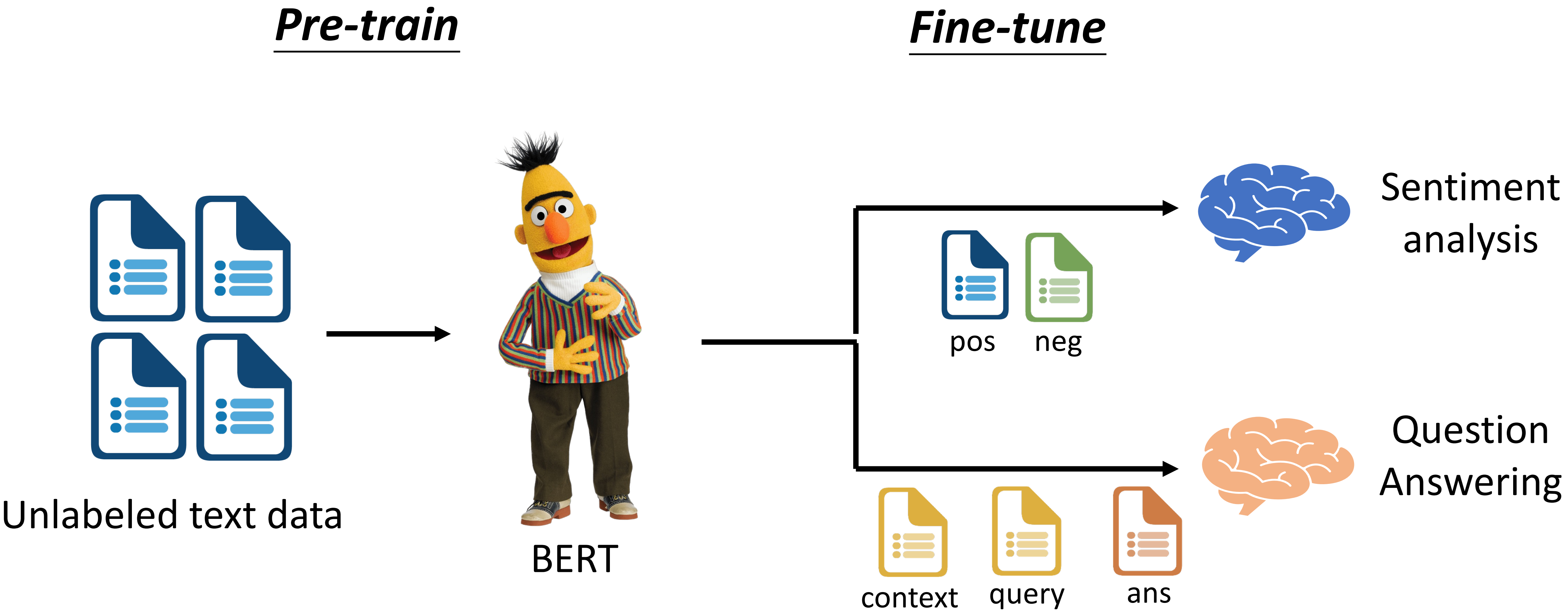
https://arxiv.org/abs/2002.12327

**Pre-trained Models for Natural Language Processing: A Survey**

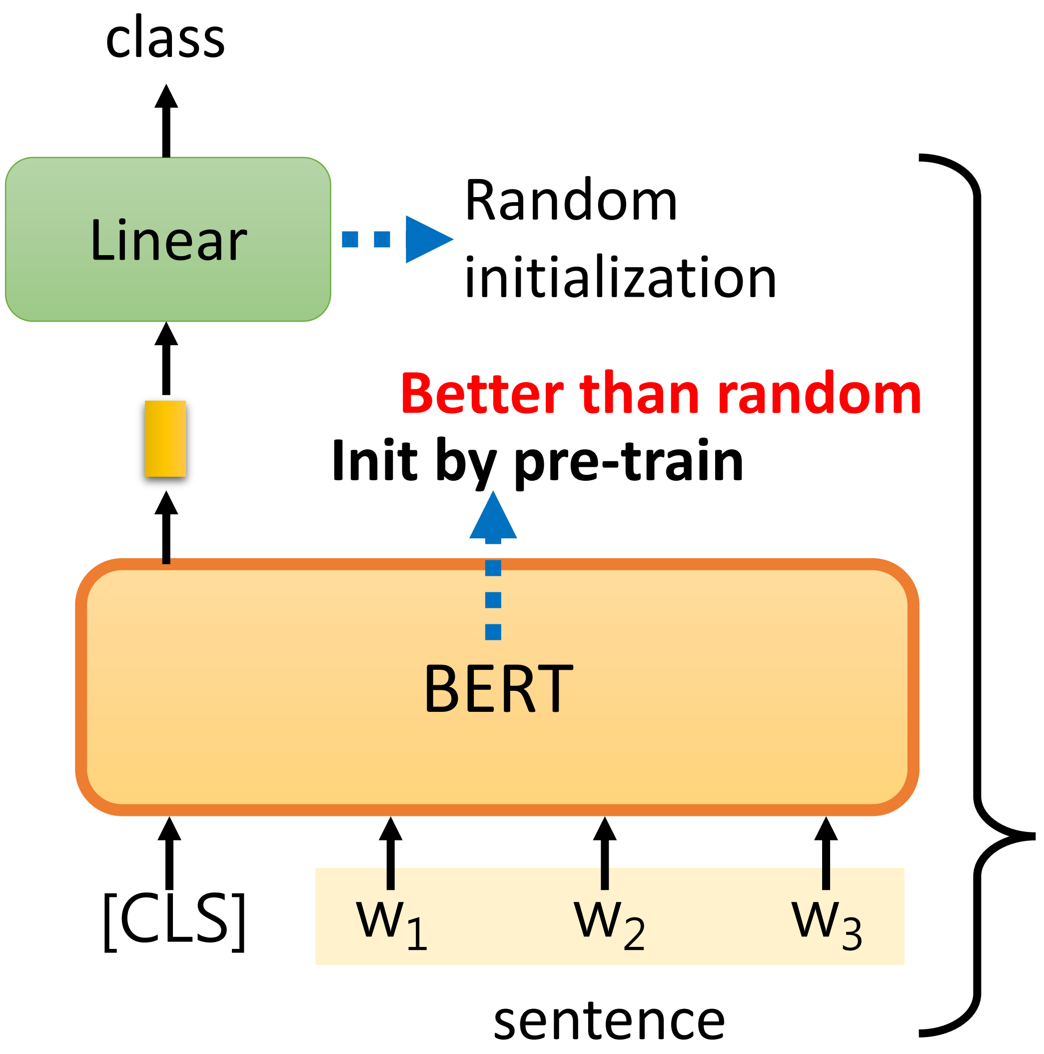
Xipeng Qiu, Tianxiang Sun, Yige Xu, Yunfan Shao, Ning Dai, Xuanjing Huang

https://arxiv.org/abs/2003.08271

# Pre-training for NLP

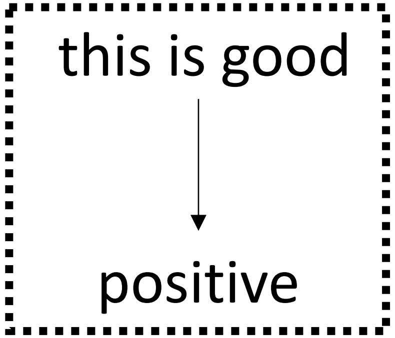


# Pre-training for NLP - Fine-tune (Example)




Input: sequence
output: class

Example:
Sentiment analysis




This is the model to be learned.

# Pre-training for NLP

## General Language Understanding Evaluation (GLUE)

https://gluebenchmark.com/

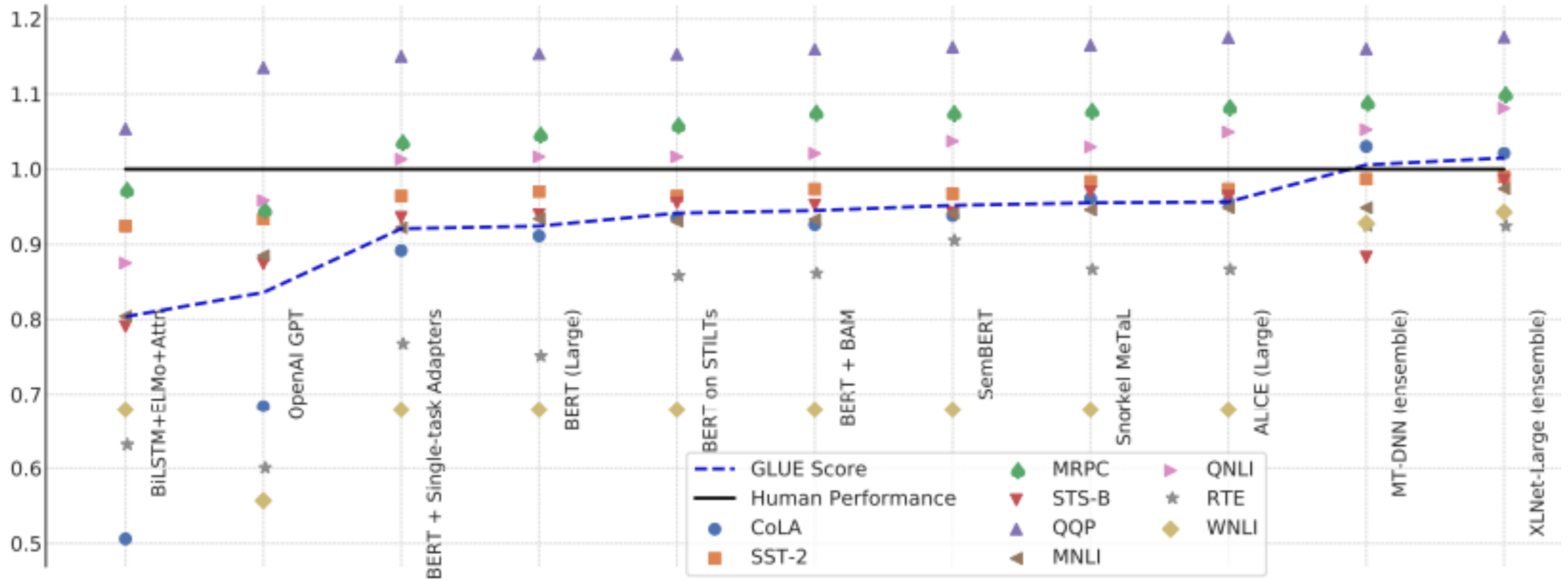
GLUE

- Corpus of Linguistic Acceptability (CoLA)
- Stanford Sentiment Treebank (SST-2)
- Microsoft Research Paraphrase Corpus (MRPC)
- Quora Question Pairs (QQP)
- Semantic Textual Similarity Benchmark (STS-B)
- Multi-Genre Natural Language Inference (MNLI)
- Question-answering NLI (QNLI)
- Recognizing Textual Entailment (RTE)
- Winograd NLI (WNLI)

Source of image: https://arxiv.org/abs/1905.00537

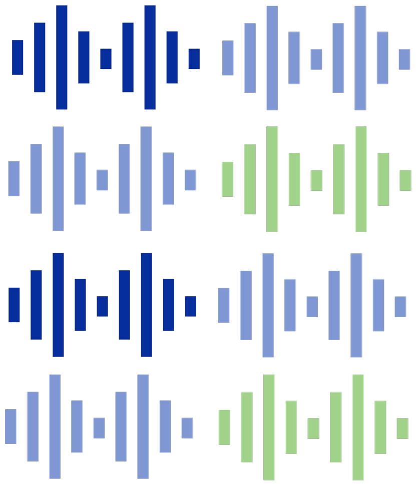
# Pre-training for NLP

- GLUE scores



# Pre-training for Speech

***Pre-train***



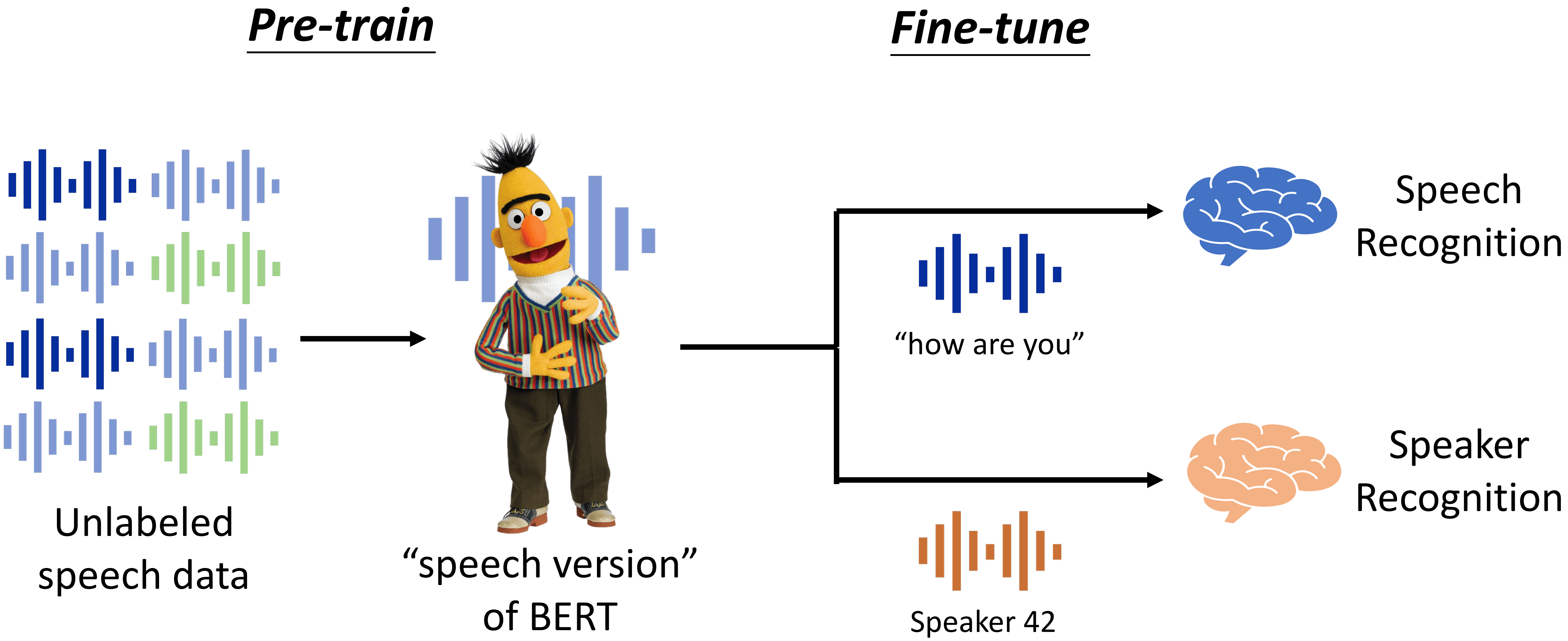
Unlabeled
speech data

"speech version"
of BERT

| | | |
|---|---|---|
| PASE+ | APC | NPC |
| Tera | DeCoAR | Wav2vec |
| HuBERT | WavLM | |

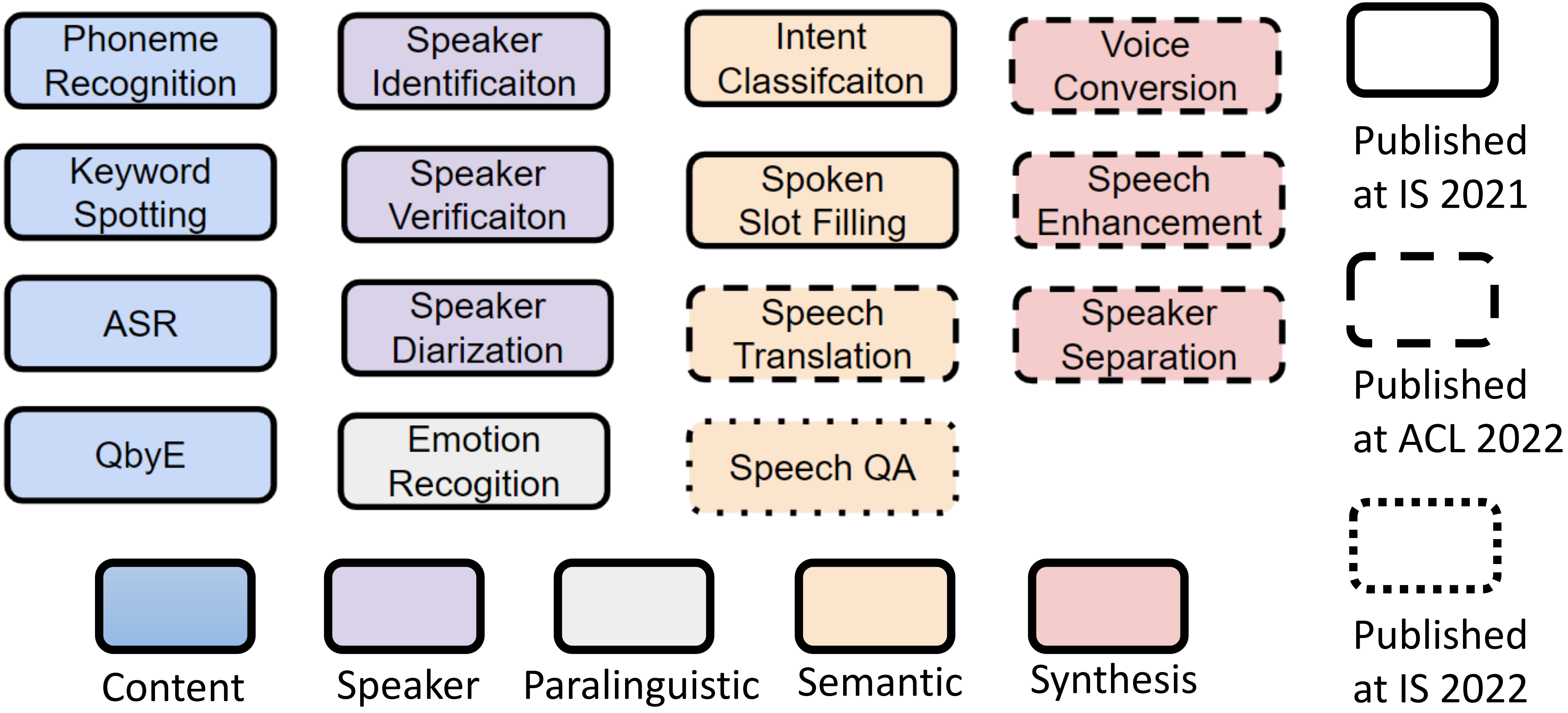
Just name a few ...

# Pre-training for Speech



# Speech processing Universal PERformance Benchmark (SUPERB)

https://superbbenchmark.org/



## SUPERB: Speech processing Universal PERformance Benchmark

*Shu-wen Yang[1], Po-Han Chi[1*], Yung-Sung Chuang[1*], Cheng-I Jeff Lai[2*], Kushal Lakhotia[3*], Yist Y. Lin[1*], Andy T. Liu[1*], Jiatong Shi[4*], Xuankai Chang[6], Guan-Ting Lin[1], Tzu-Hsien Huang[1], Wei-Cheng Tseng[1], Ko-tik Lee[1], Da-Rong Liu[1], Zili Huang[4], Shuyan Dong[5†], Shang-Wen Li[5†], Shinji Watanabe[6], Abdelrahman Mohamed[3], Hung-yi Lee[1]*

Presented at INTERSPEECH 2021

https://arxiv.org/abs/2105.01051

## SUPERB-SG: Enhanced Speech processing Universal PERformance Benchmark for Semantic and Generative Capabilities

**Hsiang-Sheng Tsai[1*], Heng-Jui Chang[1*], Wen-Chin Huang[2*], Zili Huang[3*], Kushal Lakhotia[4*], Shu-wen Yang[1], Shuyan Dong[5], Andy T. Liu[1], Cheng-I Lai[6], Jiatong Shi[7], Xuankai Chang[7], Phil Hall[8], Hsuan-Jui Chen[1], Shang-Wen Li[5], Shinji Watanabe[7], Abdelrahman Mohamed[5], Hung-yi Lee[1]**

Presented at ACL 2022

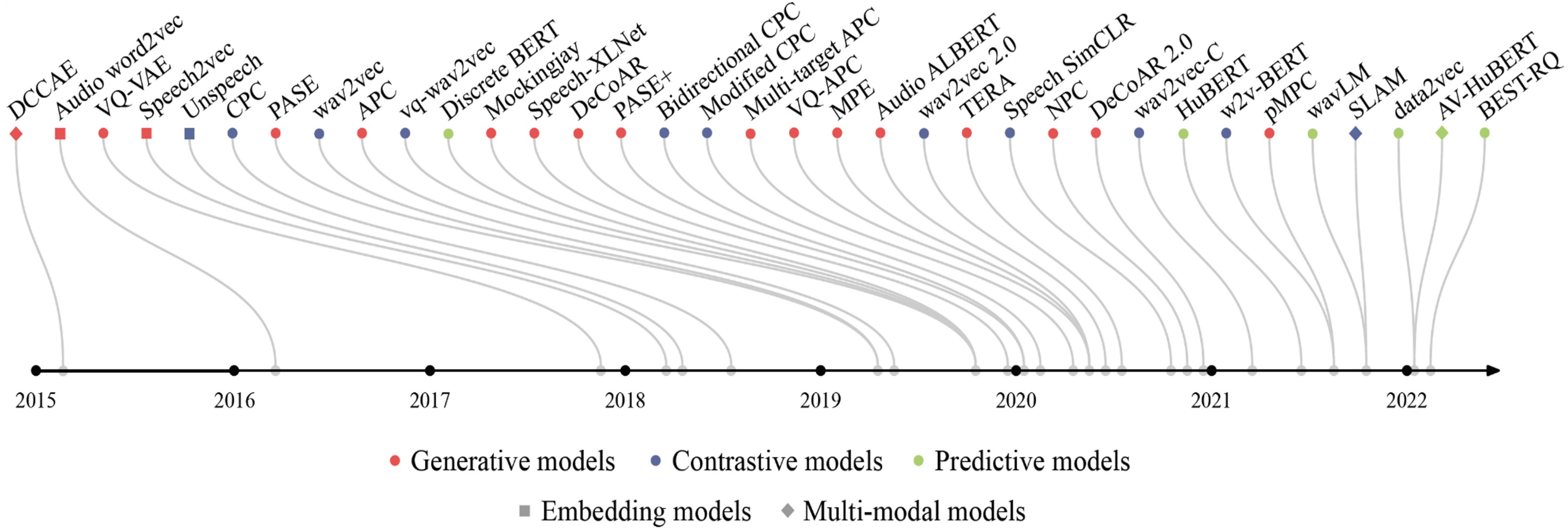
https://arxiv.org/abs/2203.06849

https://youtu.be/GTjwYzFG54E

# Self-Supervised Speech Representation Learning: A Review

Abdelrahman Mohamed*, Hung-yi Lee*, Lasse Borgholt*, Jakob D. Havtorn*, Joakim Edin, Christian Igel
Katrin Kirchhoff, Shang-Wen Li, Karen Livescu, Lars Maaløe, Tara N. Sainath, Shinji Watanabe

https://arxiv.org/abs/2205.10643



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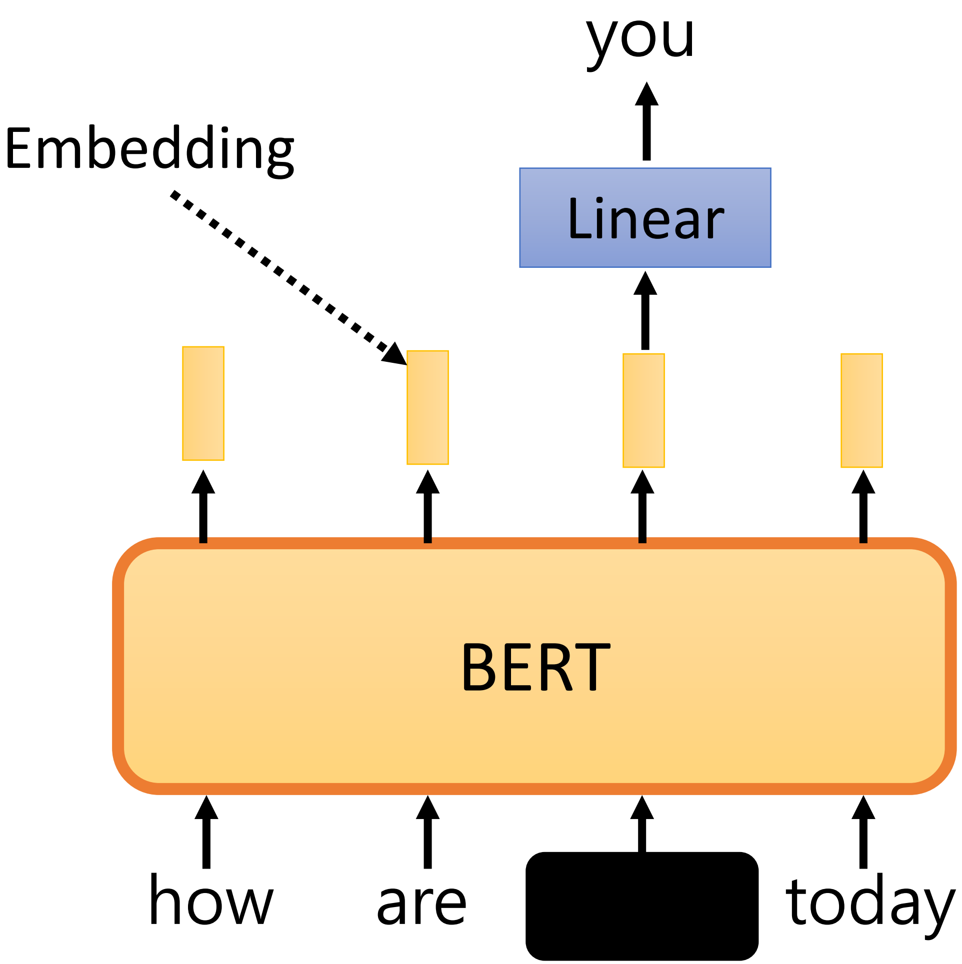
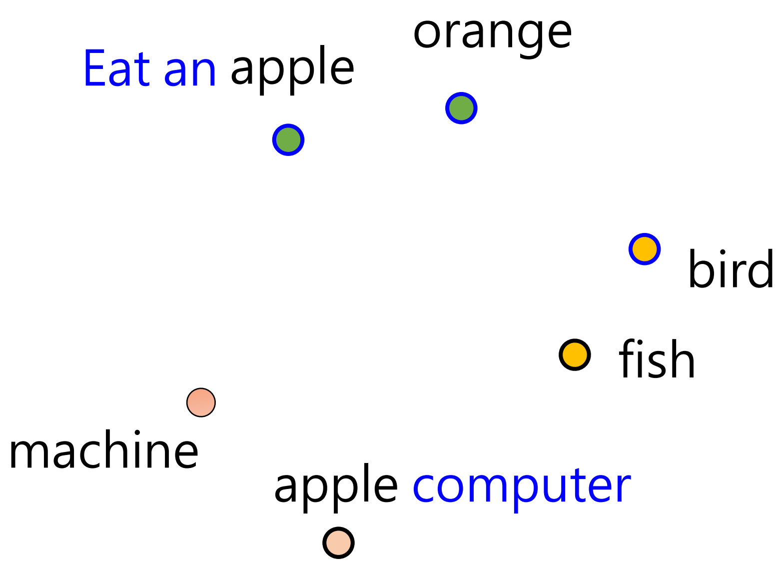
# Part 2:
# Why do PLMs work

Hung-yi Lee
**National Taiwan University**

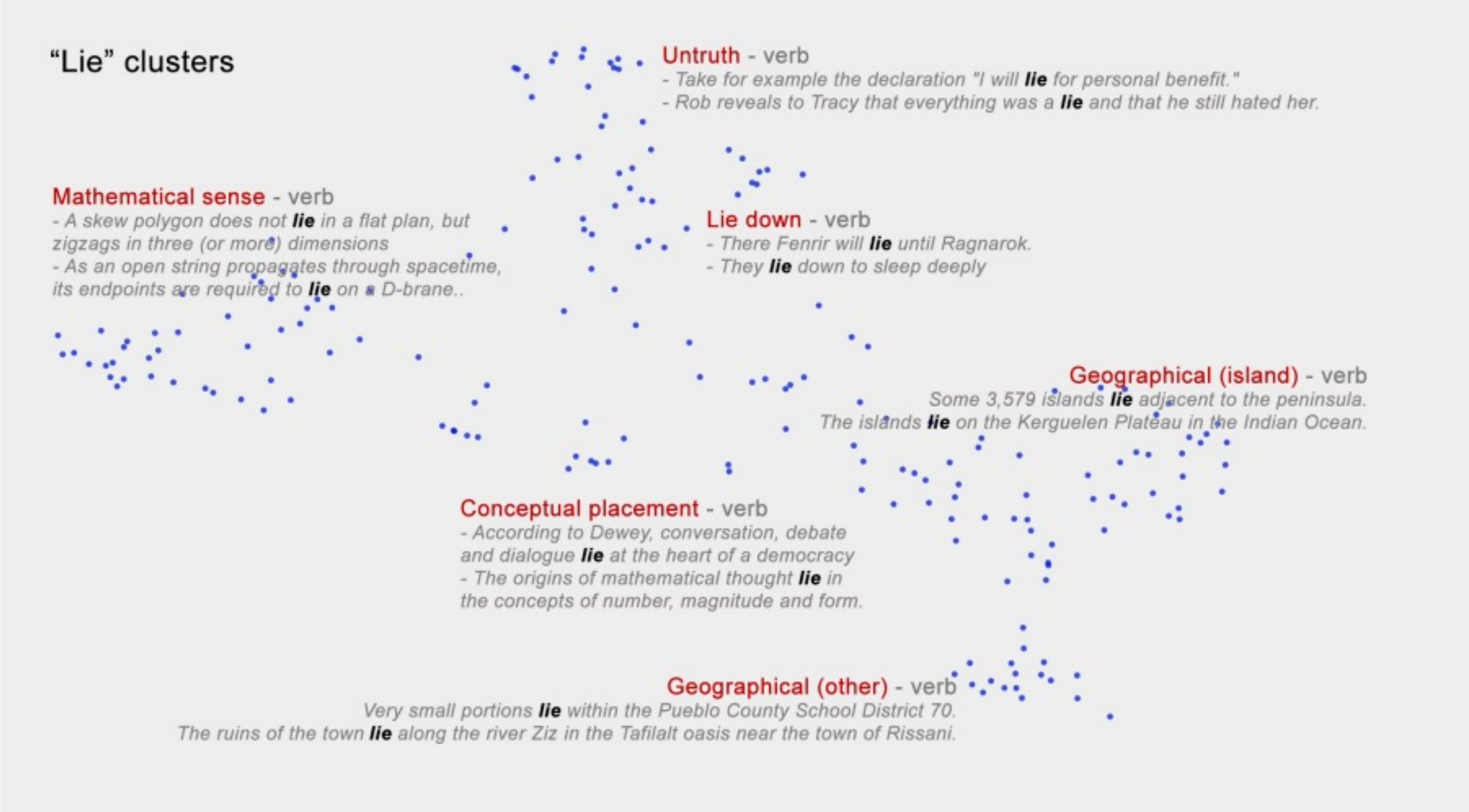
# Contextualized Word Representations




The tokens with similar meaning have similar embedding.

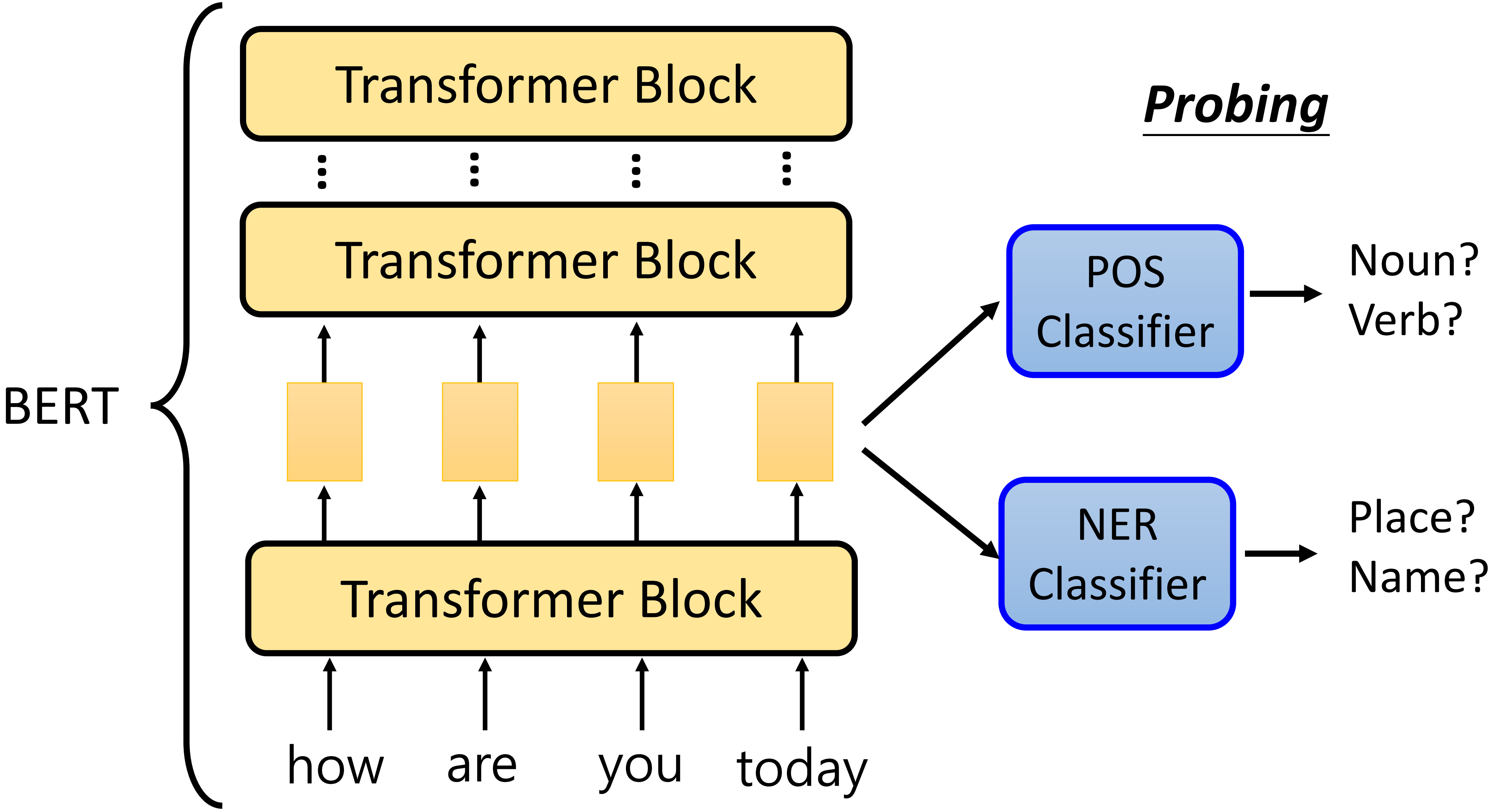



**Context is considered.**




Andy Coenen, Emily Reif, Ann Yuan, Been Kim, Adam Pearce, Fernanda Viégas, Martin Wattenberg, Visualizing and Measuring the Geometry of BERT, NeurIPS, 2019

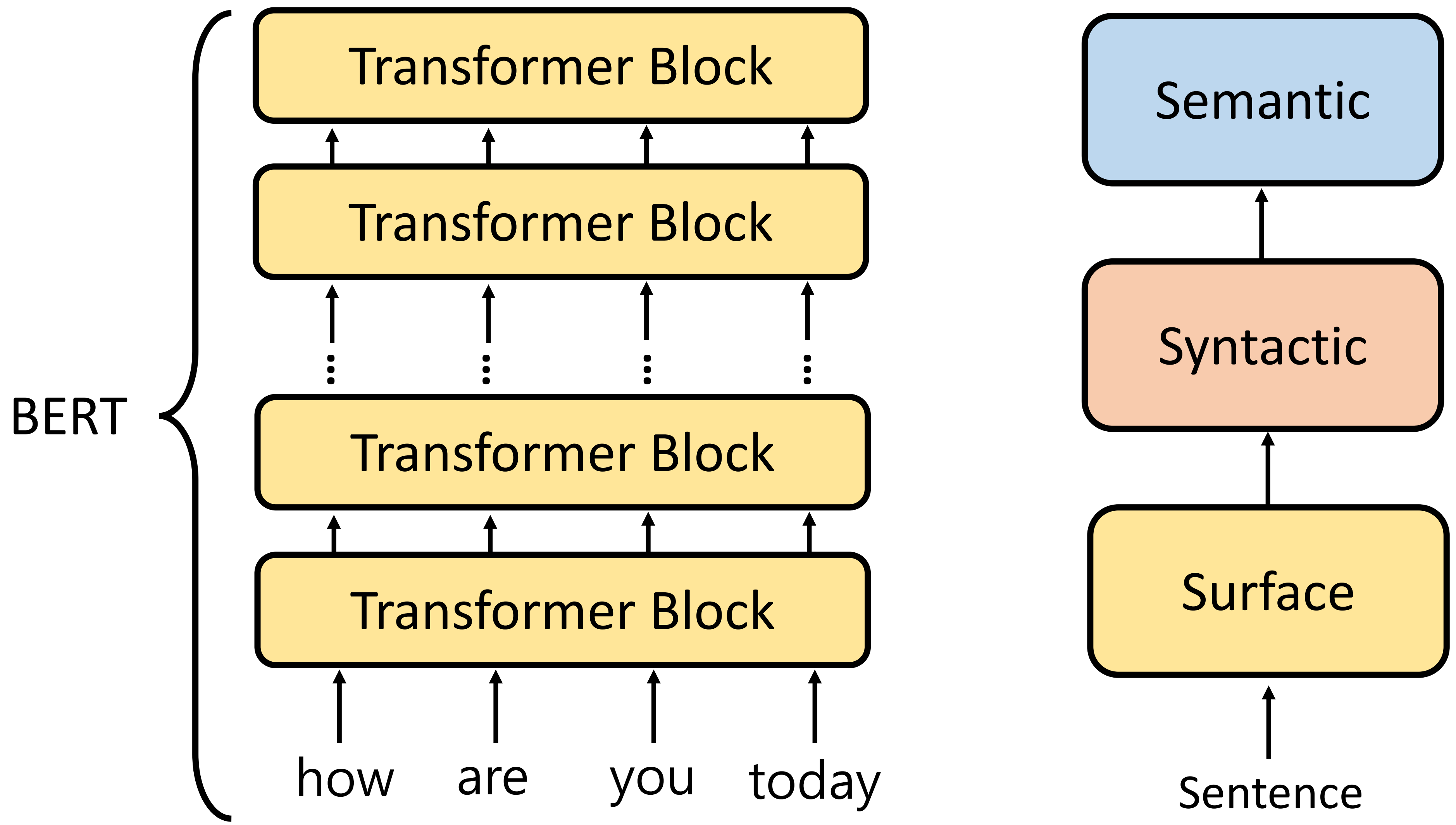
# BERTology - What does each layer learn?



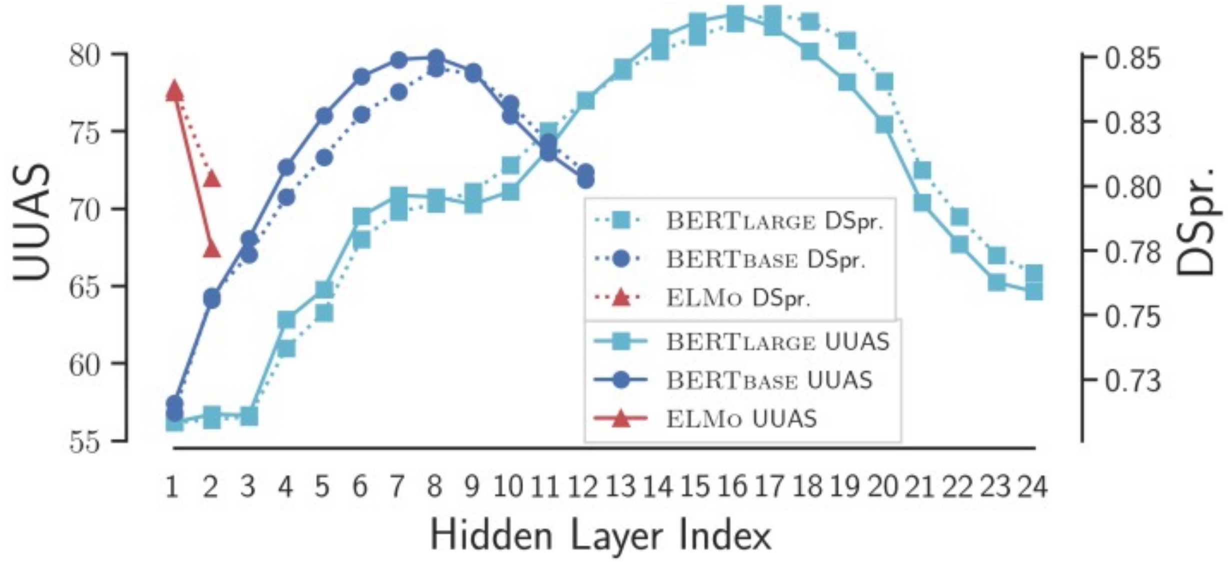
# BERTology - What does each layer learn?

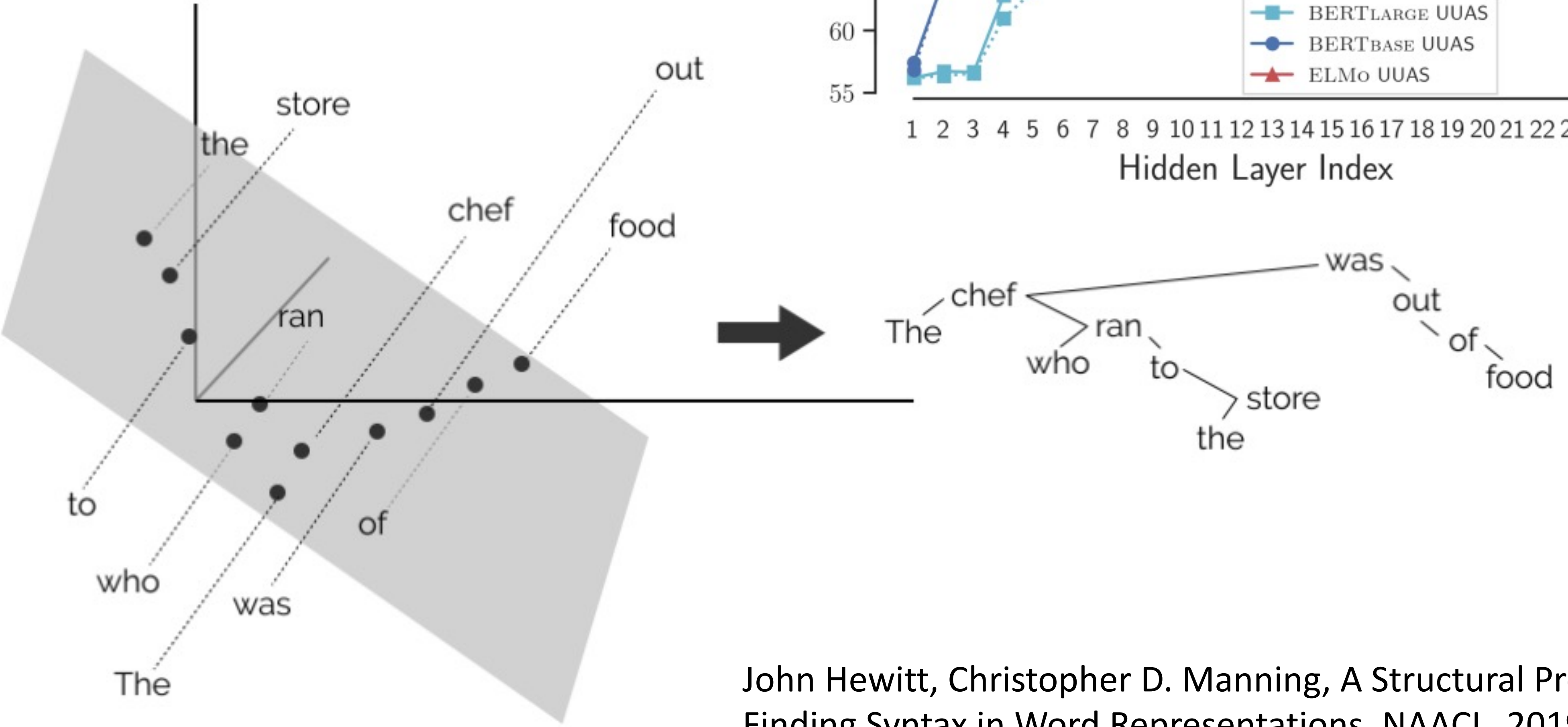
- Higher classifier accuracy does not always mean encoding more information.
- Interpret the prob results with care ☺
  - John Hewitt, Percy Liang, Designing and Interpreting Probes with Control Tasks, EMNLP, 2019
  - Elena Voita, Ivan Titov, Information-Theoretic Probing with Minimum Description Length, EMNLP, 2020
  - John Hewitt, Kawin Ethayarajh, Percy Liang, Christopher Manning, Conditional probing: measuring usable information beyond a baseline, ENMLP, 2021
  - Jiaoda Li, Ryan Cotterell, Mrinmaya Sachan, Probing via Prompting, NAACL, 2022

# BERTology - What does each layer learn?



# Encoding Syntax



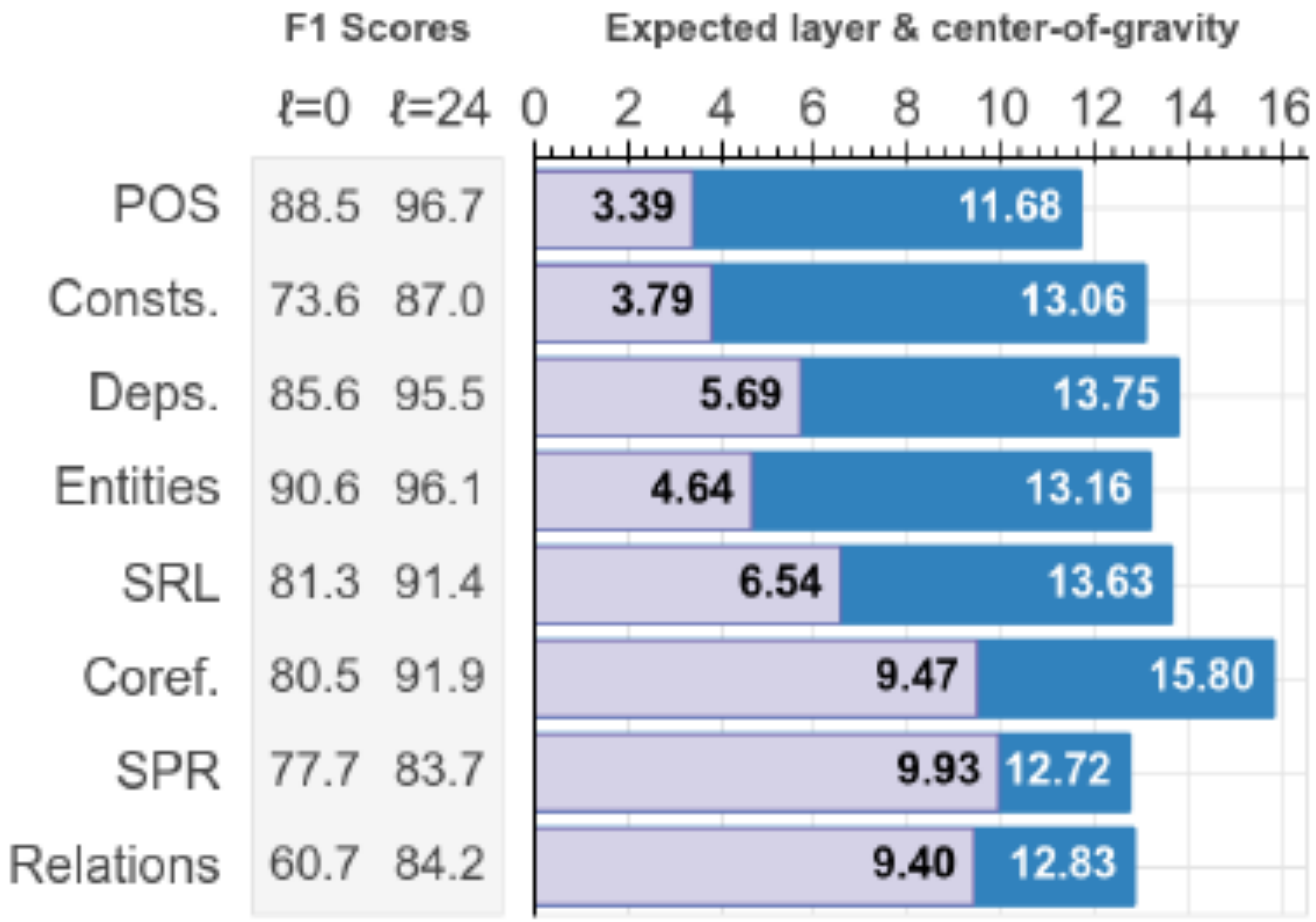

John Hewitt, Christopher D. Manning, A Structural Probe for Finding Syntax in Word Representations, NAACL, 2019

# BERTology - What does each layer learn?

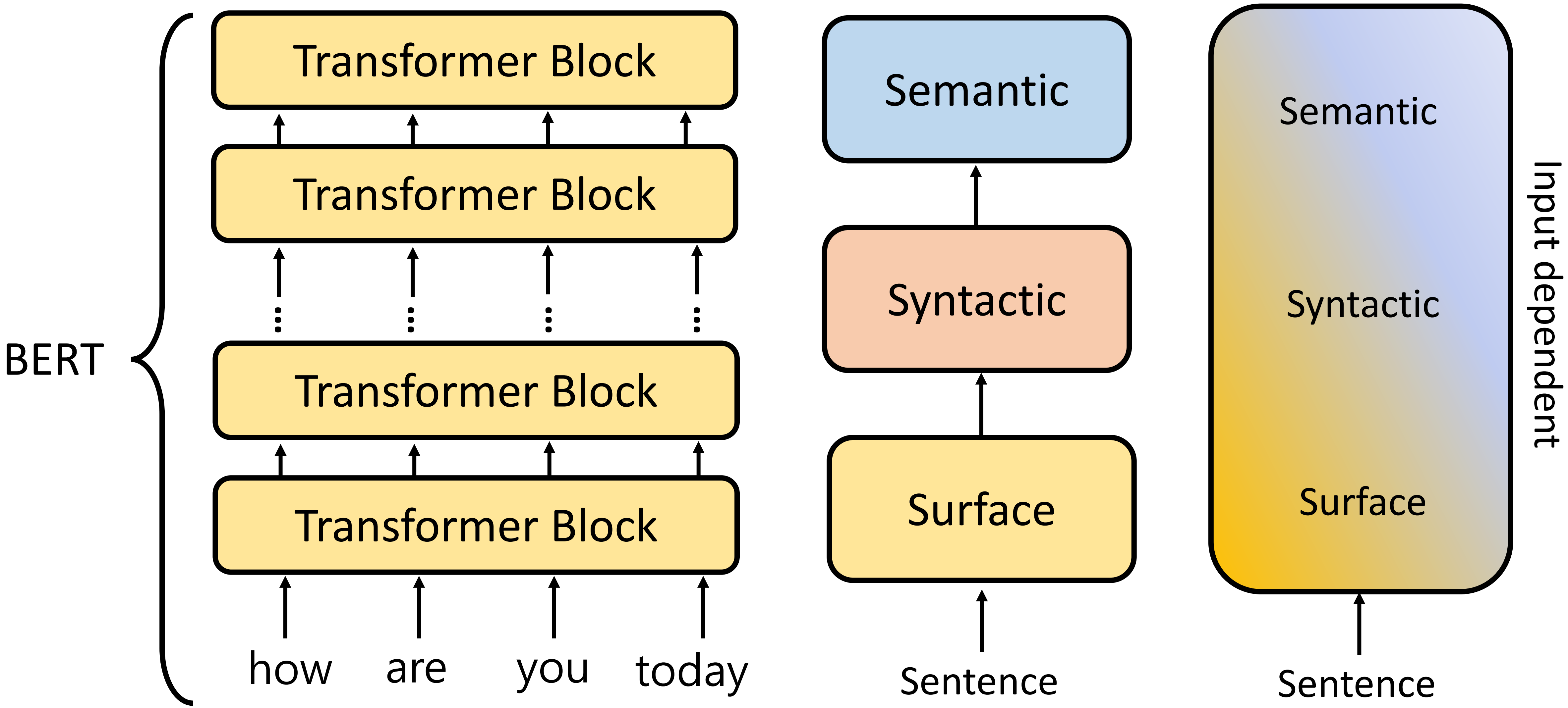
| Layer | SentLen (Surface) | WC (Surface) | TreeDepth (Syntactic) | TopConst (Syntactic) | BShift (Syntactic) | Tense (Semantic) | SubjNum (Semantic) | ObjNum (Semantic) | SOMO (Semantic) | CoordInv (Semantic) |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 93.9 (2.0) | 24.9 (24.8) | 35.9 (6.1) | 63.6 (9.0) | 50.3 (0.3) | 82.2 (18.4) | 77.6 (10.2) | 76.7 (26.3) | 49.9 (-0.1) | 53.9 (3.9) |
| 2 | 95.9 (3.4) | 65.0 (64.8) | 40.6 (11.3) | 71.3 (16.1) | 55.8 (5.8) | 85.9 (23.5) | 82.5 (15.3) | 80.6 (17.1) | 53.8 (4.4) | 58.5 (8.5) |
| 3 | **96.2 (3.9)** | 66.5 (66.0) | 39.7 (10.4) | 71.5 (18.5) | 64.9 (14.9) | 86.6 (23.8) | 82.0 (14.6) | 80.3 (16.6) | 55.8 (5.9) | 59.3 (9.3) |
| 4 | 94.2 (2.3) | **69.8 (69.6)** | 39.4 (10.8) | 71.3 (18.3) | 74.4 (24.5) | 87.6 (25.2) | 81.9 (15.0) | 81.4 (19.1) | 59.0 (8.5) | 58.1 (8.1) |
| 5 | 92.0 (0.5) | 69.2 (69.0) | 40.6 (11.8) | 81.3 (30.8) | 81.4 (31.4) | 89.5 (26.7) | 85.8 (19.4) | 81.2 (18.6) | 60.2 (10.3) | 64.1 (14.1) |
| 6 | 88.4 (-3.0) | 63.5 (63.4) | **41.3 (13.0)** | 83.3 (36.6) | 82.9 (32.9) | 89.8 (27.6) | **88.1 (21.9)** | 82.0 (20.1) | 60.7 (10.2) | 71.1 (21.2) |
| 7 | 83.7 (-7.7) | 56.9 (56.7) | 40.1 (12.0) | **84.1 (39.5)** | 83.0 (32.9) | 89.9 (27.5) | 87.4 (22.2) | **82.2 (21.1)** | 61.6 (11.7) | 74.8 (24.9) |
| 8 | 82.9 (-8.1) | 51.1 (51.0) | 39.2 (10.3) | 84.0 (39.5) | 83.9 (33.9) | 89.9 (27.6) | 87.5 (22.2) | 81.2 (19.7) | 62.1 (12.2) | 76.4 (26.4) |
| 9 | 80.1 (-11.1) | 47.9 (47.8) | 38.5 (10.8) | 83.1 (39.8) | **87.0 (37.1)** | **90.0 (28.0)** | 87.6 (22.9) | 81.8 (20.5) | 63.4 (13.4) | **78.7 (28.9)** |
| 10 | 77.0 (-14.0) | 43.4 (43.2) | 38.1 (9.9) | 81.7 (39.8) | 86.7 (36.7) | 89.7 (27.6) | 87.1 (22.6) | 80.5 (19.9) | 63.3 (12.7) | 78.4 (28.1) |
| 11 | 73.9 (-17.0) | 42.8 (42.7) | 36.3 (7.9) | 80.3 (39.1) | 86.8 (36.8) | 89.9 (27.8) | 85.7 (21.9) | 78.9 (18.6) | 64.4 (14.5) | 77.6 (27.9) |
| 12 | 69.5 (-21.4) | 49.1 (49.0) | 34.7 (6.9) | 76.5 (37.2) | 86.4 (36.4) | 89.5 (27.7) | 84.0 (20.2) | 78.7 (18.4) | **65.2 (15.3)** | 74.9 (25.4) |

Ganesh Jawahar, Benoît Sagot, Djamé Seddah, What Does BERT Learn about the Structure of Language?, ACL, 2019

# BERTology - What does each layer learn?




Ian Tenney, Dipanjan Das, Ellie Pavlick, BERT Rediscovers the Classical NLP Pipeline, ACL, 2019




- Jingcheng Niu, Wenjie Lu, Gerald Penn, Does BERT Rediscover a Classical NLP Pipeline?, COLING, 2022
- Wietse de Vries, Andreas van Cranenburgh, Malvina Nissim, What's so special about BERT's layers? A closer look at the NLP pipeline in monolingual and multilingual models, EMNLP Finding, 2020

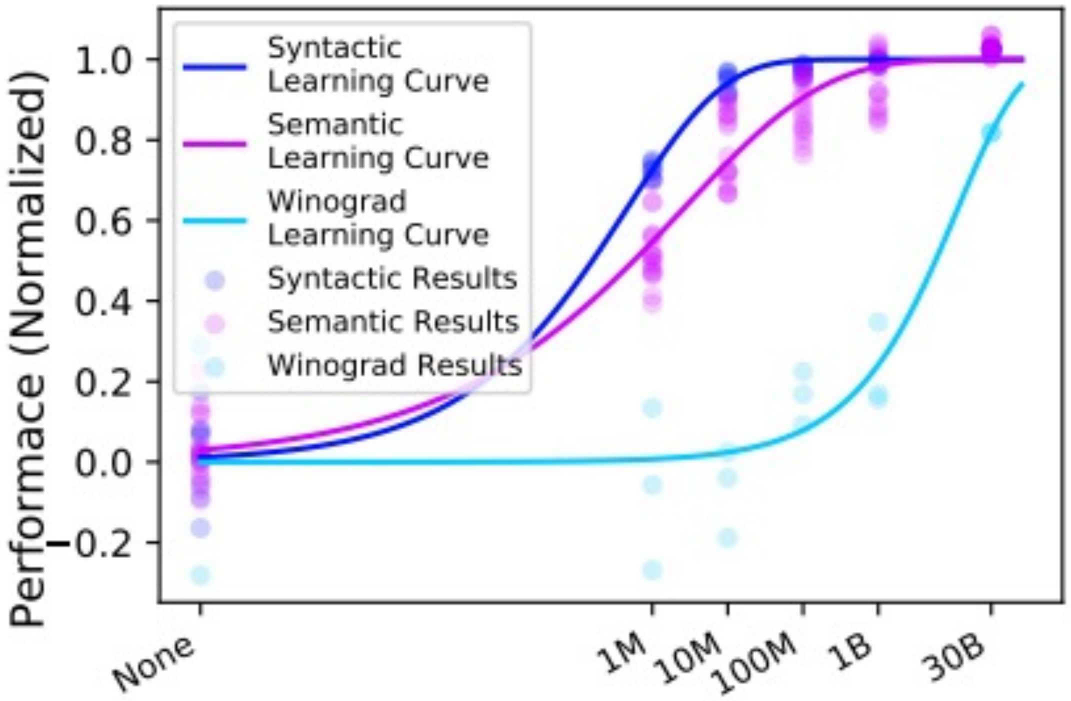
# BERT Embryology

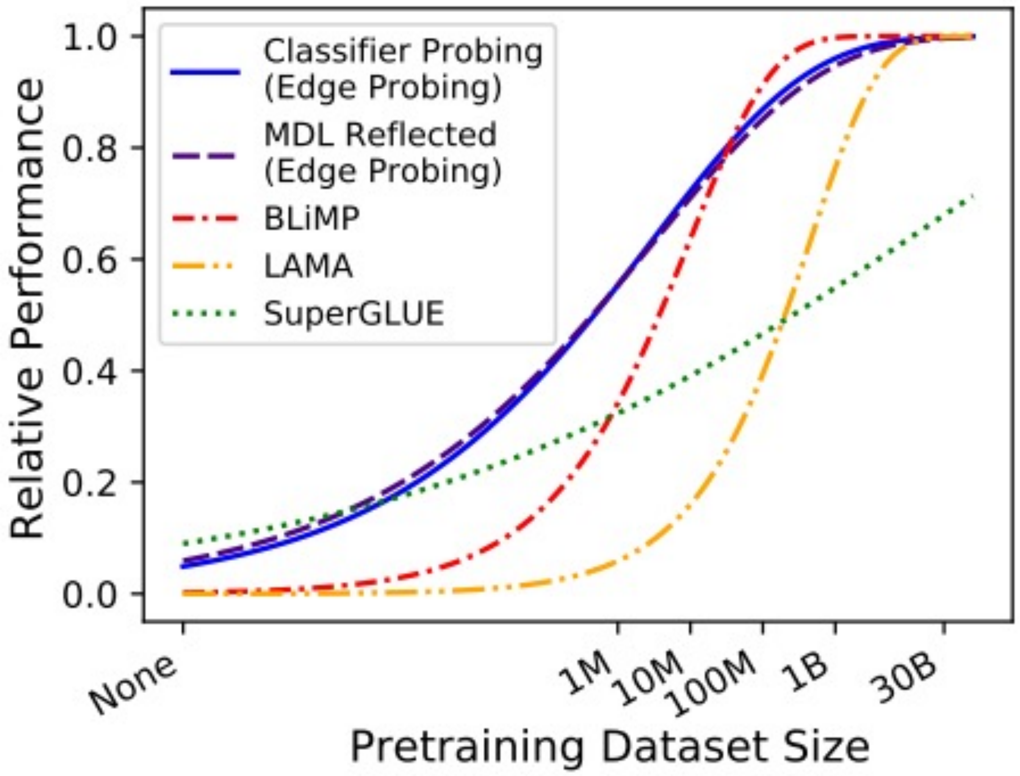
## Analyzing what BERT learned during training

- Cheng-Han Chiang, Sung-Feng Huang, Hung-yi Lee, Pretrained Language Model Embryology: The Birth of ALBERT, EMNLP, 2020
- Leo Z. Liu, Yizhong Wang, Jungo Kasai, Hannaneh Hajishirzi, Noah A. Smith, Probing Across Time: What Does RoBERTa Know and When? EMNLP-finding, 2021

When does BERT know POS tagging, syntactic parsing, semantics?

# When Do You Need Billions of Words of Pretraining Data?

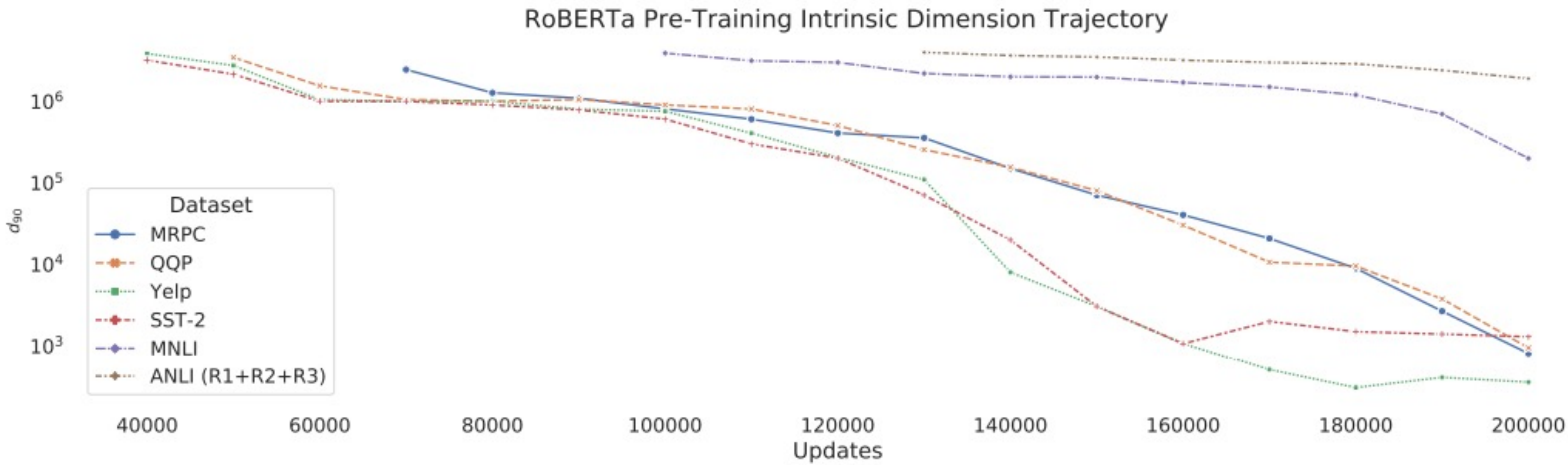



Yian Zhang, Alex Warstadt, Xiaocheng Li, Samuel R. Bowman, When Do You Need Billions of Words of Pretraining Data? ACL 2021

# Pre-trained Intrinsic Dimension

- Smaller intrinsic dimension means better generalization




Armen Aghajanyan, Sonal Gupta, Luke Zettlemoyer, Intrinsic Dimensionality Explains the Effectiveness of Language Model Fine-Tuning, ACL, 2021

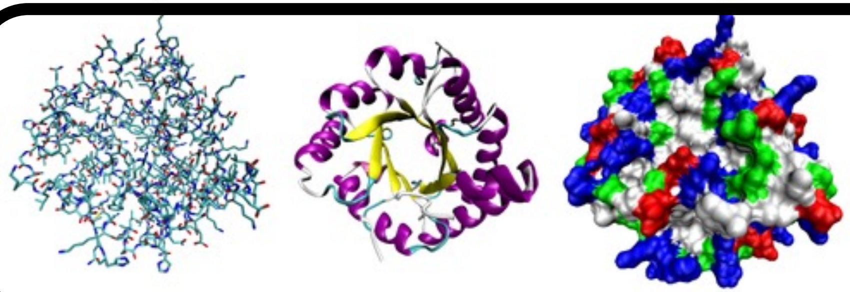
# Cross-discipline Capability

***Pre-train***

Human Language

***Fine-tune*** ***Testing***

DNA Classification



Protein Classification

Wei-Tsung Kao, Hung-yi Lee, Is BERT a Cross-Disciplinary Knowledge Learner? A Surprising Finding of Pre-trained Models' Transferability, EMNLP finding, 2021

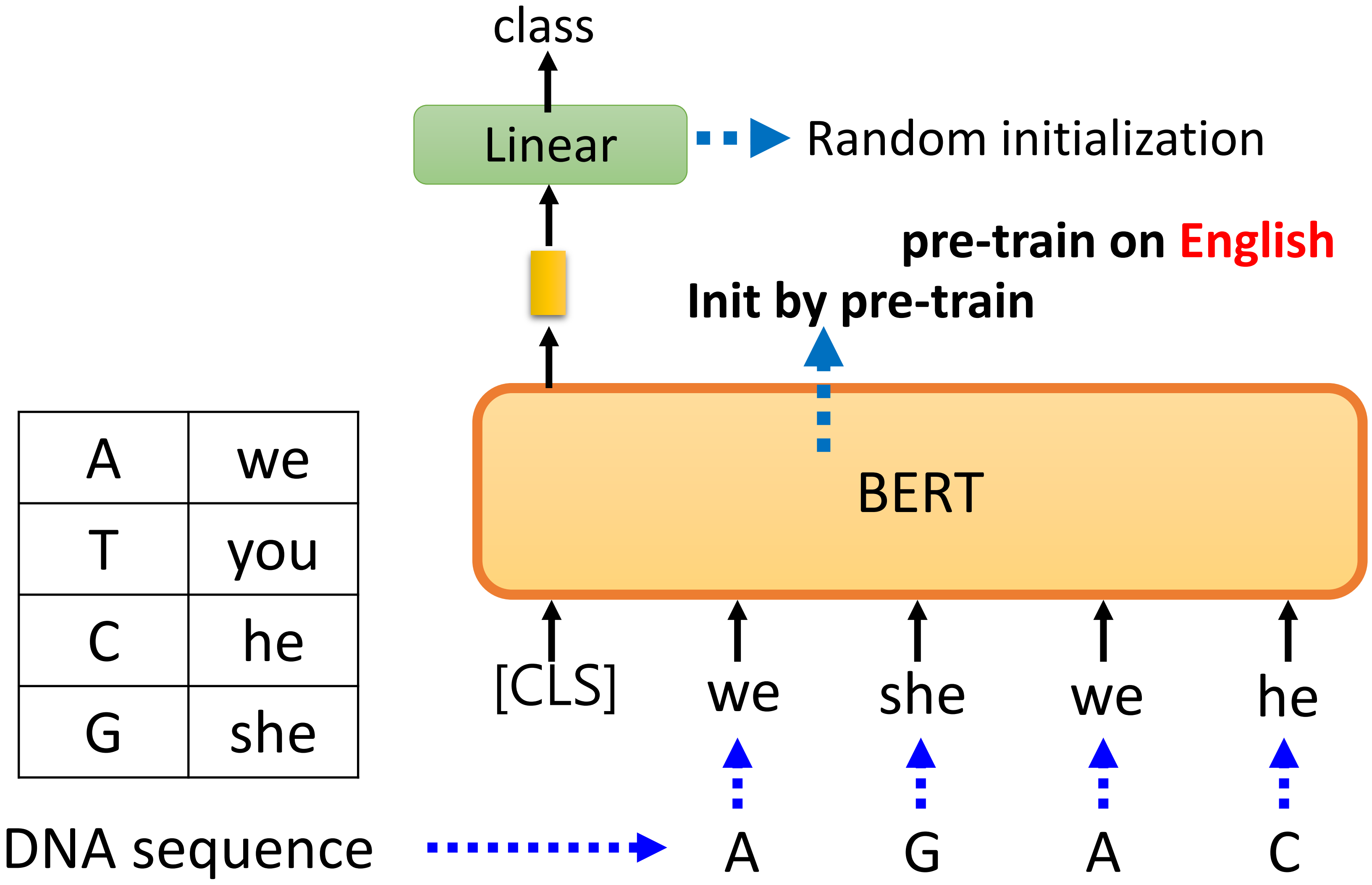
# Cross-discipline Capability


**<u>Downstream task</u>**

| | |
|---|---|
| EI | CCAGCTGCATCACAGGAGGCCAGCGAGCAGGTCTGTTCCAAG |
| EI | AGACCCGCCGGGAGGCGGAGGACCTGCAGGGTGAGCCCCAC |
| IE | AACGTGGCCTCCTTGTGCCCTTCCCCACAGTGCCCTCTTCCAGG |
| IE | CCACTCAGCCAGGCCCTTCTTCTCCTCCAGGTCCCCCACGGCCC |
| IE | CCTGATCTGGGTCTCCCCTCCCACCCTCAGGGAGCCAGGCTCG |
| IE | AGCCCTCAACCCTTCTGTCTCACCCTCCAGCCTAAAGCTCCTTG |
| IE | CCACTCAGCCAGGCCCTTCTTCTCCTCCAGGTCCCCCACGGCCC |
| N | CTGTGTTCACCACATCAAGCGCCGGGACATCGTGCTCAAGTGG |
| N | GTGTTACCGAGGGCATTTCTAACAGTCTTCTTACTACGGCCTCC |
| N | TCTGAGCTCTGCATTTGTCTATTCTCCAGCTGACCCTGGTTCTCT |
| class | DNA sequence |

# Cross-discipline Capability


| | |
|---|---|
| A | we |
| T | you |
| C | he |
| G | she |



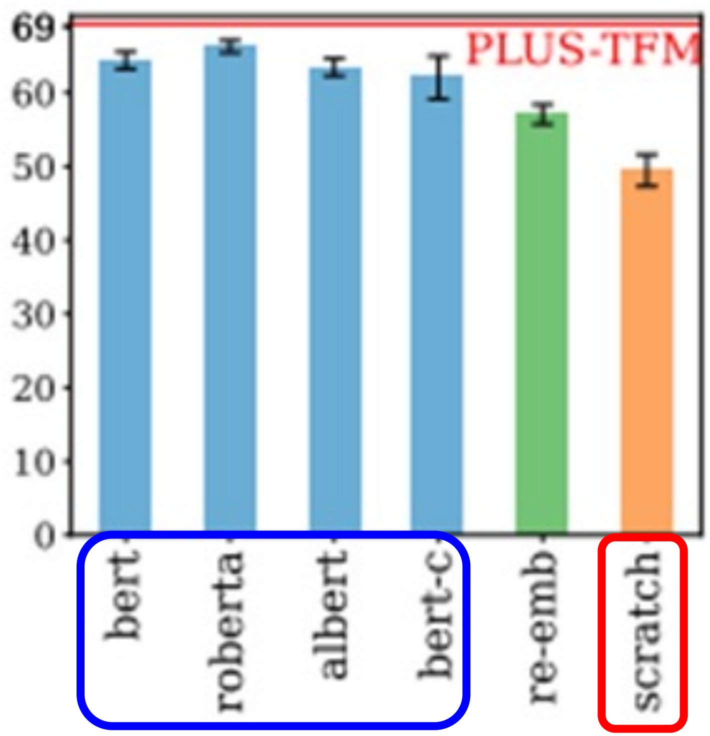
# Cross-discipline Capability

- Applying BERT to **protein**, **DNA**, **music classification**

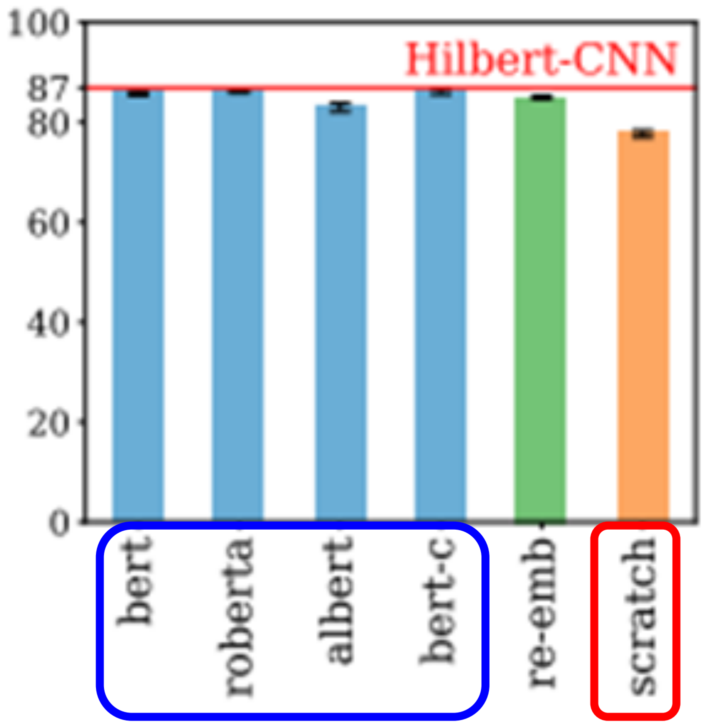
| | Protein | | | DNA | | | | Music |
|---|---|---|---|---|---|---|---|---|
| | localization | stability | fluorescence | H3 | H4 | H3K9ac | Splice | composer |
| specific | 69.0 | 76.0 | 63.0 | 87.3 | 87.3 | 79.1 | 94.1 | - |
| BERT | 64.8 | 74.5 | 63.7 | 83.0 | 86.2 | 78.3 | 97.5 | 55.2 |
| re-emb | 63.3 | 75.4 | 37.3 | 78.5 | 83.7 | 76.3 | 95.6 | 55.2 |
| rand | 58.6 | 65.8 | 27.5 | 75.6 | 66.5 | 72.8 | 95 | 36 |

The pretrained models learn some general skills for the classification.

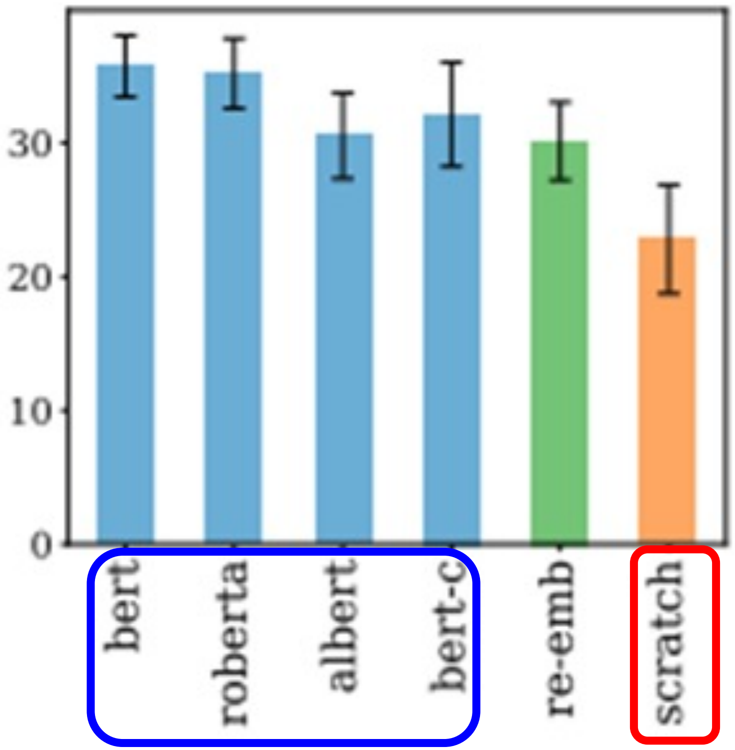
# Cross-discipline Capability




DNA Classification
(average 3 tasks)



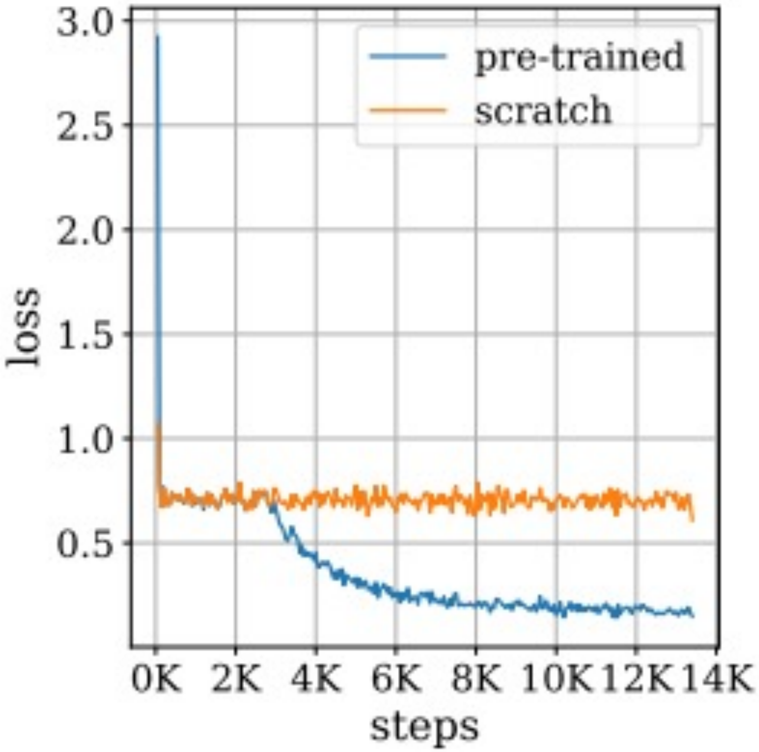

Protein Classification
(average 4 tasks)




Music Classification

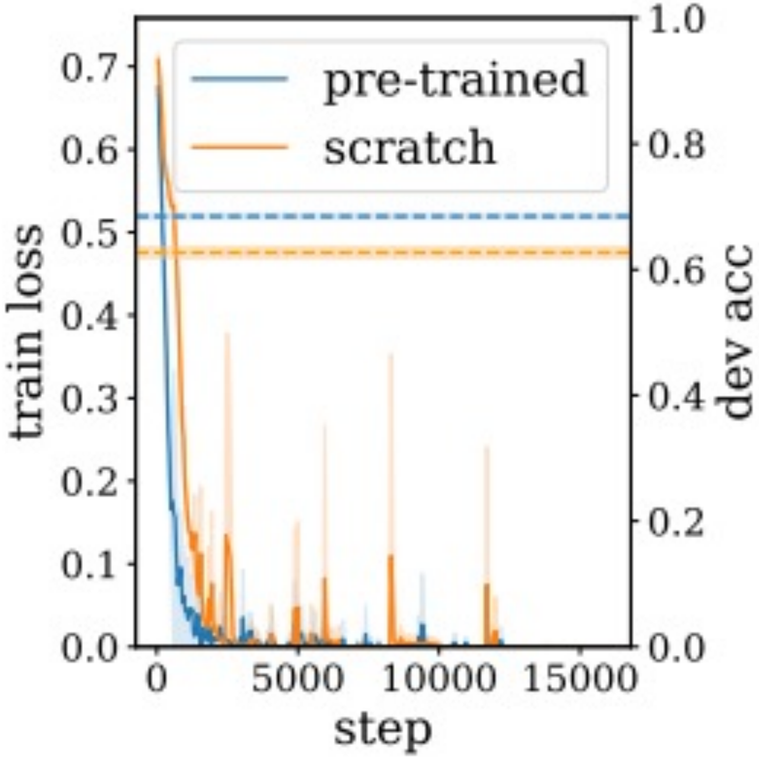
# How pre-trained model improve the performance?

## *Optimization*

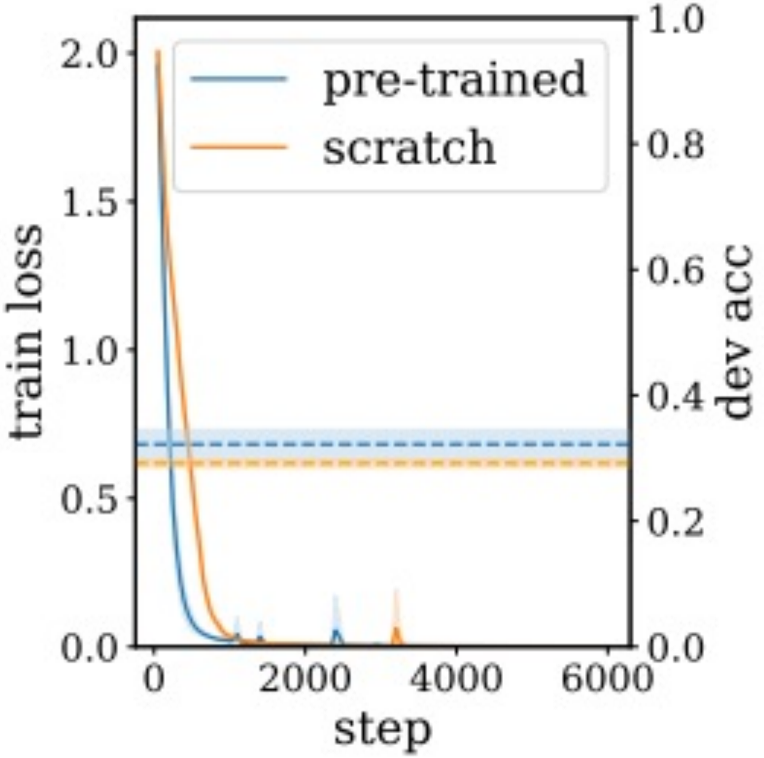



(b) fluorescence

## *Generalization*




(a) H3K9ac

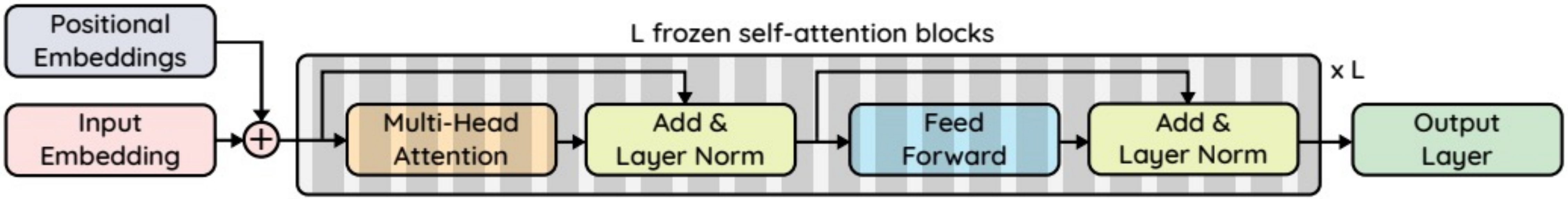


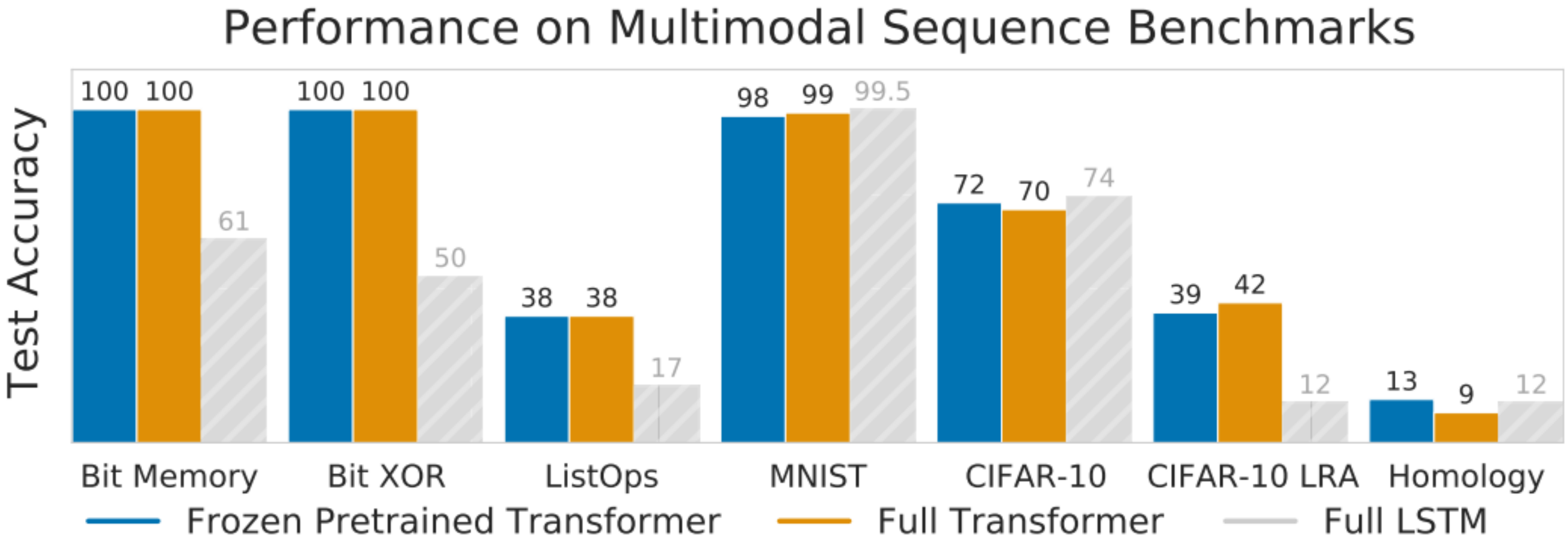

(b) localization

The pretrained models help both **optimization** and **generalization**.

# To learn more …

Kevin Lu, Aditya Grover, Pieter Abbeel, Igor Mordatch, Pretrained Transformers as Universal Computation Engines, arXiv, 2021



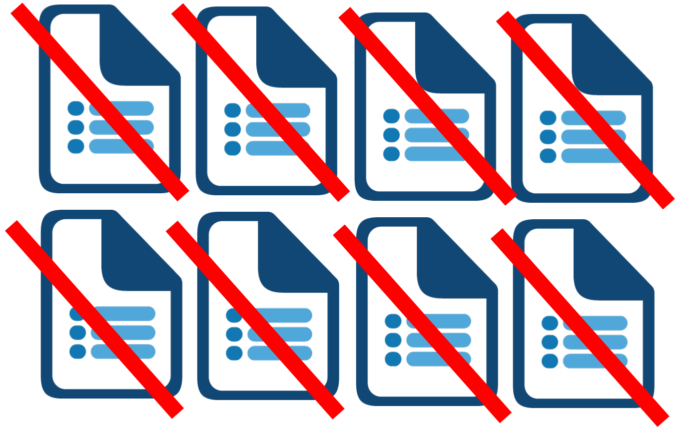



Cheng-Han Chiang, Hung-yi Lee, On the Transferability of Pre-trained Language Models: A Study from Artificial Datasets, AAAI, 2022

# Pre-training on Artificial Data

We have see the cross-discipline capability of self-supervised model ……

***Pre-train***



We can pre-train model on data other than text.

***Fine-tune***

***Testing***

GLUE

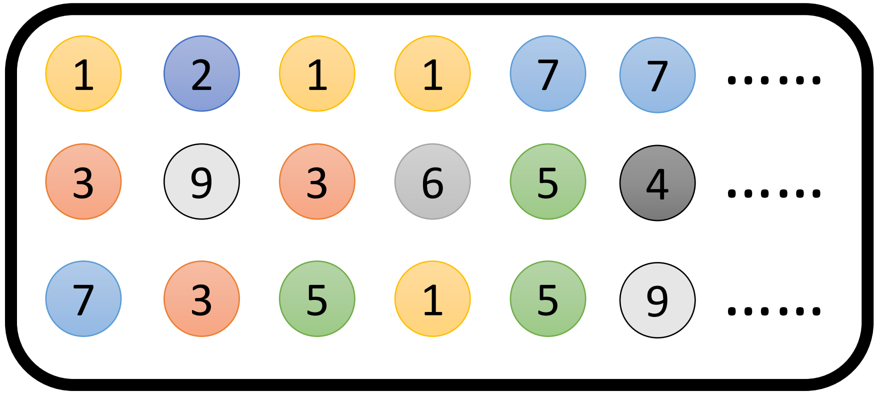
A set of NLP Tasks

# Pre-training on Artificial Data

Cheng-Han Chiang, Hung-yi Lee, On the Transferability of Pre-trained Language Models: A Study from Artificial Datasets, AAAI, 2022

We have seen the cross-discipline capability of self-supervised model ……

***Pre-train*** ***Fine-tune*** ***Testing***



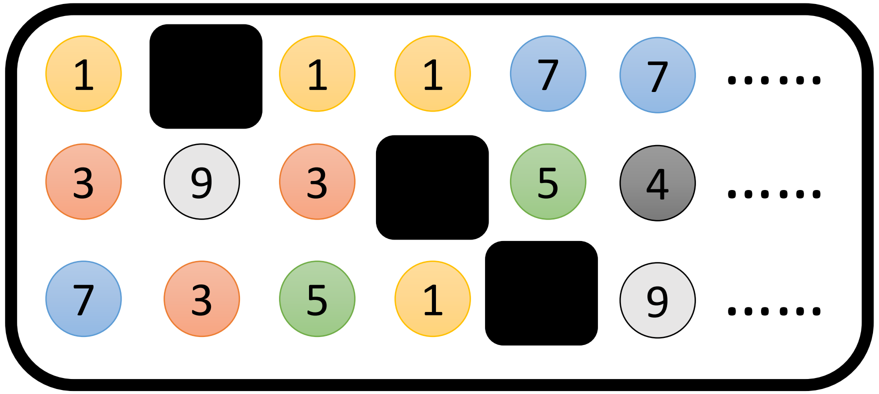

Token generation by rules

GLUE

A set of NLP Tasks

By generating artificial data with different rules, we can know what are the key factors for the success of pre-training.

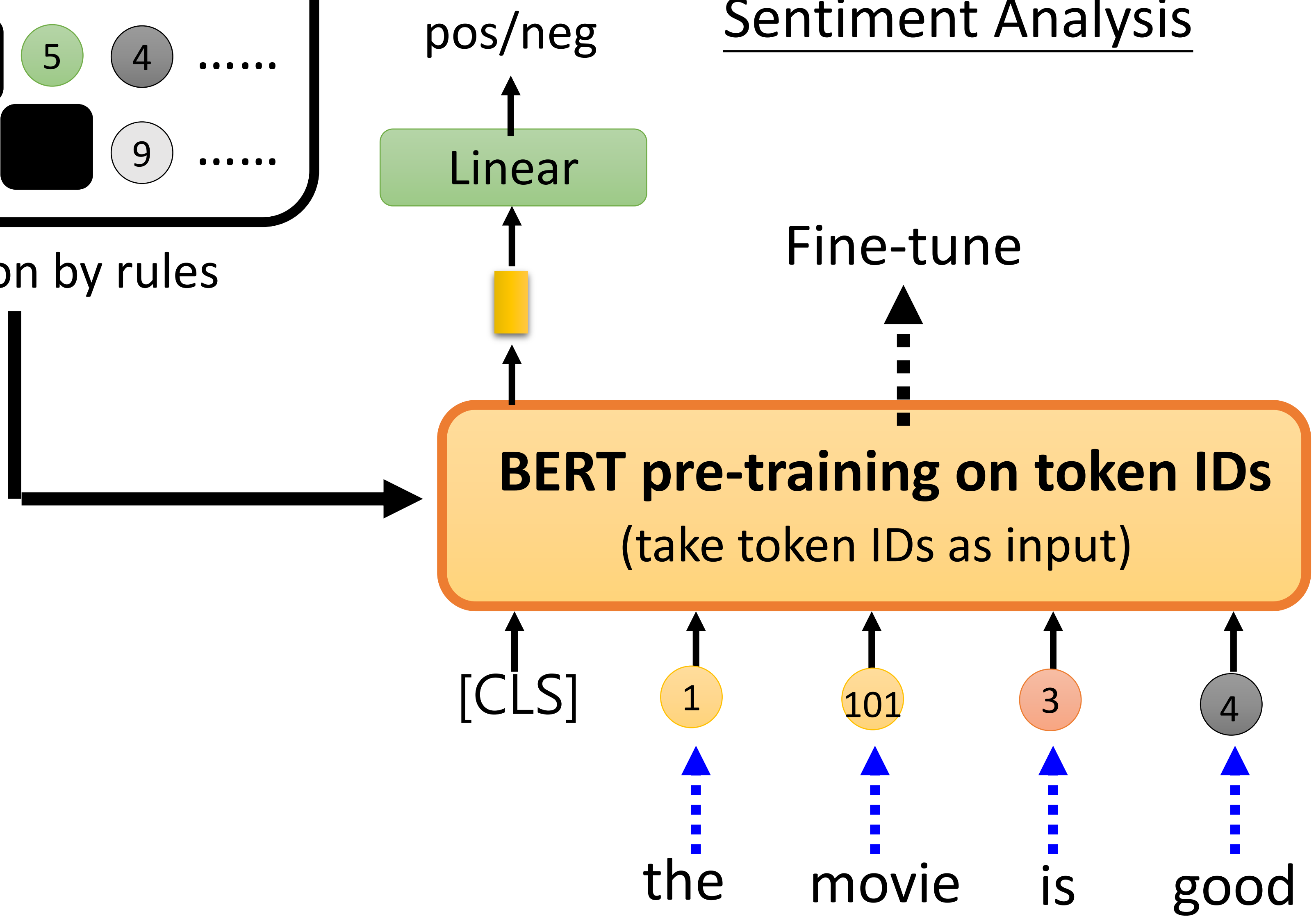
***Pre-train***




Token generation by rules

| ID | text |
|---|---|
| 1 | the |
| 2 | a |
| 3 | Is |
| 4 | good |
| … | … |
| 101 | movie |
| … | … |

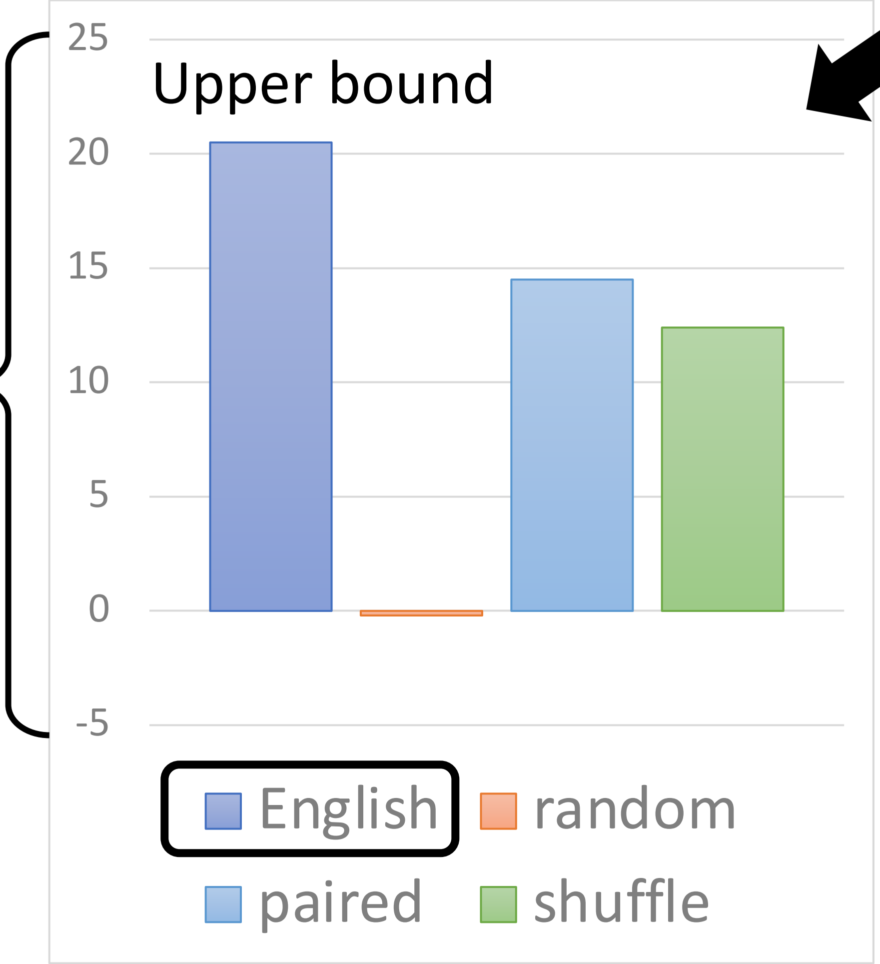
NLP Downstream Task: Sentiment Analysis



# Pre-training on Artificial Data

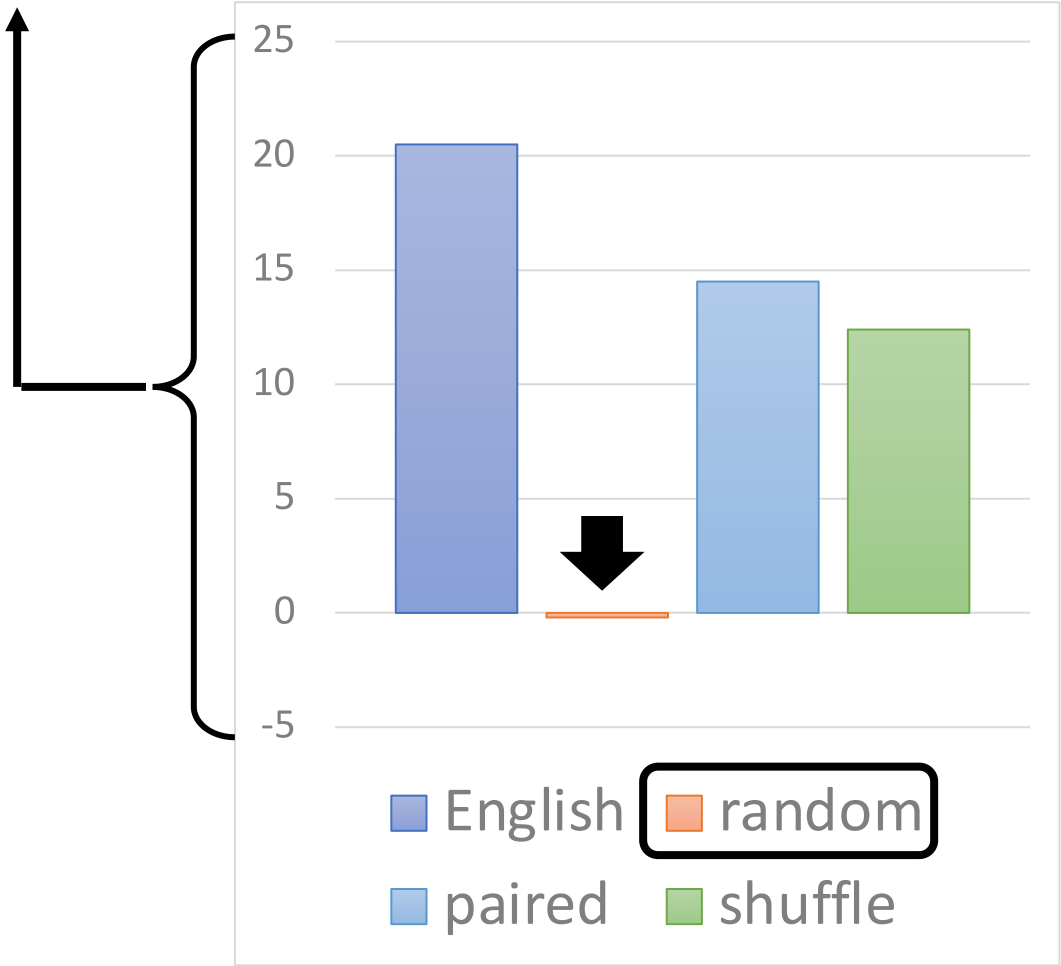
Absolute improvement (%) compared to training from scratch

Average performance on GLUE tasks



# Pre-training on Artificial Data

Absolute improvement (%) compared to training from scratch



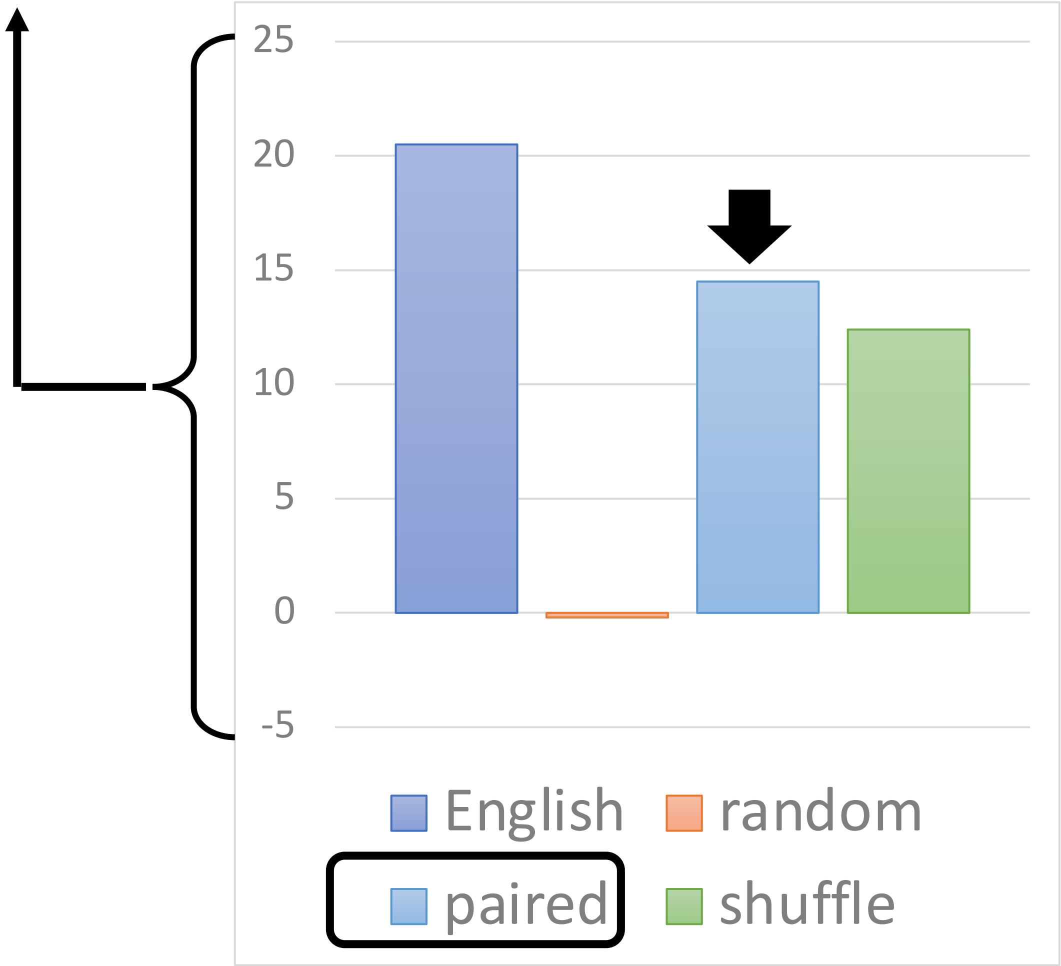

- Pre-training on random tokens yields the same performance as training from scratch.

**Data plays the role.**

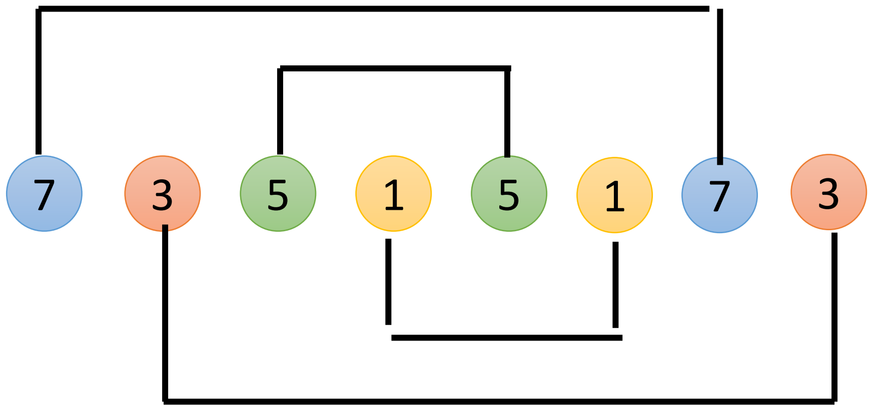
# Pre-training on Artificial Data

Also refer to:
Isabel Papadimitriou, Dan Jurafsky,
Learning Music Helps You Read: Using Transfer to Study Linguistic Structure in Language Models, EMNLP, 2020

Absolute improvement (%) compared to training from scratch




- All the tokens in the generated sequences are paired.

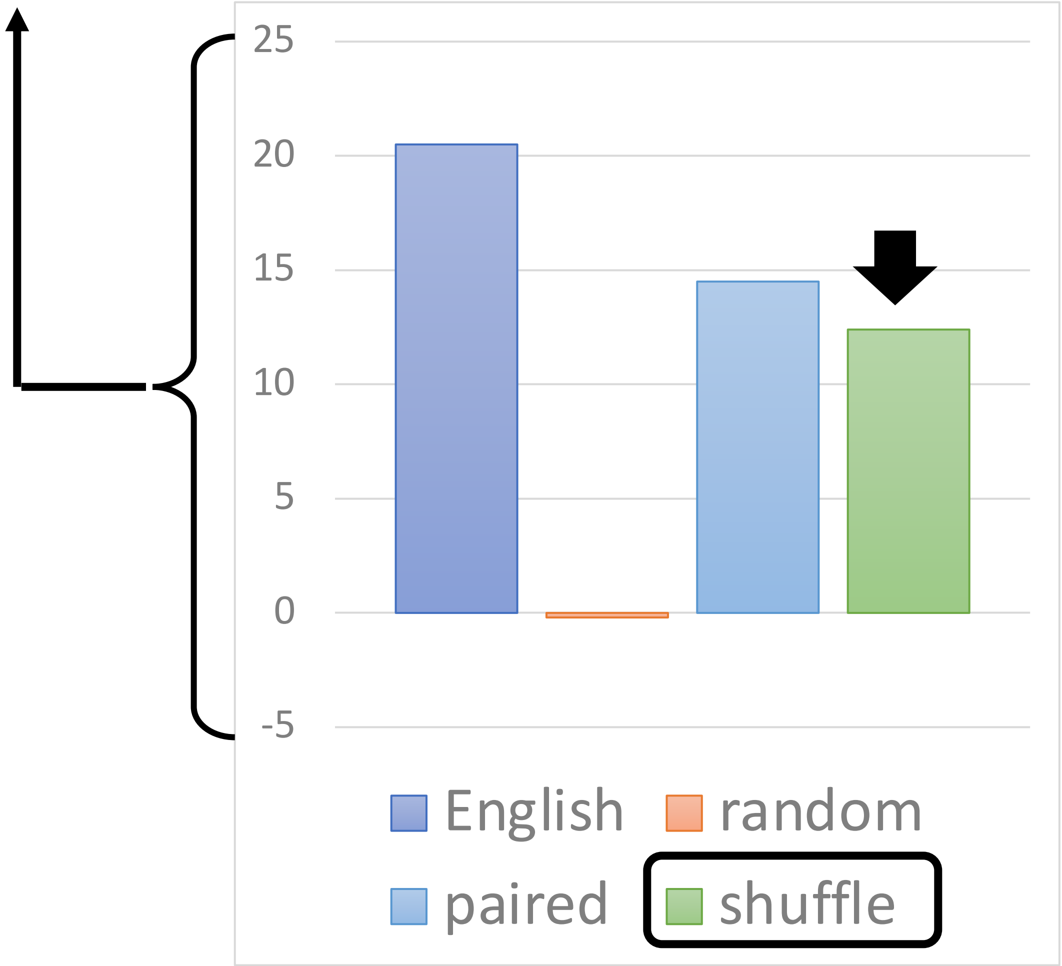



Structured data is critical for learning useful skills for NLP.

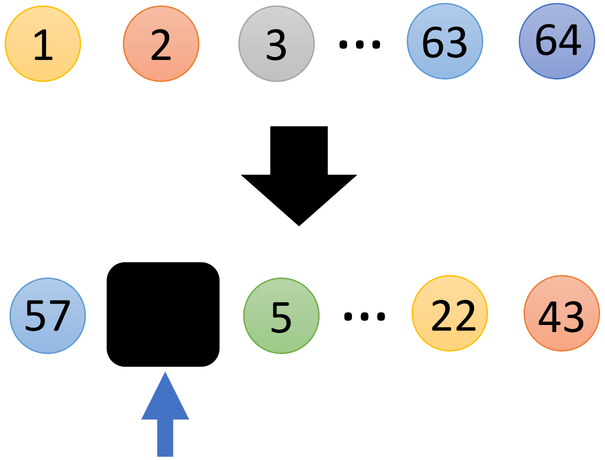
Is it true?

# Pre-training on Artificial Data

Absolute improvement (%) compared to training from scratch



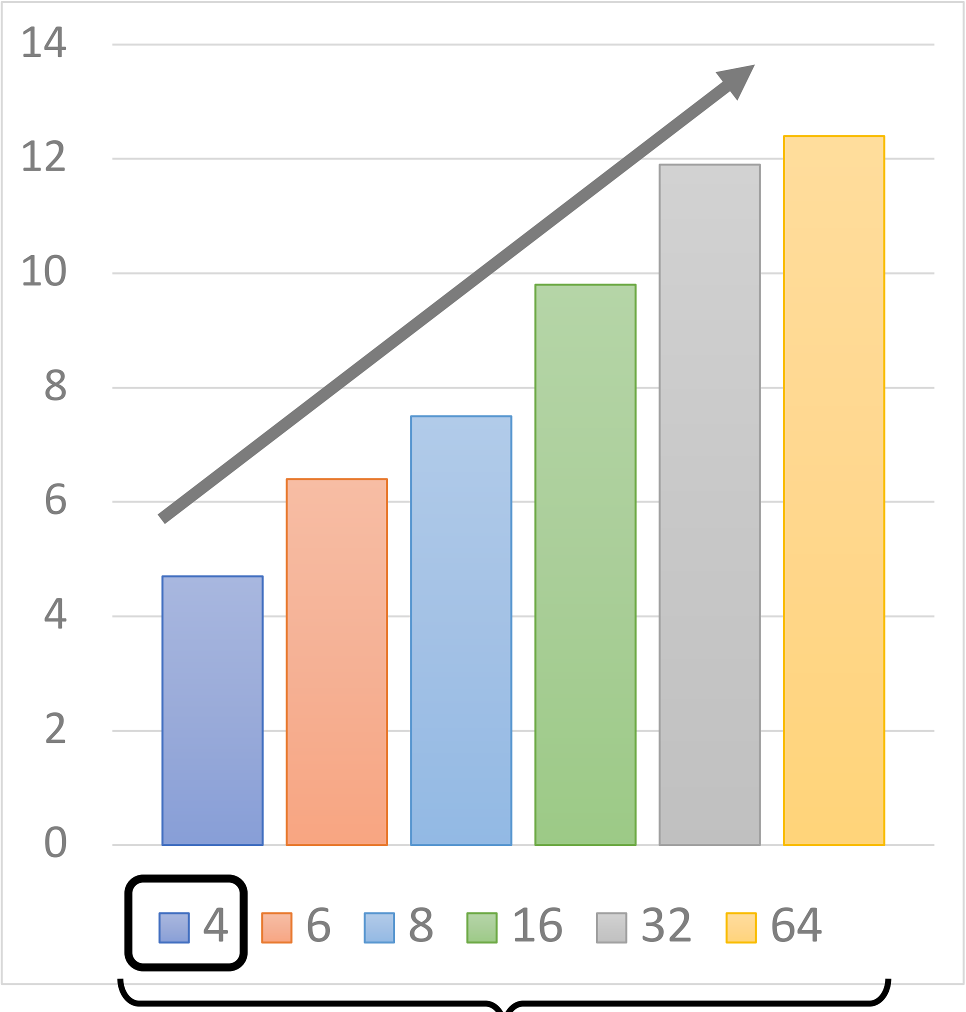

- Shuffle



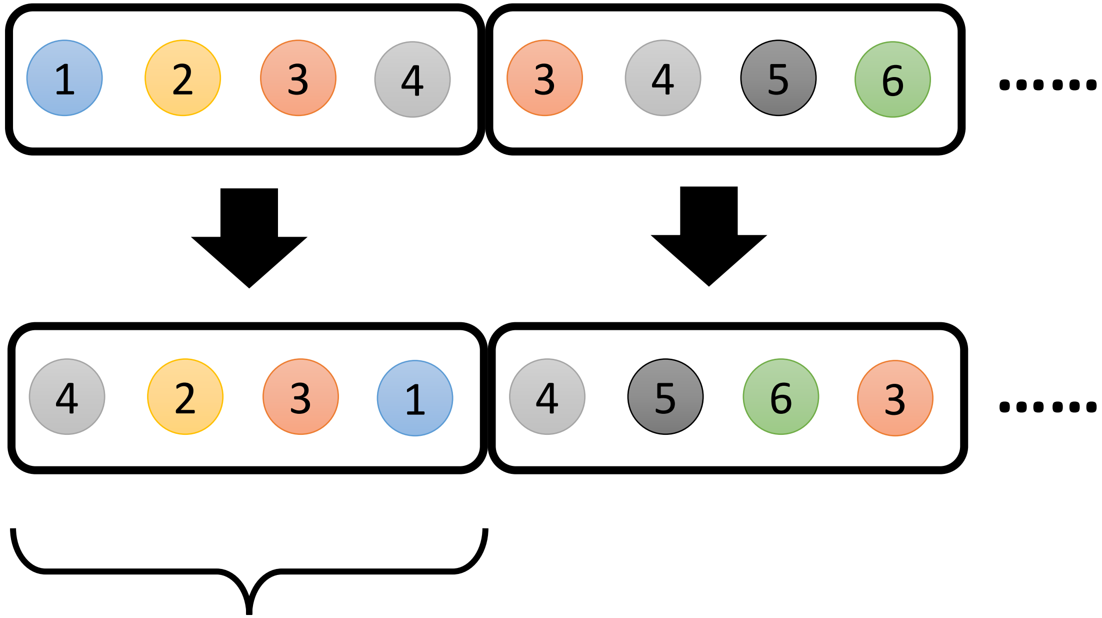

To predict this token, model needs to go through the whole sequence.

Is long-range reading the key to the success of a pretrained model?

Absolute improvement (%) compared to training from scratch




Length of consecutive tokens




Longer consecutive tokens, better performance in NLP tasks

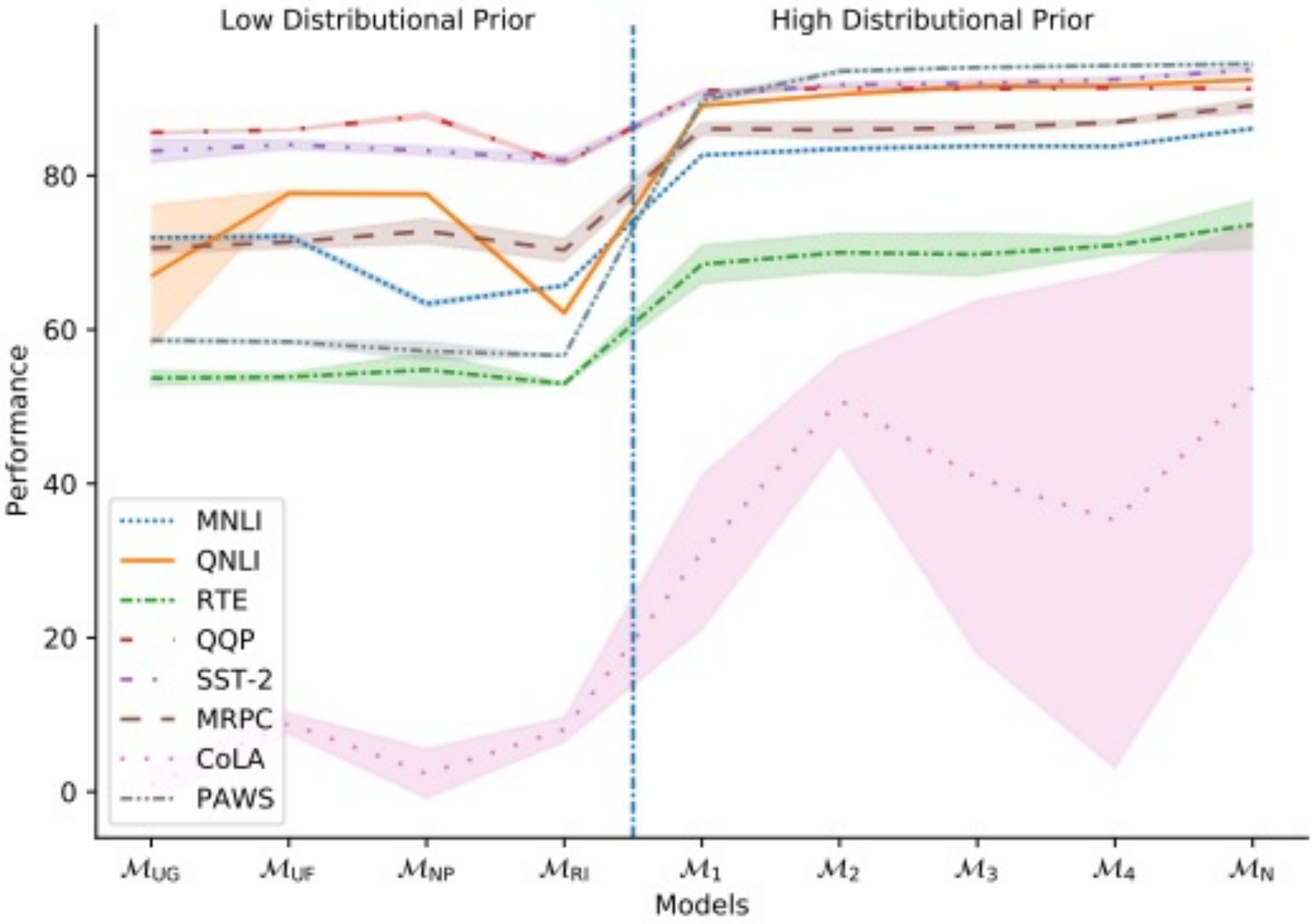
**Learning to read a long-range in a sequence is crucial.**

Are there more factors?
Need more investigation ☺

# To learn more ……

AACL-IJCNLP 2022 will be held online from November 20-23 , 2022 .

will 2022 , be November . online 2022 from held 20-23 AACL-IJCNLP



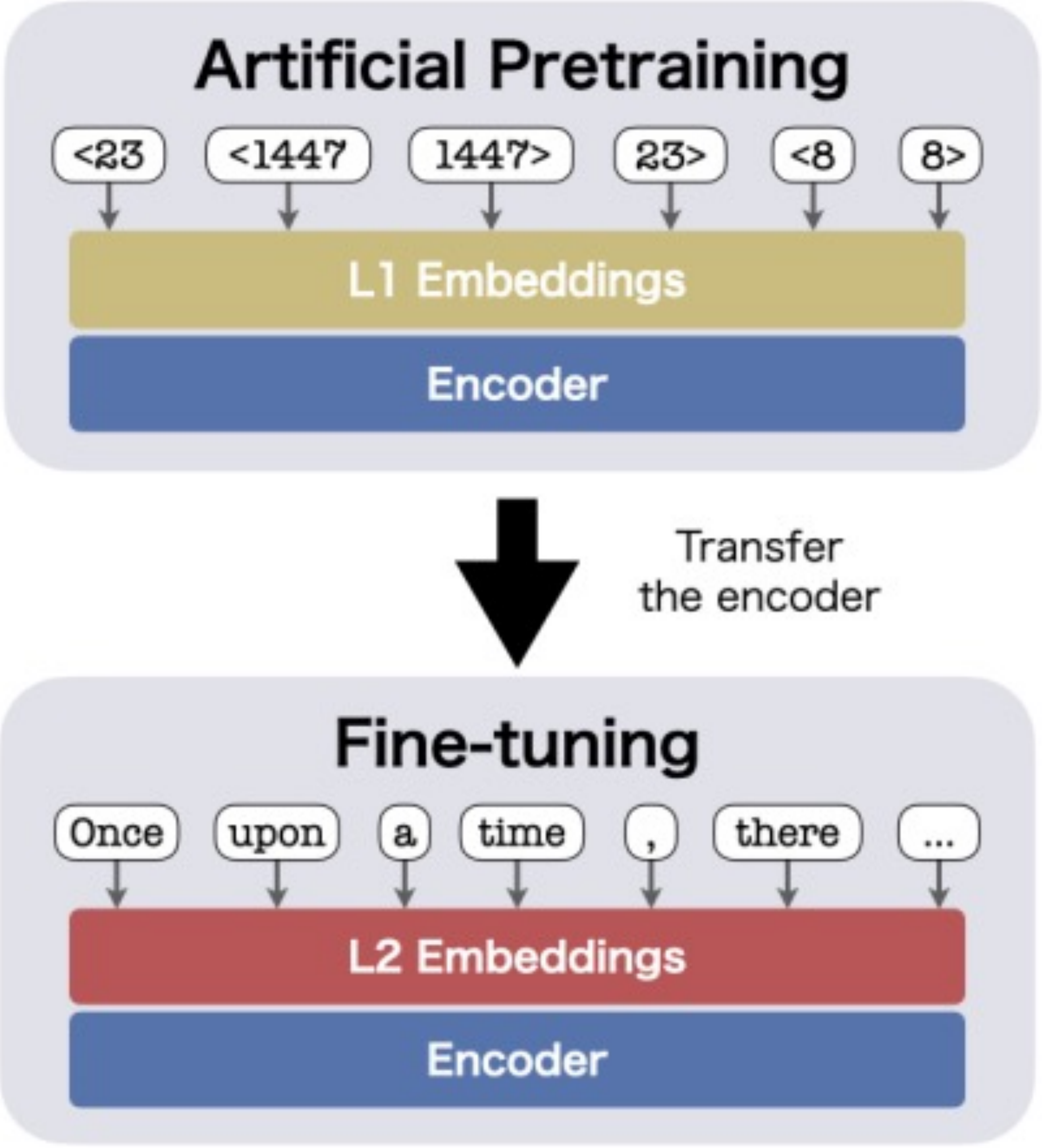

Koustuv Sinha, Robin Jia, Dieuwke Hupkes, Joelle Pineau, Adina Williams, Douwe Kiela, Masked Language Modeling and the Distributional Hypothesis: Order Word Matters Pre-training for Little, EMNLP, 2021

# To learn more ……

- What knowledge in pretrained encoders are transferred across different languages?

  “tokens in a sequence can be characterized by its neighbor tokens at specific positions”

Ryokan Ri, Yoshimasa Tsuruoka, Pretraining with Artificial Language: Studying Transferable Knowledge in Language Models, ACL, 2022



# Concluding Remarks of Part 2

- Why do PLMs work?

**Don't know the answer yet.**

  - Contextualized word representations
  - BERTology: Analyzing what is learned by BERT
  - BERT Embryology: Analyzing what BERT learned during training

  - Cross-discipline Capability
  - Pre-training on Artificial Data

# Schedule

17:00 – 17:10 **Part 1** Introduction [Hung-yi]

17:10 – 17:40 **Part 2** Why do PLMs work [Hung-yi]

17:40 – 18:20 **Part 3** How to use PLMs: Contrastive Learning for PLMs [Yung-Sung]

18:20 – 18:30 Q&A for Part 1+2+3

18:30 – 18:40 Break

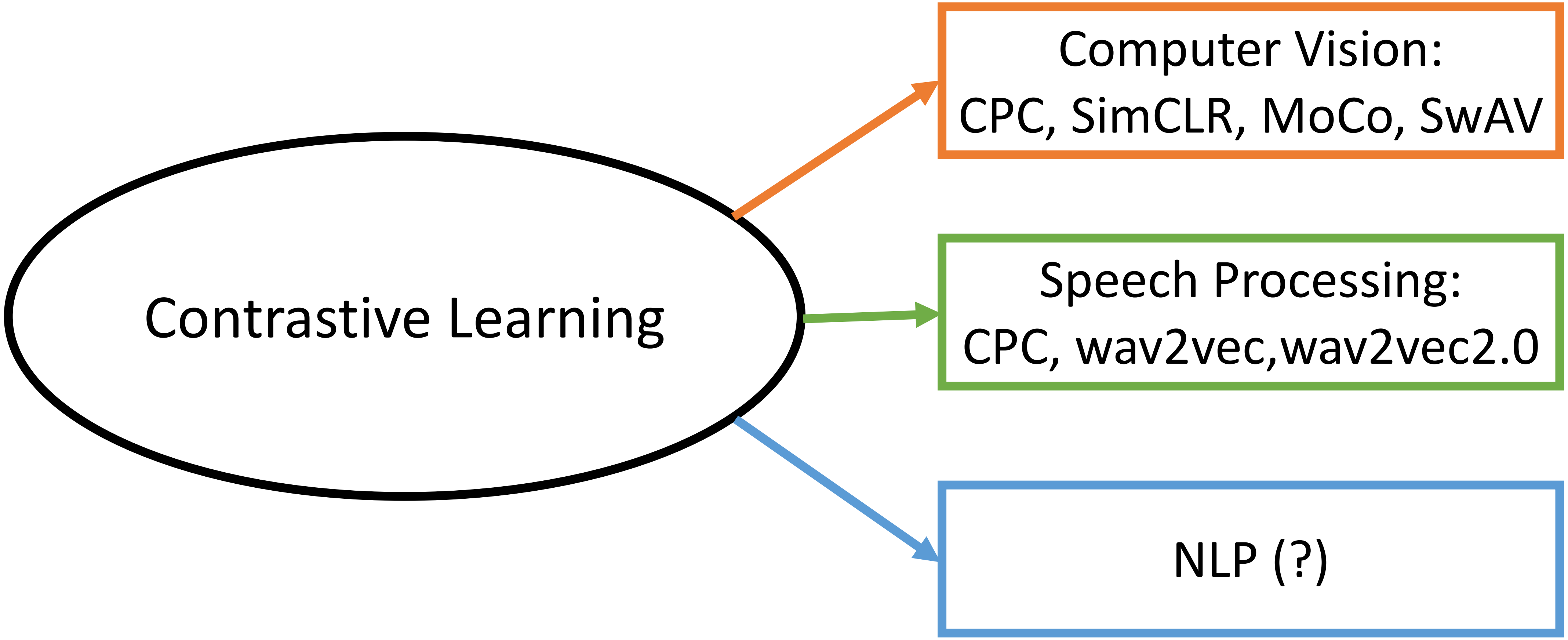
18:40 – 19:05 **Part 4** How to use PLMs: Parameter-efficient fine-tuning [Cheng-Han]

19:05 – 19:50 **Part 5** How to use PLMs: Using PLMs with different amounts of data [Cheng-Han]

19:50 – 20:00 Conclusion and Future work + Q&A

# Part 3:
# How to use PLMs:
# Contrastive Learning for PLMs

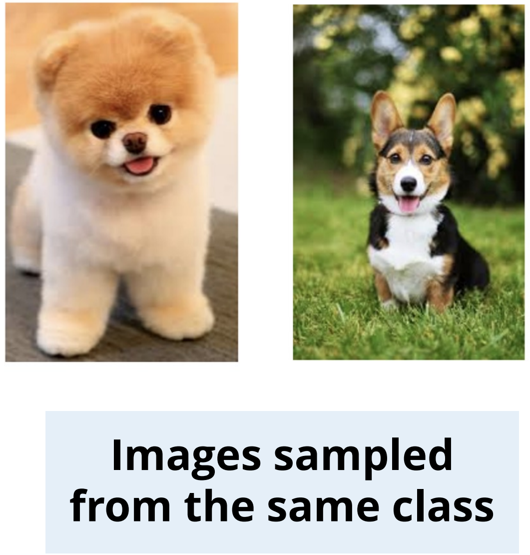
Yung-Sung Chuang
**CSAIL, MIT**


Contrastive Learning
Computer Vision:
CPC, SimCLR, MoCo, SwAV
Speech Processing:
CPC, wav2vec,wav2vec2.0
NLP (?)

# Why Contrastive?

We want to obtain a good representation space such that

1. Similar inputs have similar representations. -> Positive Pairs

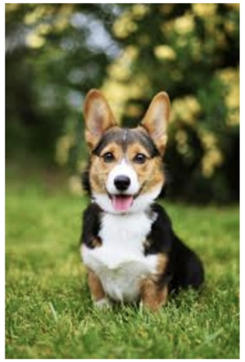




Chen, Ting, et al. "A simple framework for contrastive learning of visual representations." *International conference on machine learning*. PMLR, 2020.
Khosla, Prannay, et al. "Supervised contrastive learning." *Advances in Neural Information Processing Systems* 33 (2020): 18661-18673.

# Why Contrastive?

We want to obtain a good representation space such that

2. Dissimilar inputs have dissimilar representations. **-> Negative Pairs**



**Randomly sampled images**

Chen, Ting, et al. "A simple framework for contrastive learning of visual representations." *International conference on machine learning*. PMLR, 2020.
Khosla, Prannay, et al. "Supervised contrastive learning." *Advances in Neural Information Processing Systems* 33 (2020): 18661-18673.

# Contrastive Learning

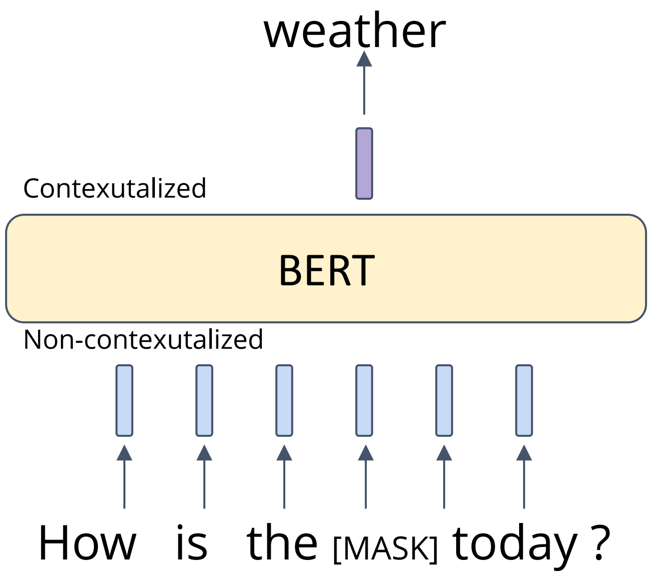
## SimCLR for Computer Vision

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

Chen, Ting, et al. "A simple framework for contrastive learning of visual representations." *International conference on machine learning*. PMLR, 2020.

# Contrastive Learning for NLP?

- Masked Language Modeling shares some similarity to contrastive learning




**Instance:**
contextualized representation of [MASK]

**Positive Pairs:**
non-contextualized representation of “weather”

**Negative Pairs:**
non-contextualized representation of all the other words in the vocabulary


Devlin, Jacob, et al. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*. 2019.

# Why Contrastive on NLP?

- MLM can be seen as a contrastive learning task using all negative pairs for training
- Finite vocabulary size (30k for BERT) prevents negative sampling issues
  -> MLM can be trained as a simple token-level classification task
- Are there any task has infinite possible inputs?

→ **Sentence-level task!**

→ We have infinite possible sentences; not possible to enumerate all the sentences in the world.

→ Good to apply contrastive learning for sentence-level representations.

# Outline of Part 3

1. Why we need sentence-level representations?
2. Pre-BERT methods
3. How to obtain sentence-level representations from BERTs?
   a. Post-processing Methods
4. Contrastive Learning Methods:
   a. Designed Positives
   b. Generating Positives
   c. Bootstrapping Methods
   d. Dropout Augmentations
   e. Equivariant Contrastive Learning
   f. Prompting
   g. Ranking-based Methods
5. Conclusion

# Outline of Part 3

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    f. Prompting
    g. Ranking-based Methods
5. Conclusion

# General-Purpose Sentence Representations

- Provide as **a backbone** that can be useful on a variety of downstream sentence-level tasks
- Good generalization ability on tasks without much training data e.g. even **linear probing** can achieve good performance
- Efficient sentence-level **clustering** or **semantic search** by inner products
- Measure **similarities** among sentence pairs
- **Unsupervised** methods are more desirable in order to be applied to languages beyond English

*We will mainly focus on unsupervised methods through this tutorial!*

# Before BERT came out…

- [Skip-Thought Vectors](), NIPS 2016 *-> Next Sentence Prdiction*

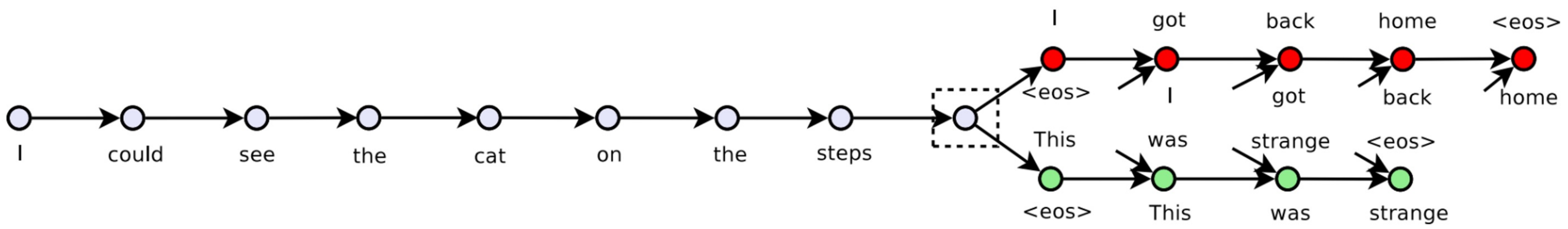
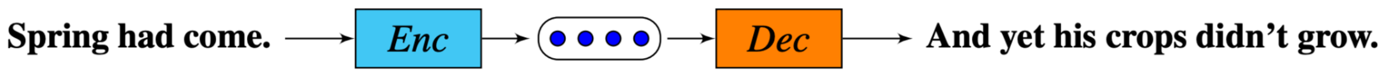



Figure 1: The skip-thoughts model. Given a tuple $(s_{i-1}, s_i, s_{i+1})$ of contiguous sentences, with $s_i$ the $i$-th sentence of a book, the sentence $s_i$ is encoded and tries to reconstruct the previous sentence $s_{i-1}$ and next sentence $s_{i+1}$. In this example, the input is the sentence triplet *I got back home. I could see the cat on the steps. This was strange.* Unattached arrows are connected to the encoder output. Colors indicate which components share parameters. $\langle$eos$\rangle$ is the end of sentence token.

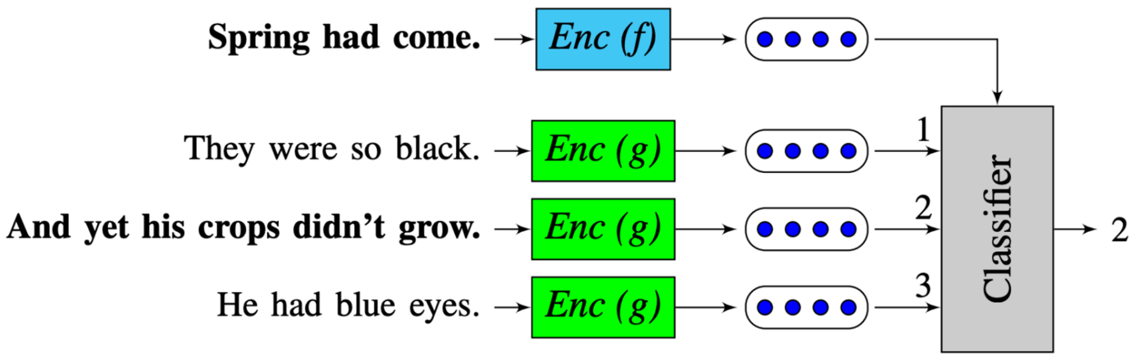
Kiros, Ryan, et al. "Skip-thought vectors." *Advances in neural information processing systems* 28 (2015).

# Before BERT came out…

- Quick-Thought vectors, ICLR 2018 *-> Next Sentence Prdiction w/o Decoder*




(a) Conventional approach




(b) Proposed approach

Logeswaran, Lajanugen, and Honglak Lee. "An efficient framework for learning sentence representations." *International Conference on Learning Representations*. 2018.

# Oct 2018:

https://leemeng.tw/attack_on_bert_transfer_learning_in_nlp.html

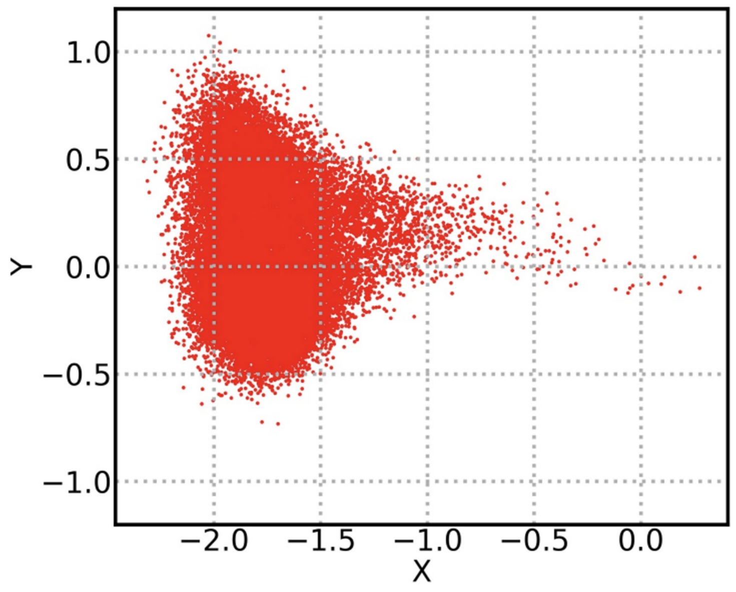
# How to obtain sentence representations from BERT?

- It cannot be trivially obtained from token-level representations
- Average pooling performs even worse than avg. GloVe embeddings

| Dataset | STS-B | SICK-R | STS-12 | STS-13 | STS-14 | STS-15 | STS-16 |
|---|---|---|---|---|---|---|---|
| *Published in (Reimers and Gurevych, 2019)* | | | | | | | |
| Avg. GloVe embeddings | 58.02 | 53.76 | 55.14 | 70.66 | 59.73 | 68.25 | 63.66 |
| Avg. BERT embeddings | 46.35 | 58.40 | 38.78 | 57.98 | 57.98 | 63.15 | 61.06 |
| BERT CLS-vector | 16.50 | 42.63 | 20.16 | 30.01 | 20.09 | 36.88 | 38.03 |

Li, Bohan, et al. "On the Sentence Embeddings from Pre-trained Language Models." *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 2020.

# Anisotropy problem in BERT’s representation space




- **Representation degeneration**:
  the learned embeddings occupy a narrow cone in the vector space
- Limits the expressiveness of the vector space.

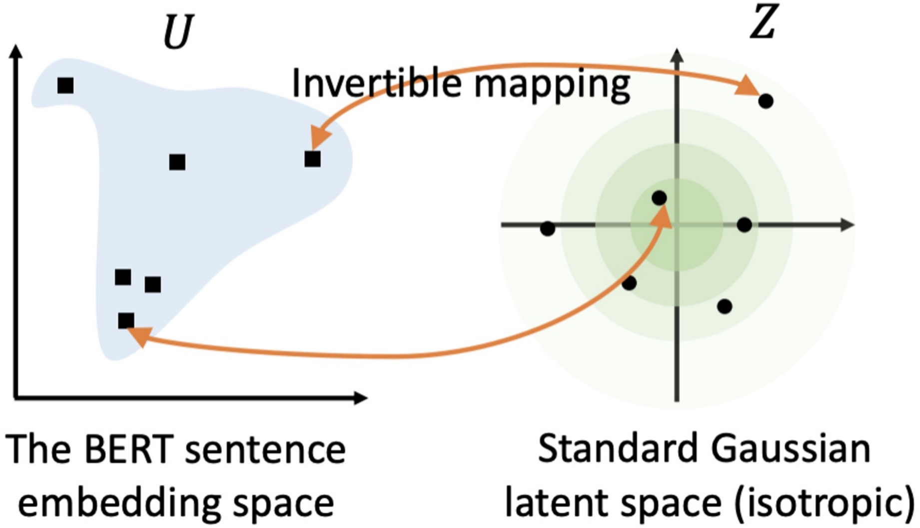

Gao, Jun, et al. "Representation Degeneration Problem in Training Natural Language Generation Models." *International Conference on Learning Representations*. 2018.

Ethayarajh, Kawin. "How Contextual are Contextualized Word Representations? Comparing the Geometry of BERT, ELMo, and GPT-2 Embeddings." *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*. 2019.

Wang, Lingxiao, et al. "Improving neural language generation with spectrum control." *International Conference on Learning Representations*. 2019.

# BERT-flow

**non-smooth anisotropic semantic space**




**smooth isotropic semantic space**

Li, Bohan, et al. "On the Sentence Embeddings from Pre-trained Language Models." *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 2020.

# BERT-flow

- **Sentence Textual Similarity (STS) Task**
  Data: Sentence pairs with 1-5 human ratings for the similarity
  Metric: Spearman Correlation between model predictions and human ratings

| Dataset | STS-B | SICK-R | STS-12 | STS-13 | STS-14 | STS-15 | STS-16 |
|---|---|---|---|---|---|---|---|
| *Published in (Reimers and Gurevych, 2019)* | | | | | | | |
| Avg. GloVe embeddings | 58.02 | 53.76 | 55.14 | 70.66 | 59.73 | 68.25 | 63.66 |
| Avg. BERT embeddings | 46.35 | 58.40 | 38.78 | 57.98 | 57.98 | 63.15 | 61.06 |
| BERT CLS-vector | 16.50 | 42.63 | 20.16 | 30.01 | 20.09 | 36.88 | 38.03 |
| *Our Implementation* | | | | | | | |
| $\text{BERT}_{\text{base}}$ | 47.29 | 58.21 | 49.07 | 55.92 | 54.75 | 62.75 | 65.19 |
| $\text{BERT}_{\text{base}}$-last2avg | 59.04 | 63.75 | 57.84 | 61.95 | 62.48 | 70.95 | 69.81 |
| $\text{BERT}_{\text{base}}$-flow (NLI*) | 58.56 (↓) | **65.44** (↑) | 59.54 (↑) | 64.69 (↑) | 64.66 (↑) | 72.92 (↑) | 71.84 (↑) |
| $\text{BERT}_{\text{base}}$-flow (target) | 70.72 (↑) | 63.11(↓) | 63.48 (↑) | 72.14 (↑) | 68.42 (↑) | 73.77 (↑) | 75.37 (↑) |

Li, Bohan, et al. "On the Sentence Embeddings from Pre-trained Language Models." *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 2020.

# BERT-whitening

- Using a simple whitening post-processing can outperform BERT-flow

| | STS-B | STS-12 | STS-13 | STS-14 | STS-15 | STS-16 | SICK-R |
|---|---|---|---|---|---|---|---|
| | *Published in (Reimers and Gurevych, 2019)* | | | | | | |
| Avg. GloVe embeddings | 58.02 | 55.14 | 70.66 | 59.73 | 68.25 | 63.66 | 53.76 |
| Avg. BERT embeddings | 46.35 | 38.78 | 57.98 | 57.98 | 63.15 | 61.06 | 58.40 |
| BERT CLS-vector | 16.50 | 20.16 | 30.01 | 20.09 | 36.88 | 38.03 | 42.63 |
| | *Published in (Li et al., 2020)* | | | | | | |
| $\text{BERT}_{\text{base}}$-first-last-avg | 59.04 | 57.84 | 61.95 | 62.48 | 70.95 | 69.81 | 63.75 |
| $\text{BERT}_{\text{base}}$-flow (NLI) | 58.56 | 59.54 | 64.69 | 64.66 | 72.92 | 71.84 | **65.44** |
| $\text{BERT}_{\text{base}}$-flow (target) | 70.72 | 63.48 | 72.14 | 68.42 | 73.77 | **75.37** | 63.11 |
| | *Our implementation* | | | | | | |
| $\text{BERT}_{\text{base}}$-first-last-avg | 59.04 | 57.86 | 61.97 | 62.49 | 70.96 | 69.76 | 63.75 |
| $\text{BERT}_{\text{base}}$-whitening (NLI) | 68.19(↑) | 61.69(↑) | 65.70(↑) | 66.02(↑) | **75.11**(↑) | 73.11(↑) | 63.6(↓) |
| $\text{BERT}_{\text{base}}$-whitening-256 (NLI) | 67.51(↑) | 61.46(↑) | 66.71(↑) | 66.17(↑) | 74.82(↑) | 72.10(↑) | 64.9(↓) |
| $\text{BERT}_{\text{base}}$-whitening (target) | 71.34(↑) | 63.62(↑) | 73.02(↑) | **69.23**(↑) | 74.52(↑) | 72.15(↓) | 60.6(↓) |
| $\text{BERT}_{\text{base}}$-whitening-256 (target) | **71.43**(↑) | **63.89**(↑) | **73.76**(↑) | 69.08(↑) | 74.59(↑) | 74.40(↓) | 62.2(↓) |

Su, Jianlin, et al. "Whitening sentence representations for better semantics and faster retrieval." *arXiv preprint arXiv:2103.15316* (2021).

We need further fine-tuning
to extract better sentence embeddings
from pre-trained language models…

# Outline of Part 3

1. Why we need sentence-level representations?
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   a. Designed Positives
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5. Conclusion

# Contrastive Learning

How can we produce augmentations in NLP?

**NLP?**

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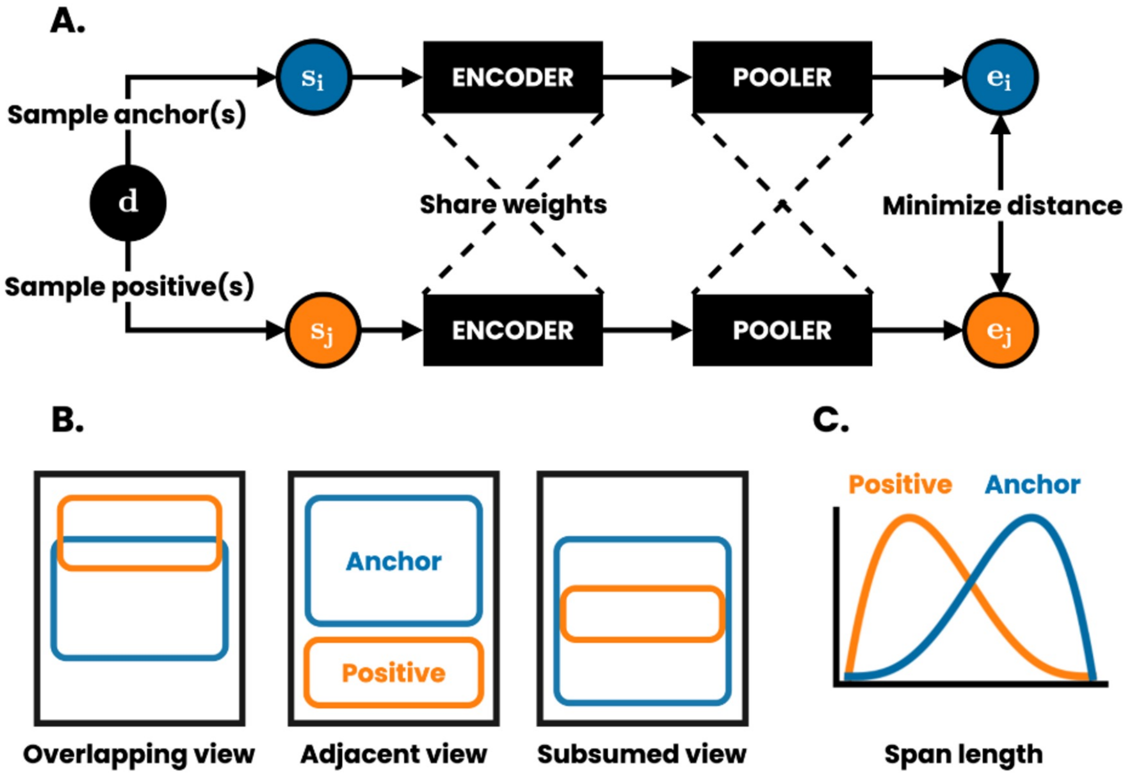
5. Conclusion

# DeCLUTR

- **Positive Pairs:**
  Overlapping/adjacent spans from the same document

- **Negative Pairs:**
  - hard negatives from the same docs
  - easy negatives from different docs




Giorgi, John, et al. "DeCLUTR: Deep Contrastive Learning for Unsupervised Textual Representations." *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. 2021.

# Results (STS)

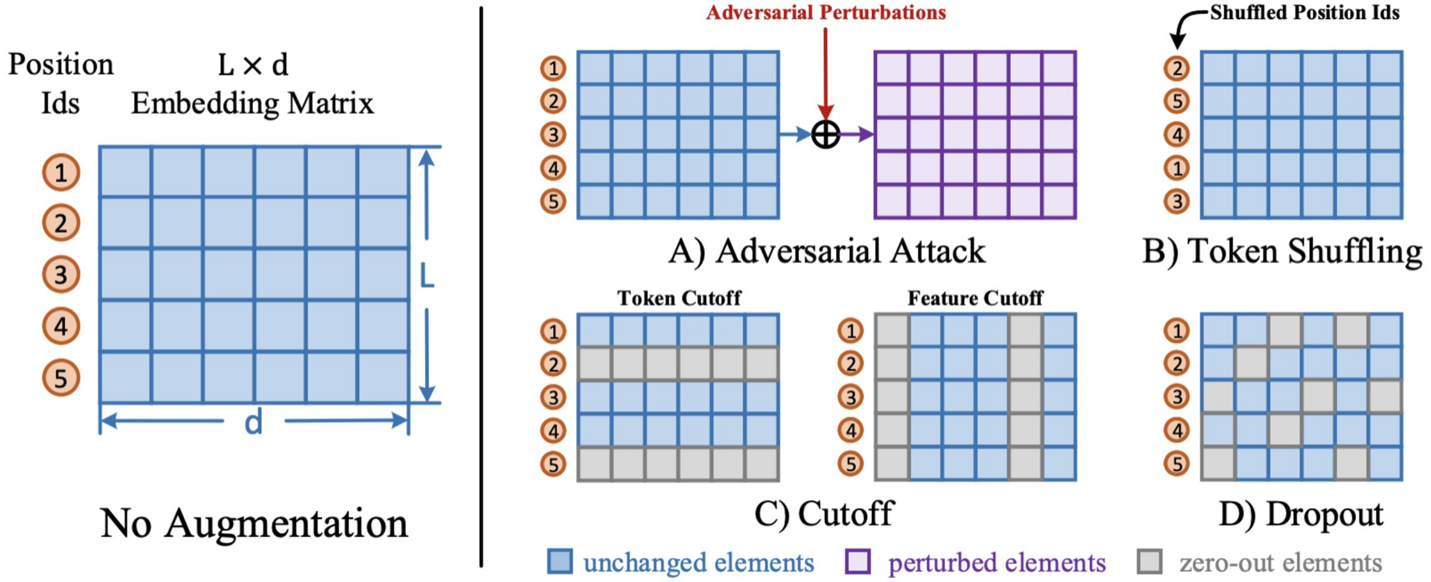
- Good improvement over post-processing methods

| Model | SICK-E | SICK-R | STS-B | COCO | STS12* | STS13* | STS14* | STS15* | STS16* |
|---|---|---|---|---|---|---|---|---|---|
| GloVe | 78.89 | 72.30 | 62.86 | 0.40 | 53.44 | 51.24 | 55.71 | 59.62 | 57.93 |
| fastText | 79.01 | 72.98 | 68.26 | 0.40 | 58.85 | 58.83 | 63.42 | 69.05 | 68.24 |
| InferSent | **86.30** | **83.06** | 78.48 | **65.84** | 62.90 | 56.08 | 66.36 | 74.01 | 72.89 |
| USE | 85.37 | 81.53 | **81.50** | 62.42 | **68.87** | 71.70 | **72.76** | **83.88** | **82.78** |
| Sent. Transformers | 82.97 | 79.17 | 74.28 | 60.96 | 64.10 | 65.63 | 69.80 | 74.71 | 72.85 |
| QuickThoughts | – | – | – | 60.55 | – | – | – | – | – |
| Transformer-small | 81.96 | 77.51 | 70.31 | 60.48 | 53.99 | 45.53 | 57.23 | 65.57 | 63.51 |
| Transformer-base | 80.29 | 76.84 | 69.62 | 60.14 | 53.28 | 46.10 | 56.17 | 64.69 | 62.79 |
| DeCLUTR-small | 83.46 ↑ | 77.66 ↑ | 77.51 ↑ | 60.85 ↑ | 63.66 ↑ | 68.93 ↑ | 70.40 ↑ | 78.25 ↑ | 77.74 ↑ |
| DeCLUTR-base | 83.84 ↑ | 78.62 ↑ | 79.39 ↑ | 62.35 ↑ | 63.56 ↑ | **72.58** ↑ | 71.70 ↑ | 79.95 ↑ | 79.59 ↑ |
| **BERT-flow** | **--** | **63.11** | **70.72** | **--** | **63.48** | **72.02** | **68.42** | **73.77** | **75.37** |
| **BERT-whitening** | **--** | **62.20** | **71.43** | **--** | **63.89** | **73.76** | **69.08** | **74.59** | **74.40** |

Giorgi, John, et al. "DeCLUTR: Deep Contrastive Learning for Unsupervised Textual Representations." *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. 2021.

# ConSERT

- All the possible augmentations on token embedding space




Yan, Yuanmeng, et al. "ConSERT: A Contrastive Framework for Self-Supervised Sentence Representation Transfer." *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. 2021.

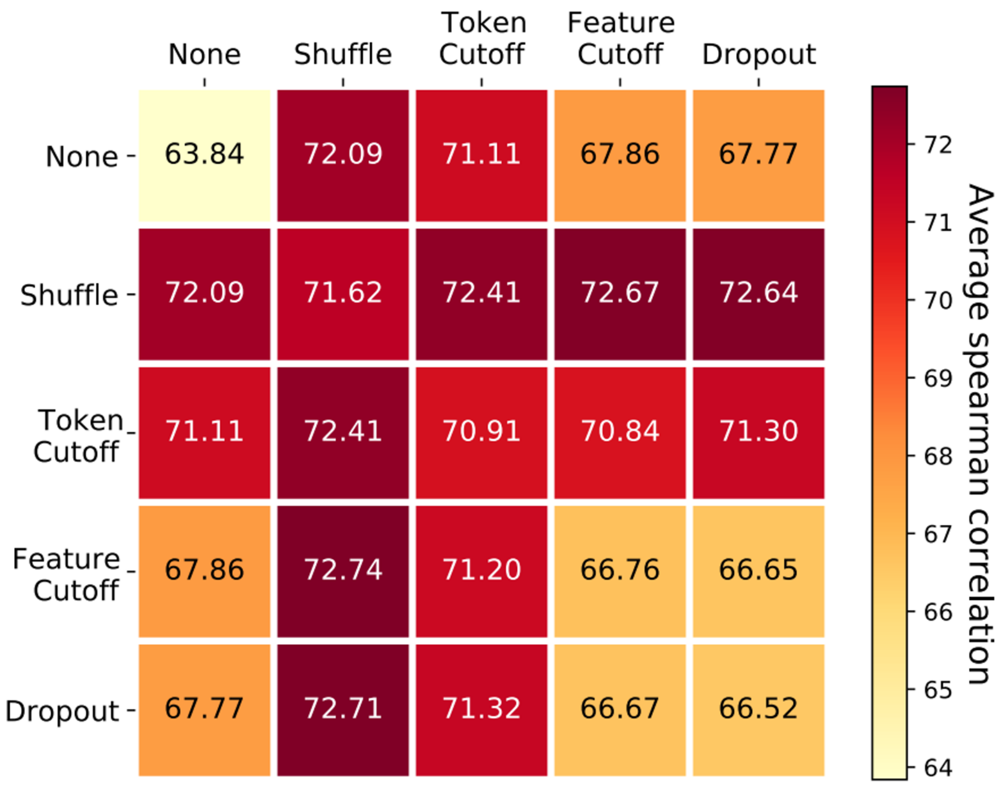
# Experiments

- Using unlabeled text to train contrastive loss for adaptation

| Method | STS12 | STS13 | STS14 | STS15 | STS16 | STSb | SICK-R | Avg. |
|---|---|---|---|---|---|---|---|---|
| | | | | *Unsupervised baselines* | | | | |
| Avg. GloVe embeddings† | 55.14 | 70.66 | 59.73 | 68.25 | 63.66 | 58.02 | 53.76 | 61.32 |
| $\text{BERT}_{\text{base}}$‡ | 35.20 | 59.53 | 49.37 | 63.39 | 62.73 | 48.18 | 58.60 | 53.86 |
| $\text{BERT}_{\text{large}}$‡ | 33.06 | 57.64 | 47.95 | 55.83 | 62.42 | 49.66 | 53.87 | 51.49 |
| $\text{CLEAR}_{\text{base}}$† | 49.0 | 48.9 | 57.4 | 63.6 | 65.6 | 75.6 | 72.5 | 61.8 |
| IS-$\text{BERT}_{\text{base}}$-NLI† | 56.77 | 69.24 | 61.21 | 75.23 | 70.16 | 69.21 | 64.25 | 66.58 |
| $\text{BERT}_{\text{base}}$-CT† | 66.86 | 70.91 | 72.37 | 78.55 | 77.78 | - | - | - |
| $\text{BERT}_{\text{large}}$-CT† | 69.50 | 75.97 | 74.22 | 78.83 | 78.92 | - | - | - |
| | | | | *Using STS unlabeled texts* | | | | |
| $\text{BERT}_{\text{base}}$-flow† | 63.48 | 72.14 | 68.42 | 73.77 | 75.37 | 70.72 | 63.11 | 69.57 |
| $\text{BERT}_{\text{large}}$-flow† | 65.20 | 73.39 | 69.42 | 74.92 | **77.63** | 72.26 | 62.50 | 70.76 |
| $\text{ConSERT}_{\text{base}}$‡ | 64.64 | 78.49 | 69.07 | 79.72 | 75.95 | 73.97 | 67.31 | 72.74 |
| $\text{ConSERT}_{\text{large}}$‡ | **70.69** | **82.96** | **74.13** | **82.78** | 76.66 | **77.53** | **70.37** | **76.45** |
| **DeCLUTR (BERT-base)** | **63.56** | **72.58** | **71.70** | **79.95** | **79.59** | **79.39** | **78.62** | **75.06** |

Yan, Yuanmeng, et al. "ConSERT: A Contrastive Framework for Self-Supervised Sentence Representation Transfer." *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. 2021.

# Effects of Augmentation Strategies




Yan, Yuanmeng, et al. "ConSERT: A Contrastive Framework for Self-Supervised Sentence Representation Transfer." *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. 2021.

# Outline of Part 3

1. Why we need sentence-level representations?
2. Pre-BERT methods
3. How to obtain sentence-level representations from BERTs?
   a. Post-processing Methods
4. Contrastive Learning Methods:
   a. Designed Positives
   b. **Generating Positives**
   c. Bootstrapping Methods
   d. Dropout Augmentations
   e. Equivariant Contrastive Learning
   f. Prompting
   g. Ranking-based Methods
5. Conclusion

# Datasets from Instructions (DINO 🦕)

- Continuations generated by GPT-2 XL

**Task:** Write two sentences that mean the same thing.

**Sentence 1:** "A man is playing a flute."

**Sentence 2:** "He's playing a flute."

**Task:** Write two sentences that are somewhat similar.

**Sentence 1:** "A man is playing a flute."

**Sentence 2:** "A woman has been playing the violin."

**Task:** Write two sentences that are on completely different topics.

**Sentence 1:** "A man is playing a flute."

**Sentence 2:** "A woman is walking down the street."

Schick, Timo, and Hinrich Schütze. "Generating Datasets with Pretrained Language Models." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

# Datasets from Instructions (DINO 🦕)

| | Model | UD | STS12 | STS13 | STS14 | STS15 | STS16 | STSb | SICK | Avg. |
|---|---|---|---|---|---|---|---|---|---|---|
| sup. | InferSent, Glove | – | 52.86 | 66.75 | 62.15 | 72.77 | 66.87 | 68.03 | 65.65 | 65.01 |
| | USE | – | 64.49 | 67.80 | 64.61 | 76.83 | 73.18 | 74.92 | 76.69 | 71.22 |
| | S-BERT (base) | – | 70.97 | 76.53 | 73.19 | 79.09 | 74.30 | 77.03 | 72.91 | 74.89 |
| | S-RoBERTa (base) | – | 71.54 | 72.49 | 70.80 | 78.74 | 73.69 | 77.77 | 74.46 | 74.21 |
| unsup. | Avg. GloVe | – | 55.14 | 70.66 | 59.73 | 68.25 | 63.66 | 58.02 | 53.76 | 61.32 |
| | Avg. BERT | – | 38.78 | 57.98 | 57.98 | 63.15 | 61.06 | 46.35 | 58.40 | 54.81 |
| | BERT CLS | – | 20.16 | 30.01 | 20.09 | 36.88 | 38.08 | 16.50 | 42.63 | 29.19 |
| | Zhang et al. (2020) | NLI | 56.77 | 69.24 | 61.21 | 75.23 | 70.16 | 69.21 | 64.25 | 66.58 |
| | Li et al. (2020) BERT-flow | NLI | 59.54 | 64.69 | 64.66 | 72.92 | 71.84 | 58.56 | 65.44 | 65.38 |
| | Li et al. (2020) | STS | 63.48 | 72.14 | 68.42 | 73.77 | 75.37 | 70.72 | 63.11 | 69.57 |
| | DINO (STS-🦕-$\mathbf{x}_1\mathbf{x}_2$) | – | 64.87 | 78.30 | 66.38 | 79.60 | 76.47 | 76.51 | **74.26** | 73.77 |
| | DINO (STS-🦕-$\mathbf{x}_2$) | STS | **70.27** | **81.26** | **71.25** | **80.49** | **77.18** | **77.82** | 68.09 | **75.20** |
| | **DeCLUTR (BERT-base)** | | **63.56** | **72.58** | **71.70** | **79.95** | **79.59** | **79.39** | **78.62** | **75.06** |
| | **ConSERT (BERT-base)** | | **64.64** | **78.49** | **69.07** | **79.72** | **75.95** | **73.97** | **67.31** | **72.74** |

Schick, Timo, and Hinrich Schütze. "Generating Datasets with Pretrained Language Models." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

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    b. Generating Positives
    c. **Bootstrapping Methods**
    d. Dropout Augmentations
    e. Equivariant Contrastive Learning
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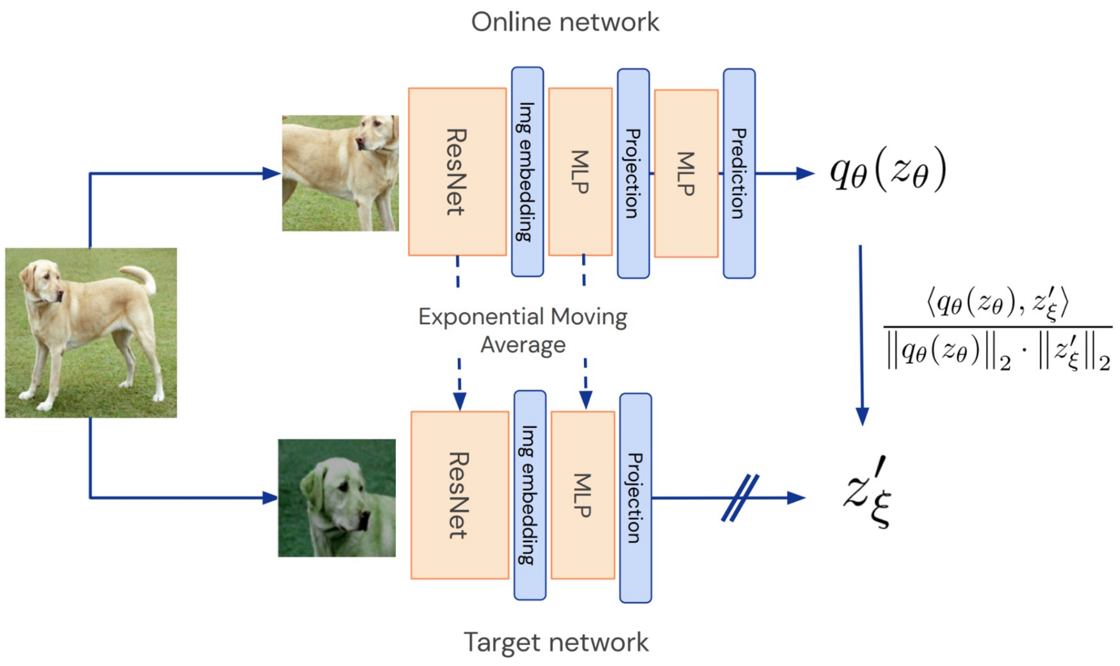
# BYOL

- Not contrastive learning
- Only positive pairs, no negatives pairs
- Use a **moving average target network** to prevent mode collapsing




Grill, Jean-Bastien, et al. "Bootstrap your own latent-a new approach to self-supervised learning." *Advances in neural information processing systems* 33 (2020): 21271-21284.

# BYOL for sentence representations

- Back-Translation as positive pairs

| Model | STS-12 | STS-13 | STS-14 | STS-15 | STS-16 | STS-B | SICK-R | Avg. |
|---|---|---|---|---|---|---|---|---|
| | | | *Unsupervised methods* | | | | | |
| Unigram-TFIDF† | - | - | 58.00 | - | - | - | 52.00 | - |
| SDAE† | - | - | 12.00 | - | - | - | 46.00 | - |
| SkipThought† | - | - | 27.00 | - | - | - | 57.00 | - |
| FastSent† | - | - | 63.00 | - | - | - | 61.00 | - |
| GloVe avg.‡ | 55.14 | 70.66 | 59.73 | 68.25 | 63.66 | 58.02 | 53.76 | 61.32 |
| BERT avg.‡ | 38.78 | 57.98 | 57.98 | 63.15 | 61.06 | 46.35 | 58.40 | 54.81 |
| BERT [CLS]‡ | 20.16 | 30.01 | 20.09 | 36.88 | 38.08 | 16.50 | 42.63 | 29.19 |
| BERT-mlm | 48.86 | 64.76 | 56.97 | 70.86 | 64.65 | 64.33 | 67.76 | 62.60 |
| IS-BERT* | 56.77 | 69.24 | 61.21 | 75.23 | 70.16 | 69.21 | 64.25 | 66.58 |
| BERT-flow° | 59.54 | 64.69 | 64.66 | 72.92 | 71.84 | 58.56 | 65.44 | 65.38 |
| **Ours: BSL-BERT** | **67.83** | **71.40** | **66.88** | **79.97** | **73.97** | **73.74** | **70.40** | **72.03** |
| **Ours: BSL-RoBERTa** | **68.47** | **72.41** | **68.48** | **78.50** | **72.77** | **78.77** | **69.97** | **72.76** |
| **DeCLUTR (BERT-base)** | **63.56** | **72.58** | **71.70** | **79.95** | **79.59** | **79.39** | **78.62** | **75.06** |
| **ConSERT (BERT-base)** | **64.64** | **78.49** | **69.07** | **79.72** | **75.95** | **73.97** | **67.31** | **72.74** |
| **DINO (RoBERTa-base)** | **70.27** | **81.26** | **71.25** | **80.49** | **77.18** | **77.82** | **68.09** | **75.20** |

Zhang, Yan, et al. "Bootstrapped unsupervised sentence representation learning." *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. 2021.

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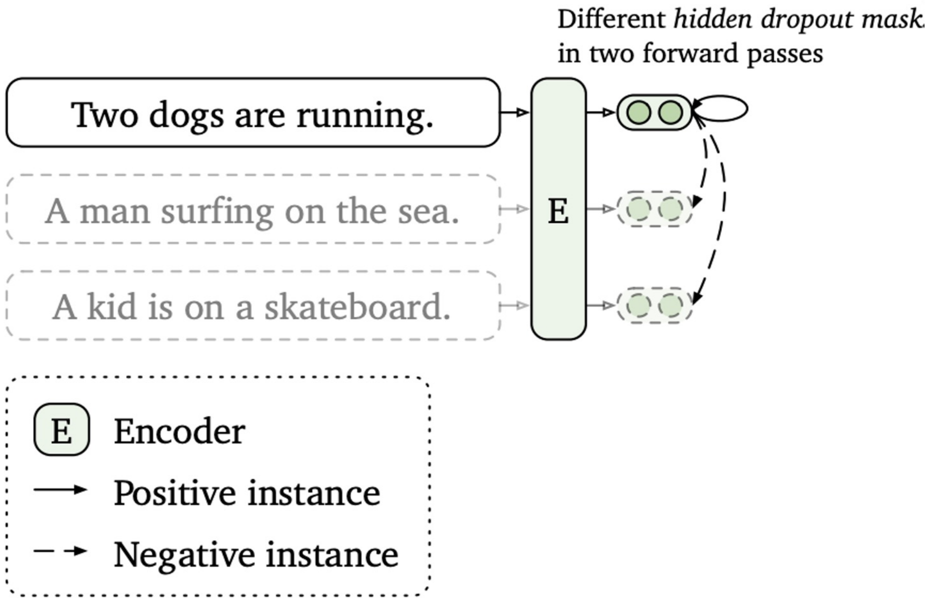
# SimCSE (Unsupervised)

- Using different dropout masks (in Transformer layers) as augmentation
  -> Model architecture is the same





Gao, Tianyu, Xingcheng Yao, and Danqi Chen. "SimCSE: Simple Contrastive Learning of Sentence Embeddings." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

# Results (STS)

| Model | STS12 | STS13 | STS14 | STS15 | STS16 | STS-B | SICK-R | Avg. |
|---|---|---|---|---|---|---|---|---|
| *Unsupervised models* | | | | | | | | |
| GloVe embeddings (avg.)♣ | 55.14 | 70.66 | 59.73 | 68.25 | 63.66 | 58.02 | 53.76 | 61.32 |
| $\text{BERT}_{\texttt{base}}$ (first-last avg.) | 39.70 | 59.38 | 49.67 | 66.03 | 66.19 | 53.87 | 62.06 | 56.70 |
| $\text{BERT}_{\texttt{base}}$-flow | 58.40 | 67.10 | 60.85 | 75.16 | 71.22 | 68.66 | 64.47 | 66.55 |
| $\text{BERT}_{\texttt{base}}$-whitening | 57.83 | 66.90 | 60.90 | 75.08 | 71.31 | 68.24 | 63.73 | 66.28 |
| $\text{IS-BERT}_{\texttt{base}}$ ♡ | 56.77 | 69.24 | 61.21 | 75.23 | 70.16 | 69.21 | 64.25 | 66.58 |
| $\text{CT-BERT}_{\texttt{base}}$ | 61.63 | 76.80 | 68.47 | 77.50 | 76.48 | 74.31 | 69.19 | 72.05 |
| ∗ $\text{SimCSE-BERT}_{\texttt{base}}$ | **68.40** | **82.41** | **74.38** | **80.91** | **78.56** | **76.85** | **72.23** | **76.25** |
| $\text{RoBERTa}_{\texttt{base}}$ (first-last avg.) | 40.88 | 58.74 | 49.07 | 65.63 | 61.48 | 58.55 | 61.63 | 56.57 |
| $\text{RoBERTa}_{\texttt{base}}$-whitening | 46.99 | 63.24 | 57.23 | 71.36 | 68.99 | 61.36 | 62.91 | 61.73 |
| $\text{DeCLUTR-RoBERTa}_{\texttt{base}}$ | 52.41 | 75.19 | 65.52 | 77.12 | 78.63 | 72.41 | **68.62** | 69.99 |
| ∗ $\text{SimCSE-RoBERTa}_{\texttt{base}}$ | **70.16** | **81.77** | **73.24** | **81.36** | **80.65** | **80.22** | 68.56 | **76.57** |
| ∗ $\text{SimCSE-RoBERTa}_{\texttt{large}}$ | **72.86** | **83.99** | **75.62** | **84.77** | **81.80** | **81.98** | **71.26** | **78.90** |
| **DeCLUTR (BERT-base)** | **63.56** | **72.58** | **71.70** | **79.95** | **79.59** | **79.39** | **78.62** | **75.06** |
| **ConSERT (BERT-base)** | **64.64** | **78.49** | **69.07** | **79.72** | **75.95** | **73.97** | **67.31** | **72.74** |
| **DINO (RoBERTa-base)** | **70.27** | **81.26** | **71.25** | **80.49** | **77.18** | **77.82** | **68.09** | **75.20** |

Gao, Tianyu, Xingcheng Yao, and Danqi Chen. "SimCSE: Simple Contrastive Learning of Sentence Embeddings." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

# Why Dropout?

- Better than crop, word deletion and replacement
- Simple but super effective

| **Data augmentation** | | | **STS-B** |
|---|---|---|---|
| None (unsup. SimCSE) | | | **82.5** |
| Crop | *10%* | *20%* | *30%* |
| | 77.8 | 71.4 | 63.6 |
| Word deletion | *10%* | *20%* | *30%* |
| | 75.9 | 72.2 | 68.2 |
| Delete one word | | | 75.9 |
| w/o dropout | | | 74.2 |
| Synonym replacement | | | 77.4 |
| MLM 15% | | | 62.2 |

Gao, Tianyu, Xingcheng Yao, and Danqi Chen. "SimCSE: Simple Contrastive Learning of Sentence Embeddings." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

# Why Self-Prediction?

STS-B results

| | Training objective | share encoder $f_\theta$ | dual encoder $(f_{\theta_1}, f_{\theta_2})$ |
|---|---|---|---|
| QuickThoughts (pos: Next Sentence) | Next sentence | 66.8 | 67.7 |
| | Next 3 sentences | 68.7 | 69.7 |
| Self-Prediction (pos: Same Sentence) | Delete one word | 74.8 | 70.4 |
| | Unsupervised SimCSE | **79.1** | 70.7 |

Gao, Tianyu, Xingcheng Yao, and Danqi Chen. "SimCSE: Simple Contrastive Learning of Sentence Embeddings." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

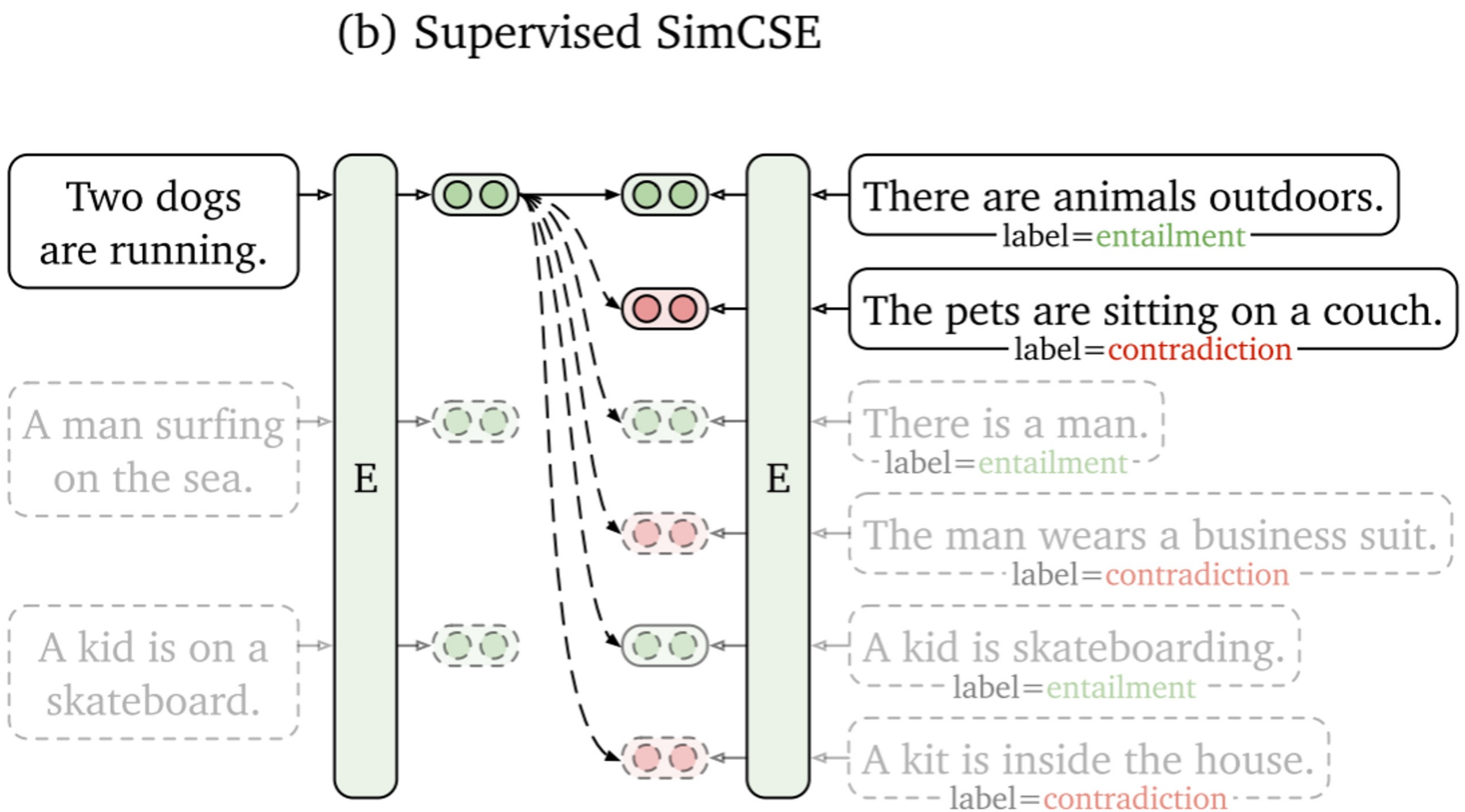
# How to Dropout?

| | | | | |
|---|---|---|---|---|
| *p* | *0.0* | *0.01* | *0.05* | *0.1* |
| STS-B | 64.9 | 69.5 | 78.0 | **79.1** |
| *p* | *0.15* | *0.2* | *0.5* | *Fixed 0.1* |
| STS-B | 78.6 | 78.2 | 67.4 | 45.2 |

- **Fixed 0.1:** apply the same dropout mask for two inputs
  -> leading to mode collapsing
- Best: Two different dropout masks with p = 0.1

Gao, Tianyu, Xingcheng Yao, and Danqi Chen. "SimCSE: Simple Contrastive Learning of Sentence Embeddings." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

# Supervised SimCSE




Gao, Tianyu, Xingcheng Yao, and Danqi Chen. "SimCSE: Simple Contrastive Learning of Sentence Embeddings." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

# Supervised SimCSE

back-translation paraphrase

use contradict as negative examples

| Dataset | sample | full |
|---|---|---|
| Unsup. SimCSE (1m) | - | 82.5 |
| QQP (134k) | 81.8 | 81.8 |
| Flickr30k (318k) | 81.5 | 81.4 |
| ParaNMT (5m) | 79.7 | 78.7 |
| SNLI+MNLI | | |
| entailment (314k) | **84.1** | **84.9** |
| neutral (314k)[8] | 82.6 | 82.9 |
| contradiction (314k) | 77.5 | 77.6 |
| all (942k) | 81.7 | 81.9 |
| SNLI+MNLI | | |
| entailment + hard neg. | - | **86.2** |
| + ANLI (52k) | - | 85.0 |

Gao, Tianyu, Xingcheng Yao, and Danqi Chen. "SimCSE: Simple Contrastive Learning of Sentence Embeddings." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

# Supervised SimCSE

**Unsupervised SImCSE v.s Supervised SimCSE**

Supervised model is still performs much better
-> Large space for unsupervised models to improve

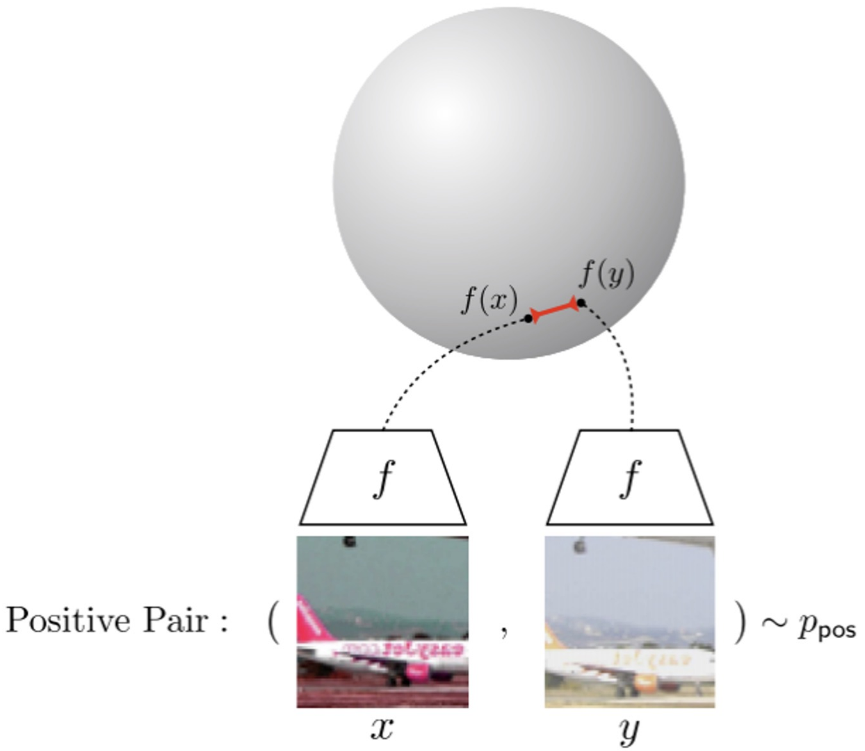
| Model | STS12 | STS13 | STS14 | STS15 | STS16 | STS-B | SICK-R | Avg. |
|---|---|---|---|---|---|---|---|---|
| | | | | *Unsupervised models* | | | | |
| ∗ SimCSE-BERT$_{\texttt{base}}$ | **68.40** | **82.41** | **74.38** | **80.91** | **78.56** | **76.85** | **72.23** | **76.25** |
| | | | | *Supervised models* | | | | |
| ∗ SimCSE-BERT$_{\texttt{base}}$ | **75.30** | **84.67** | **80.19** | **85.40** | **80.82** | **84.25** | **80.39** | **81.57** |

Gao, Tianyu, Xingcheng Yao, and Danqi Chen. "SimCSE: Simple Contrastive Learning of Sentence Embeddings." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

# Alignment & Uniformity

$$\ell_{\text{align}} \triangleq \mathop{\mathbb{E}}_{(x,x^+)\sim p_{\text{pos}}} \|f(x) - f(x^+)\|^2.$$

$$\ell_{\text{uniform}} \triangleq \log \mathop{\mathbb{E}}_{x,y \overset{i.i.d.}{\sim} p_{\text{data}}} e^{-2\|f(x)-f(y)\|^2},$$



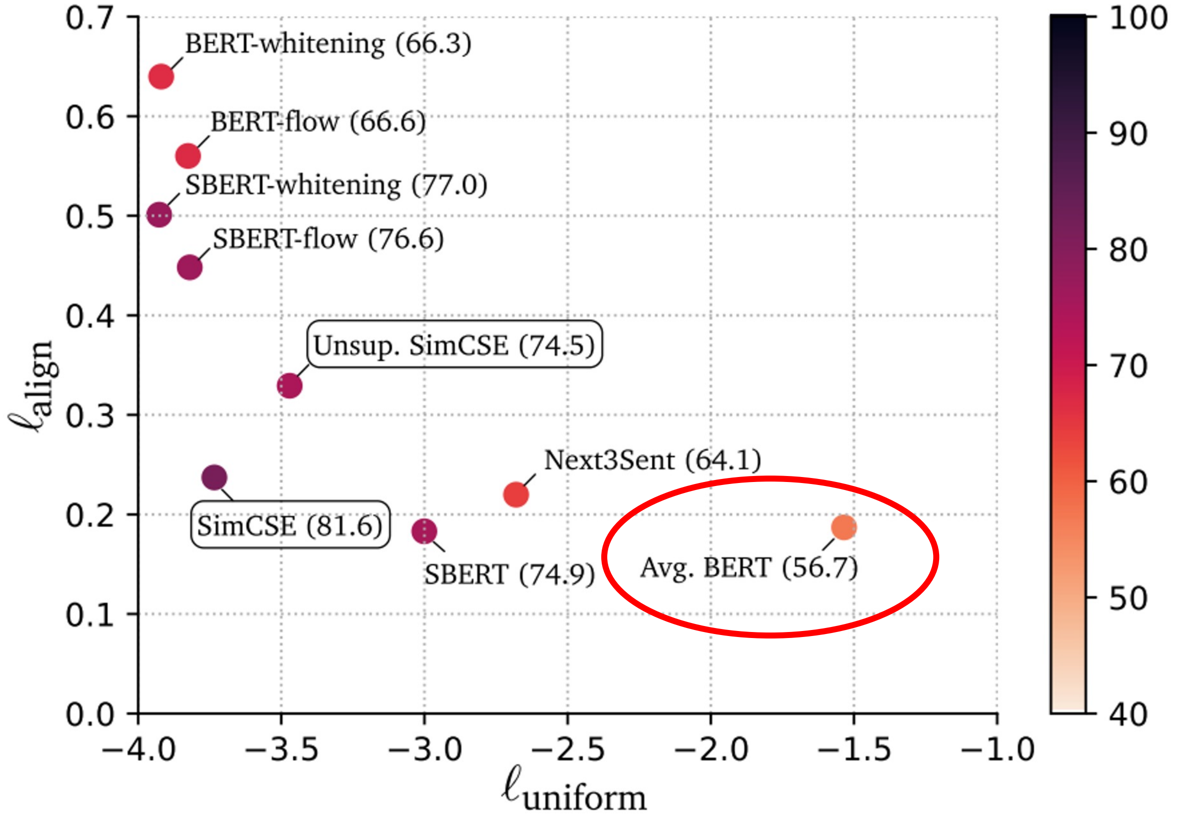

**Alignment:** Similar samples have similar features.


**Uniformity:** Preserve maximal information.

Wang, Tongzhou, and Phillip Isola. "Understanding contrastive representation learning through alignment and uniformity on the hypersphere." *International Conference on Machine Learning*. PMLR, 2020.

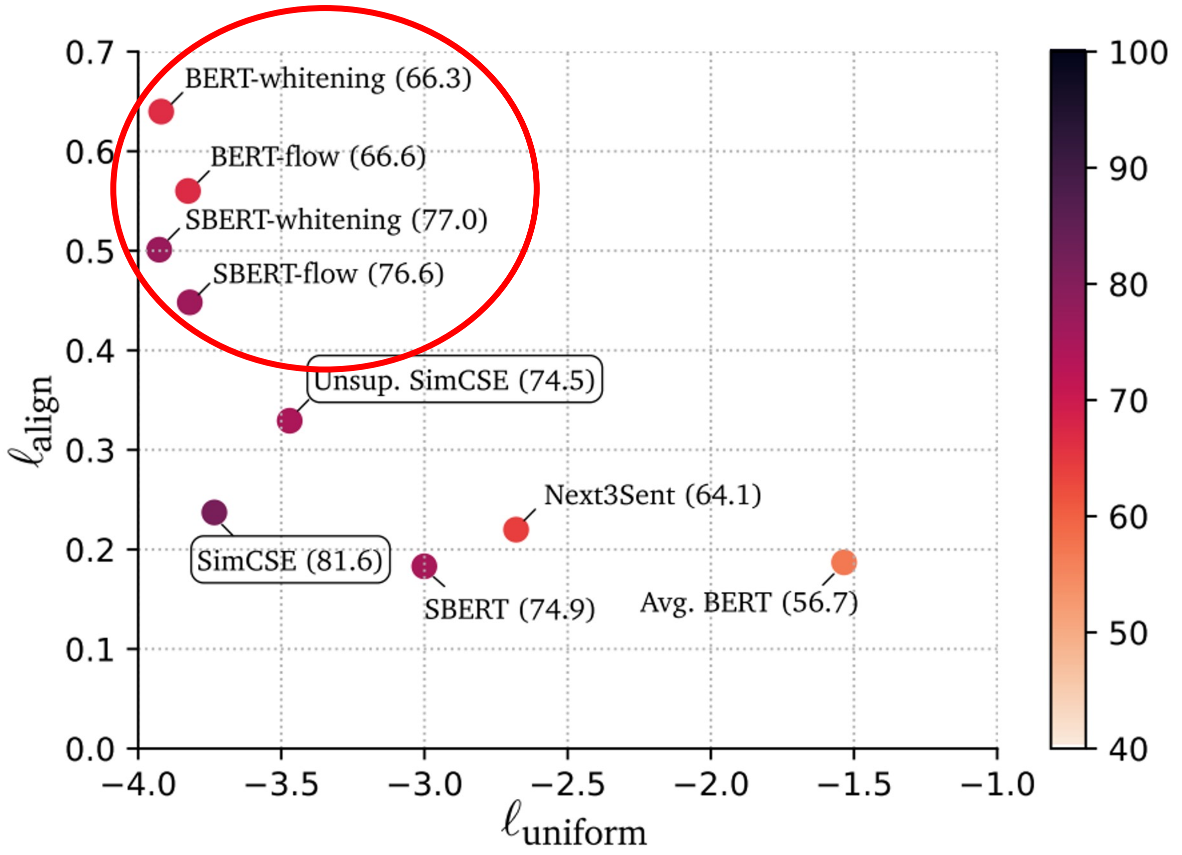
# Analysis

- **Pre-trained embedding:**
  good alignment
  poor uniformity
  => anisotropic



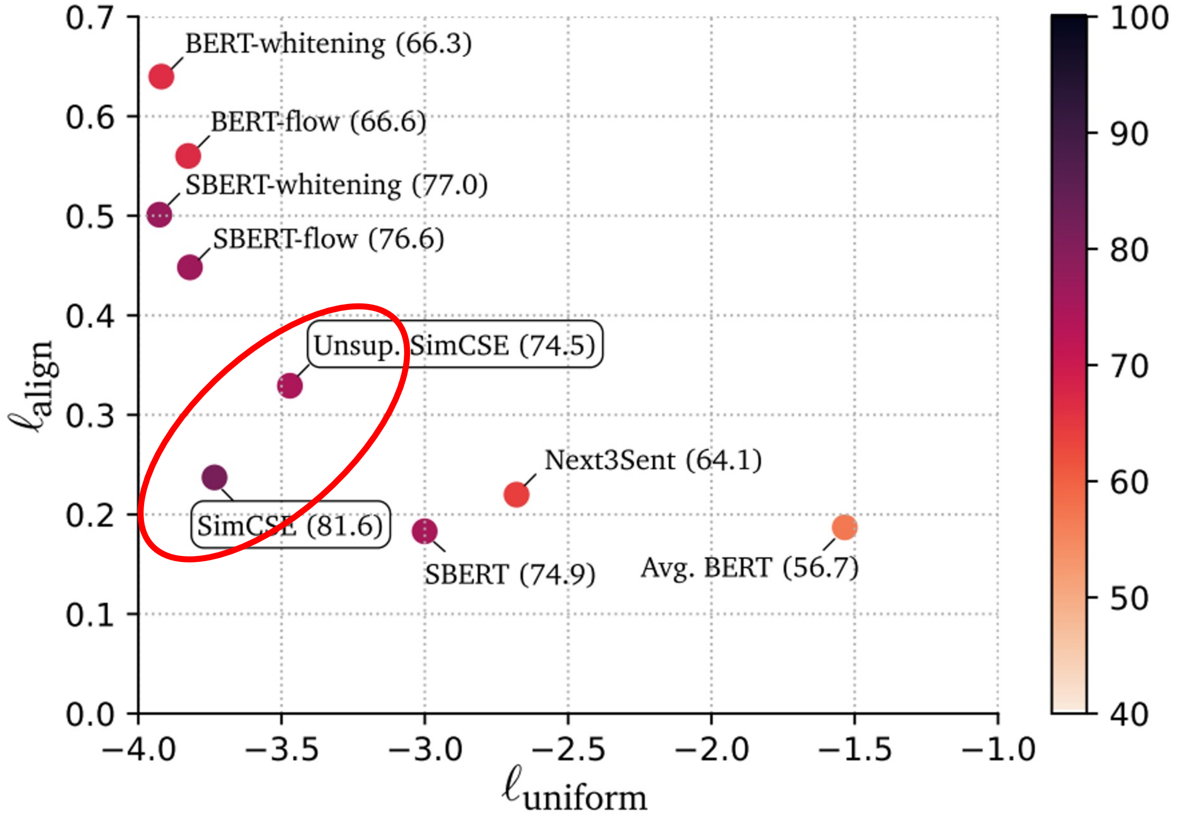
# Analysis

- **Pre-trained embedding:**
  <u>good alignment</u>
  <u>poor uniformity</u>
  => anisotropic
- **Post-processing methods**
  (BERT-whitening/flow):
  <u>good uniformity</u>
  <u>poor alignment</u>



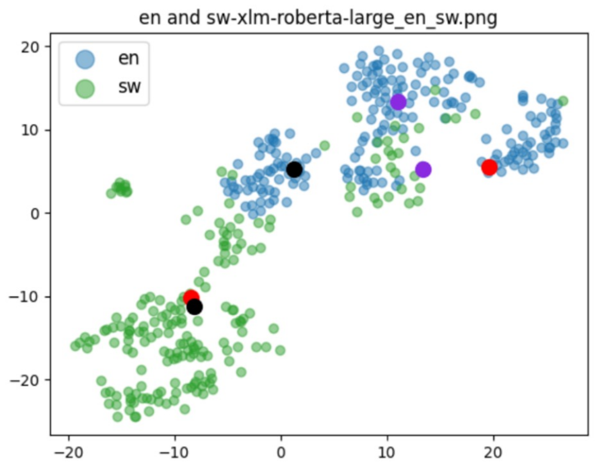
# Analysis

- **Pre-trained embedding:**
  good alignment
  poor uniformity
  => anisotropic
- **Post-processing methods** (BERT-whitening/flow):
  good uniformity
  poor alignment
- **SimCSE:**
  Best of the both worlds

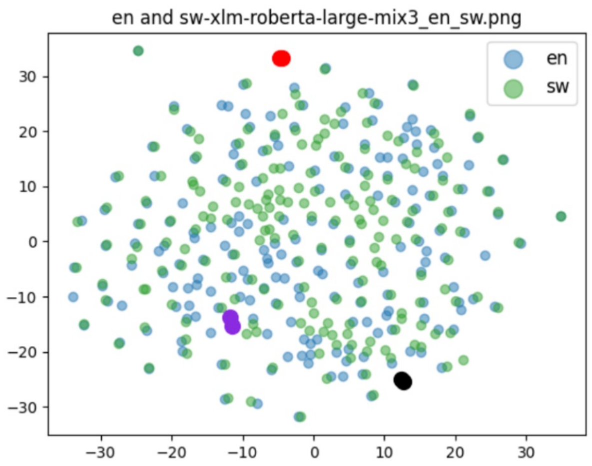


# mSimCSE

Contrastive learning on **only English** data with multilingual models (mBERT, XLM-R) can align all other other languages **without any parallel data.**




(a) XLM-R without finetuning.




(b) XLM-R fintuned on English NLI data.

Wang, Yau-Shian, Ashley Wu, and Graham Neubig. "English Contrastive Learning Can Learn Universal Cross-lingual Sentence Embeddings." *arXiv preprint arXiv:2211.06127* (2022).

# mSimCSE

- mSimCSE performs close to **supervised** multilingual sentence encoder such as **LaBSE**.

| Models | BUCC | Tatoeba-14 | Tatoeba-36 |
|---|---|---|---|
| **Unsupervised** | | | |
| XLM-R | 66.0 | 57.6 | 53.4 |
| INFOXLM | - | 77.8 | 67.3 |
| DuEAM | 77.2 | - | - |
| XLM-E | - | 72.3 | 62.3 |
| HiCTL | 68.4 | - | 59.7 |
| $mSimCSE_{en}$ | 87.5 | 82.0 | 78.0 |
| **English NLI supervised** | | | |
| (Phang et al., 2020) | 71.9 | - | 81.2 |
| $mSimCSE_{en}$ | **93.6** | **89.9** | **87.7** |
| **Cross-lingual NLI supervised** | | | |
| $mSimCSE_{en,fr}$ | 94.2 | 90.8 | 88.8 |
| $mSimCSE_{en,fr,sw}$ | 94.3 | 93.3 | 90.3 |
| $mSimCSE_{all}$ | **95.2** | 93.2 | 91.4 |
| DuEAM | 81.7 | - | - |
| **Fully Supervised** | | | |
| LASER | 92.9 | 95.3 | 84.4 |
| LaBSE | 93.5 | 95.3 | 95.0 |
| $mSimCSE_{sw}$ | 86.8 | 87.7 | 86.3 |
| $mSimCSE_{fr}$ | 87.1 | 87.9 | 85.9 |
| $mSimCSE_{sw,fr}$ | 88.8 | 90.2 | 88.3 |
| $mSimCSE_{sw,fr}$+NLI | 93.6 | 91.9 | 90.0 |

Wang, Yau-Shian, Ashley Wu, and Graham Neubig. "English Contrastive Learning Can Learn Universal Cross-lingual Sentence Embeddings." *arXiv preprint arXiv:2211.06127* (2022).

# Outline of Part 3

1. Why we need sentence-level representations?
2. Pre-BERT methods
3. How to obtain sentence-level representations from BERTs?
    a. Post-processing Methods
4. Contrastive Learning Methods:
    a. Designed Positives
    b. Generating Positives
    c. Bootstrapping Methods
    d. Dropout Augmentations
    e. **Equivariant Contrastive Learning**
    f. Prompting
    g. Ranking-based Methods
5. Conclusion

# What we’ve learned from SimCSE?

Augmentations for natural language is hard:

- Word deletion is not a good augmentation
- Synonym replacement is not a good augmentation
- Sentence cropping is not a good augmentation
- Back-translation is not a good augmentation
- …

They are all outperformed by simply changing dropout masks :(

# Let's take a step back…

Q: Why do we need positive pairs in contrastive learning?
A: to make the representations invariant to these kinds of augmentations.

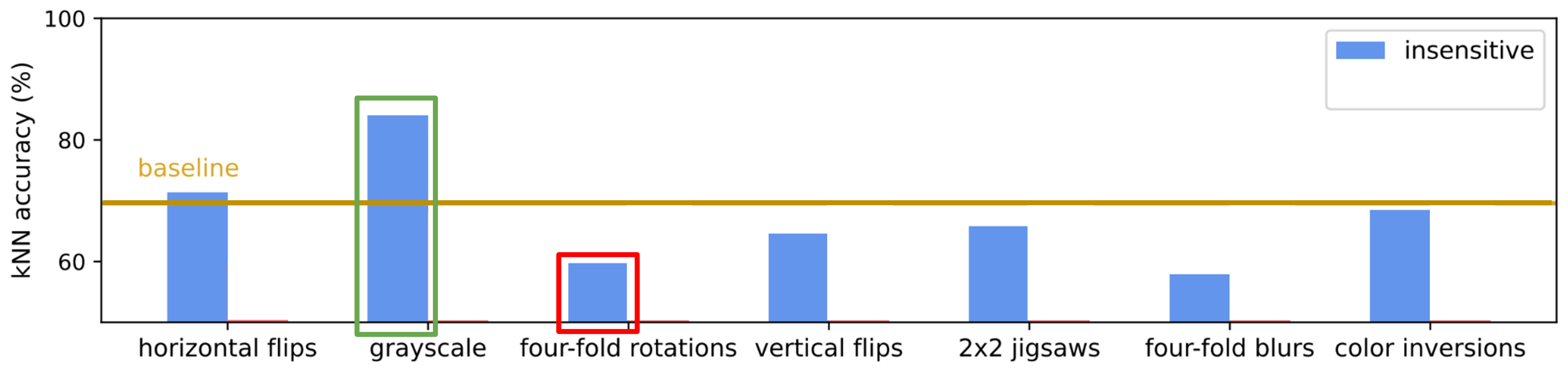
Problem:
It’s hard to produce semantically similar augmentations for natural language.
Making the representations invariant to augmentations will hurt performance.

Q: Is there another way to utilize augmentations…?

A: we can make the representations be aware of,

but not necessarily invariant to the augmentations.

# Background: Equivariant Contrastive Learning




Dangovski, Rumen, et al. "Equivariant Self-Supervised Learning: Encouraging Equivariance in Representations." *International Conference on Learning Representations*. 2022.

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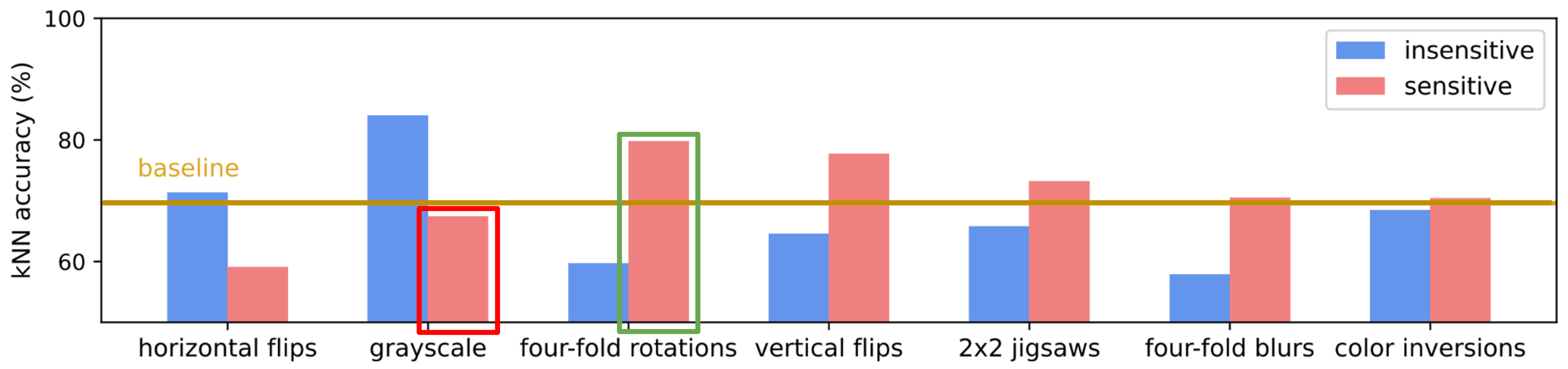


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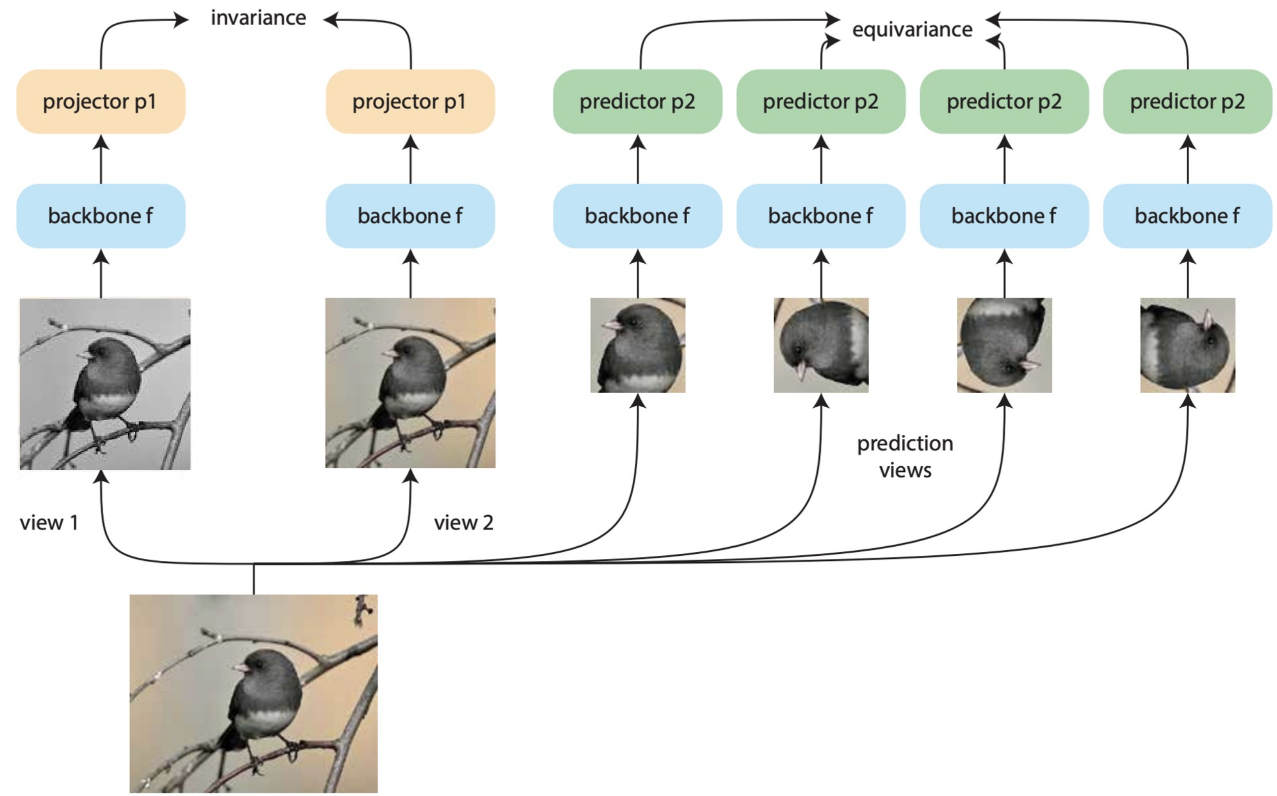


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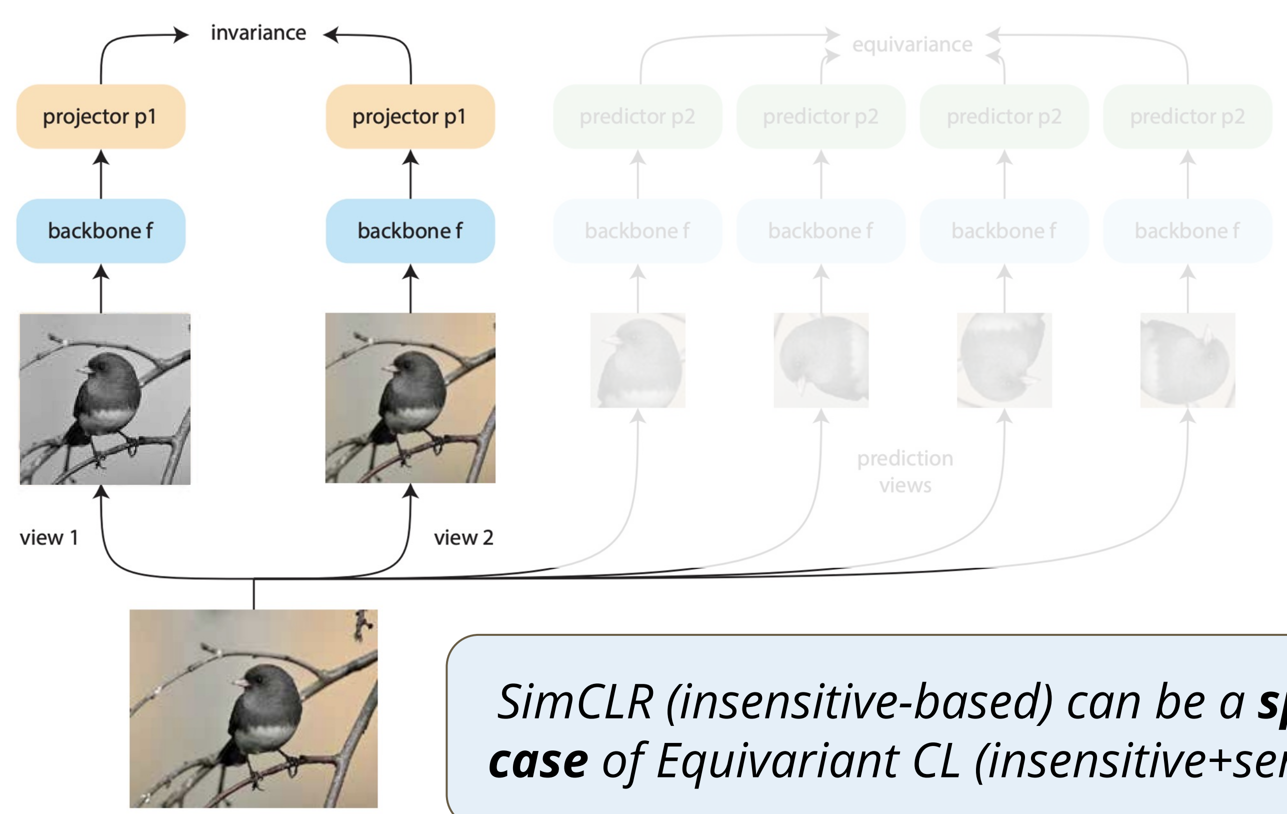


*SimCLR (insensitive-based) can be a **special case** of Equivariant CL (insensitive+sensitive)*

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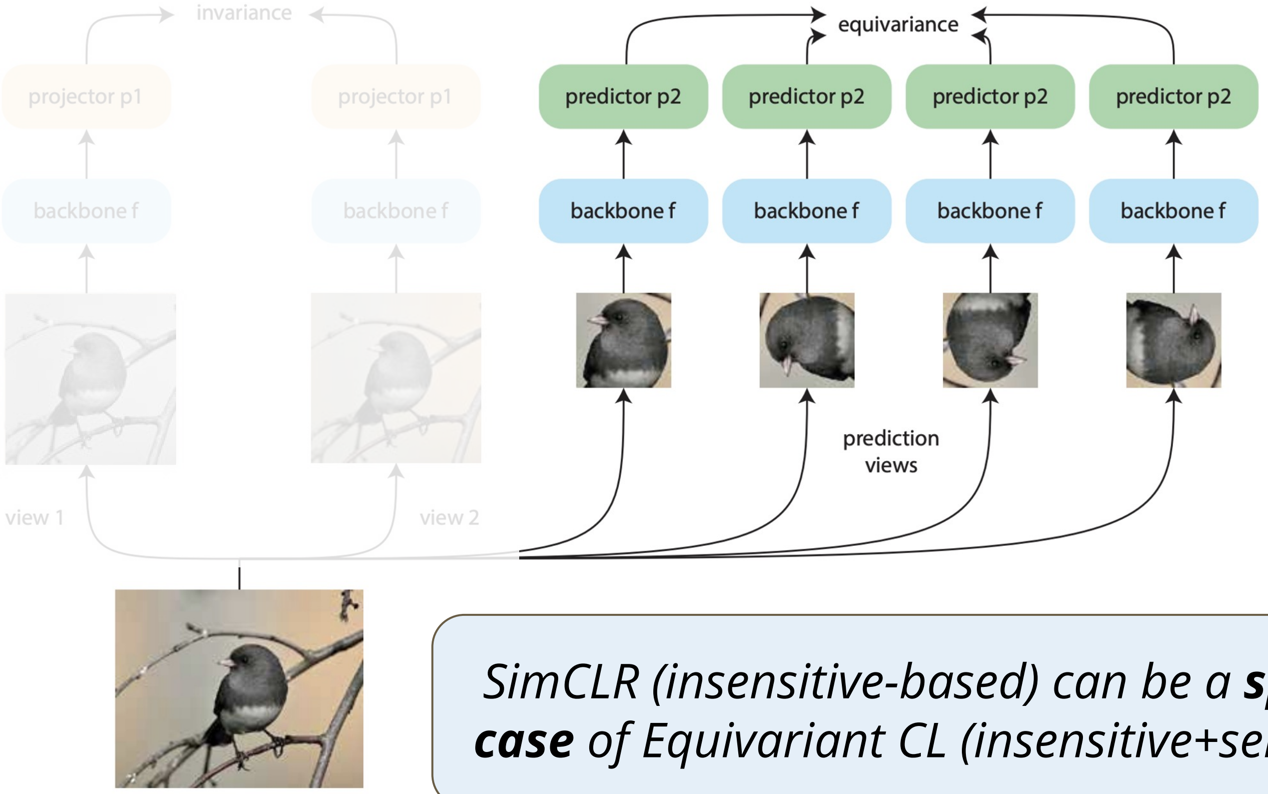


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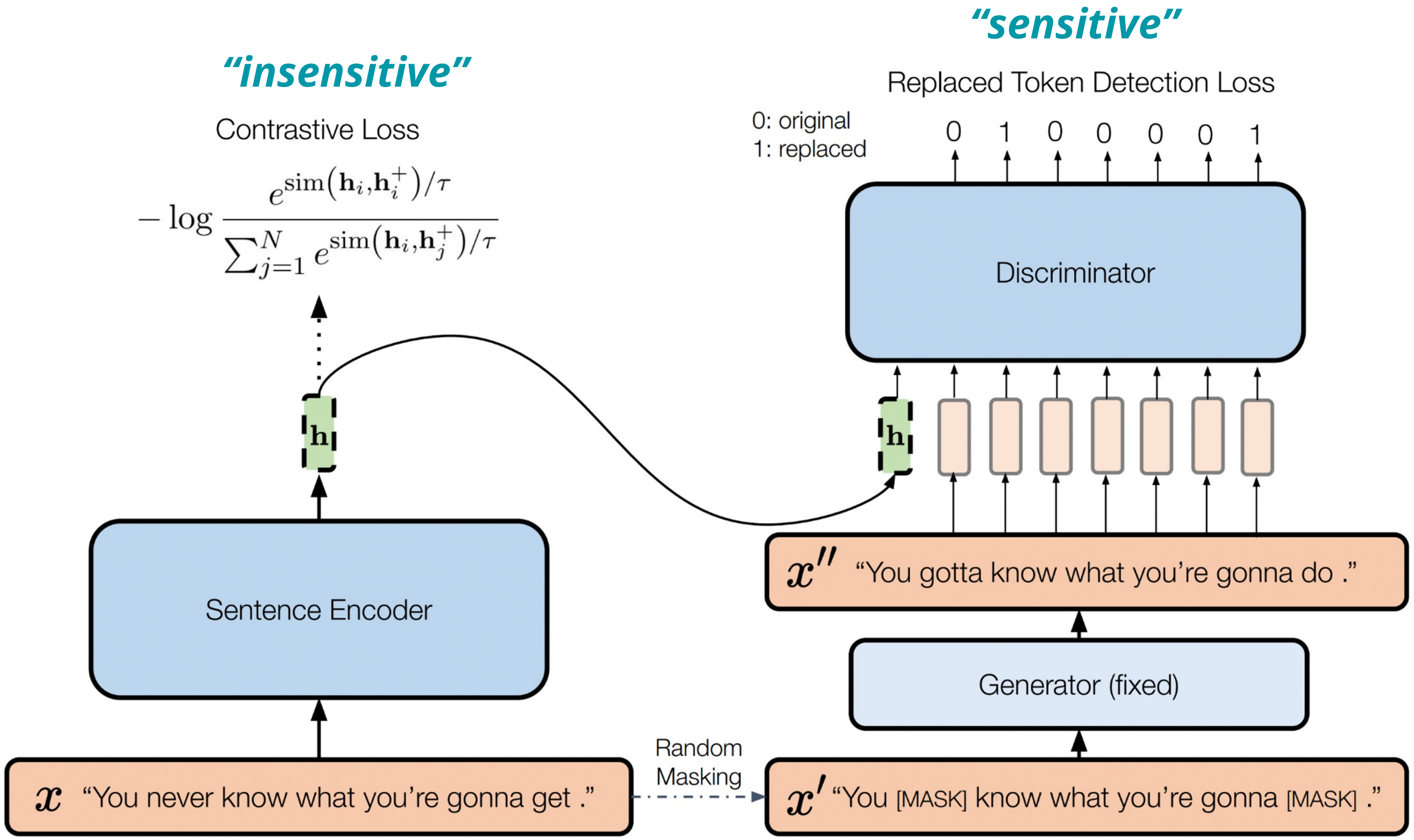
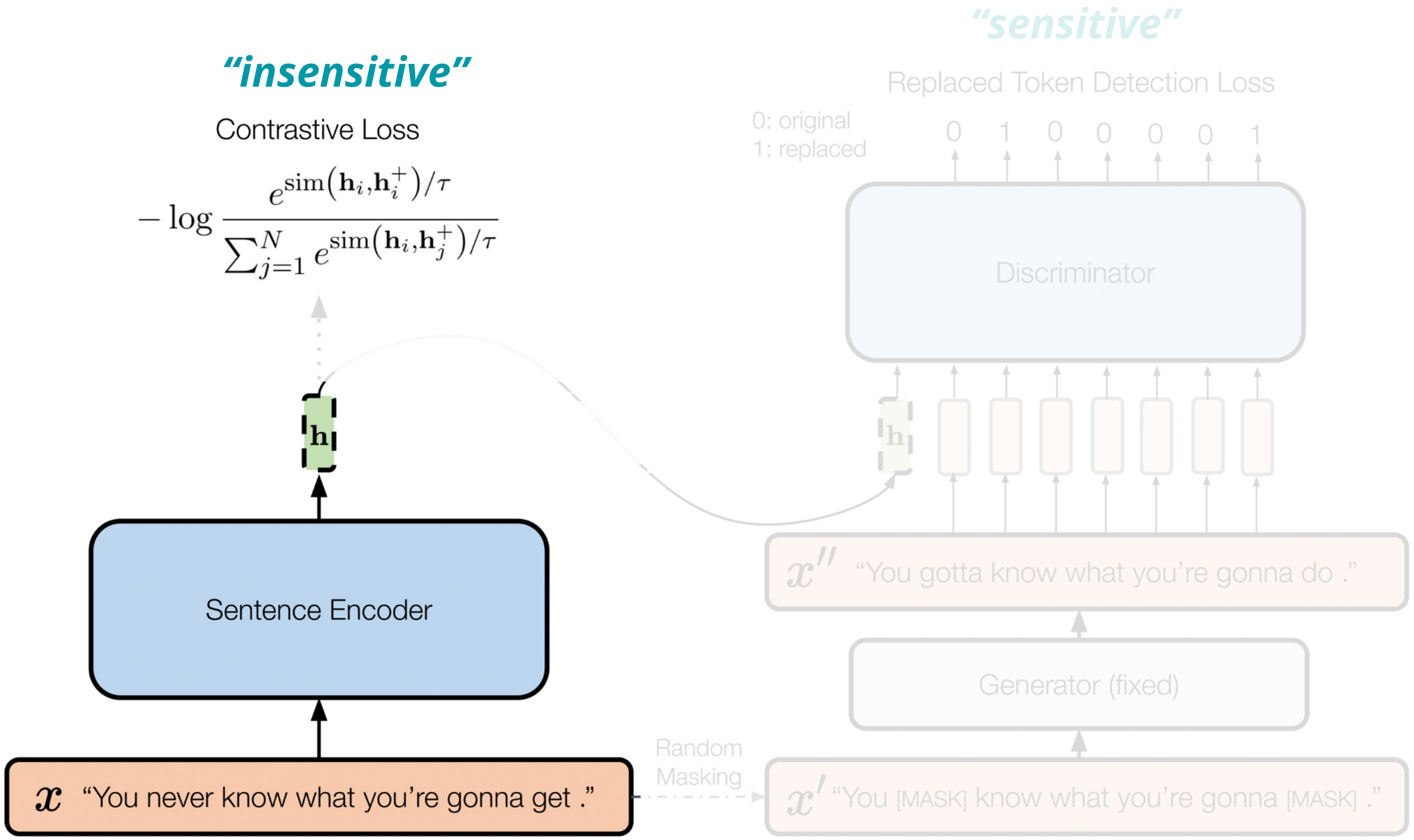
# DiffCSE





Chuang, Yung-Sung, et al. "DiffCSE: Difference-based Contrastive Learning for Sentence Embeddings. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. 2022.

# DiffCSE

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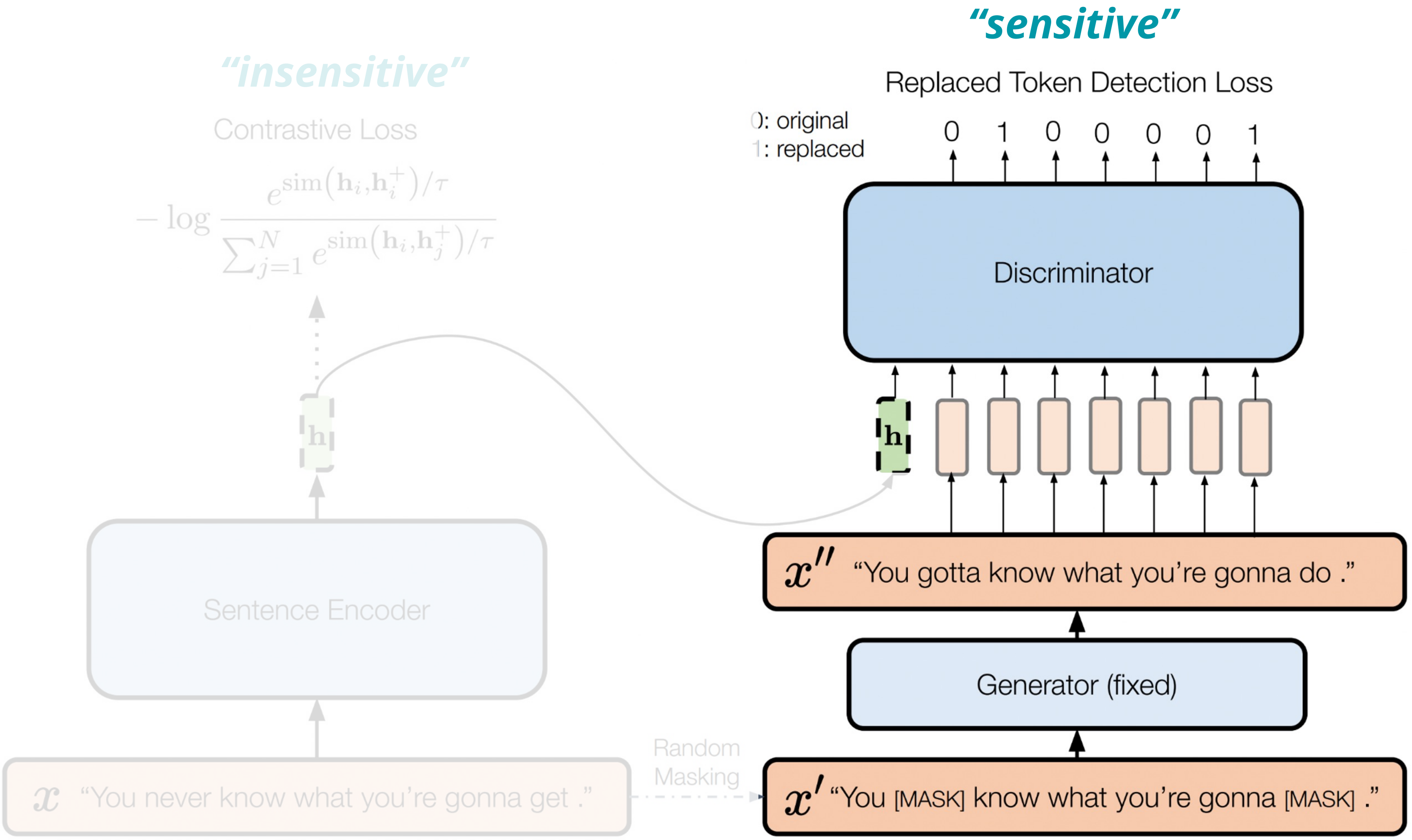


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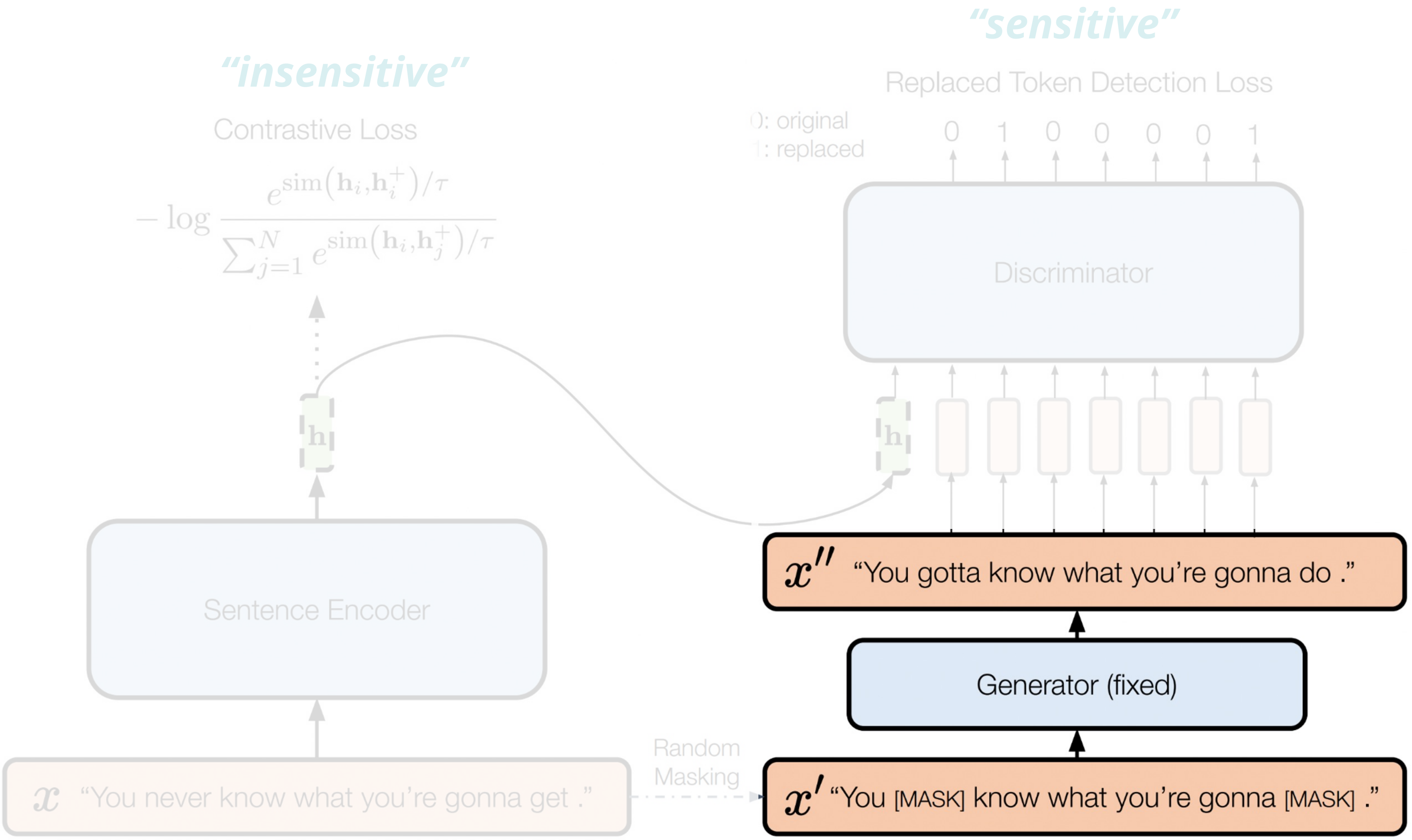


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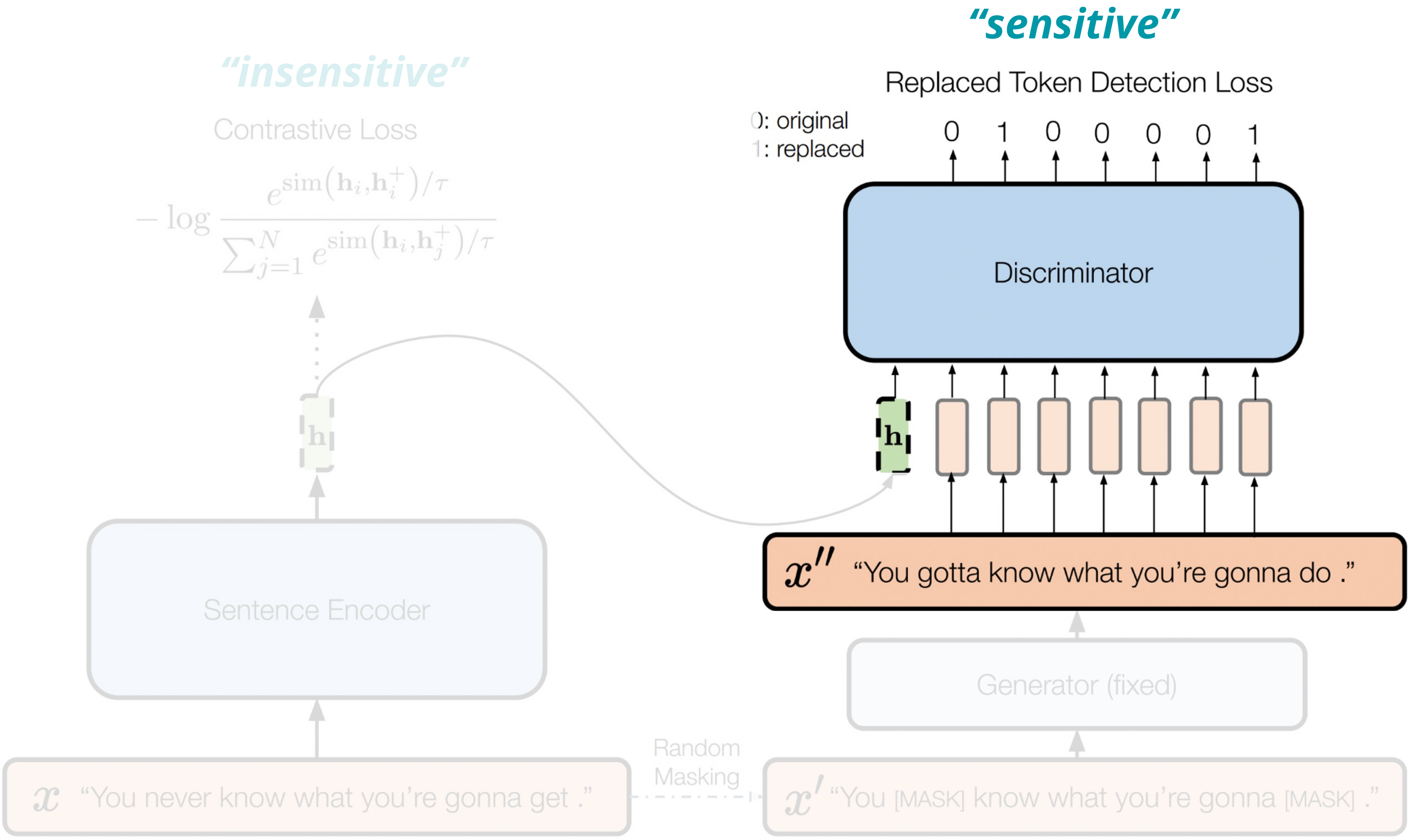


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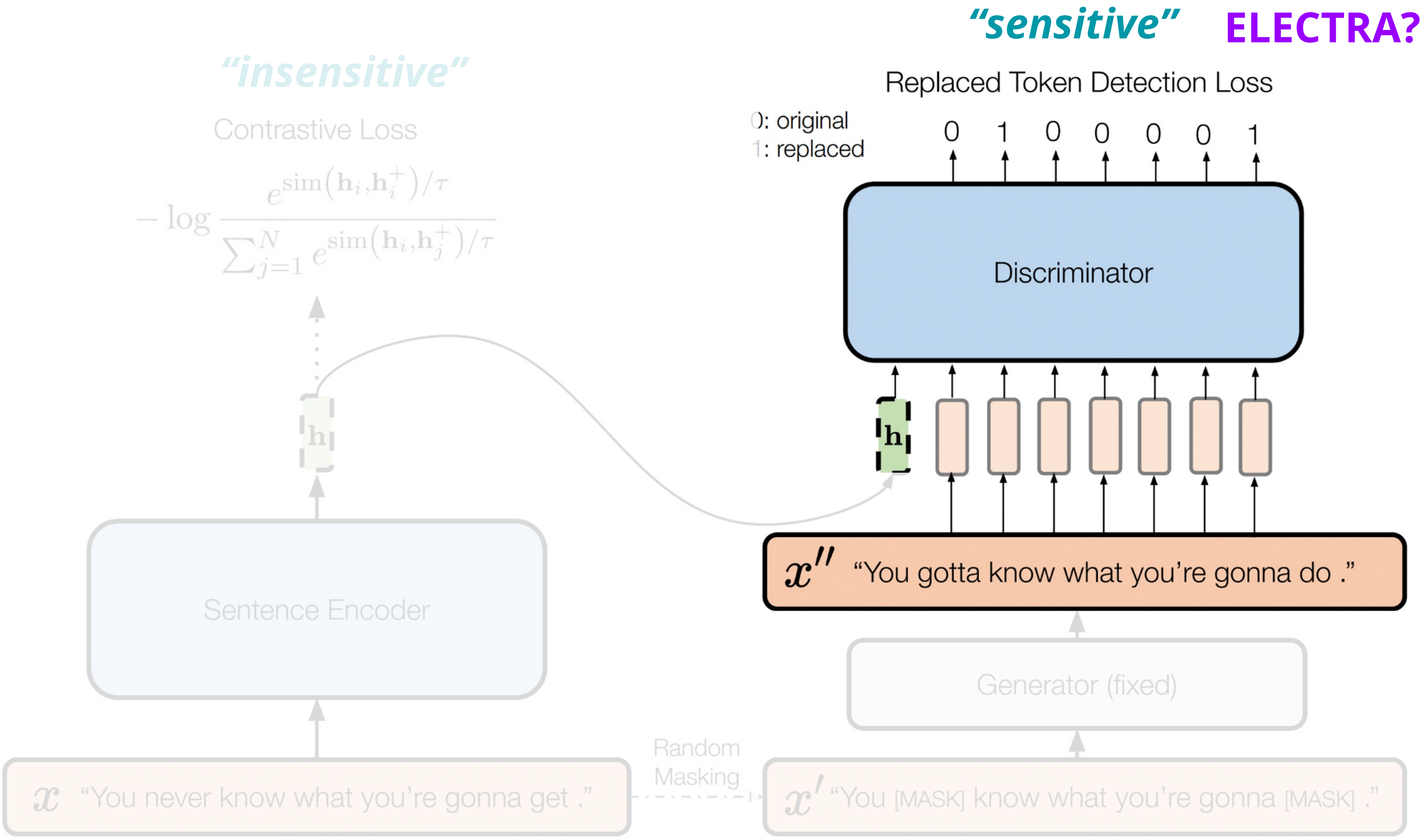


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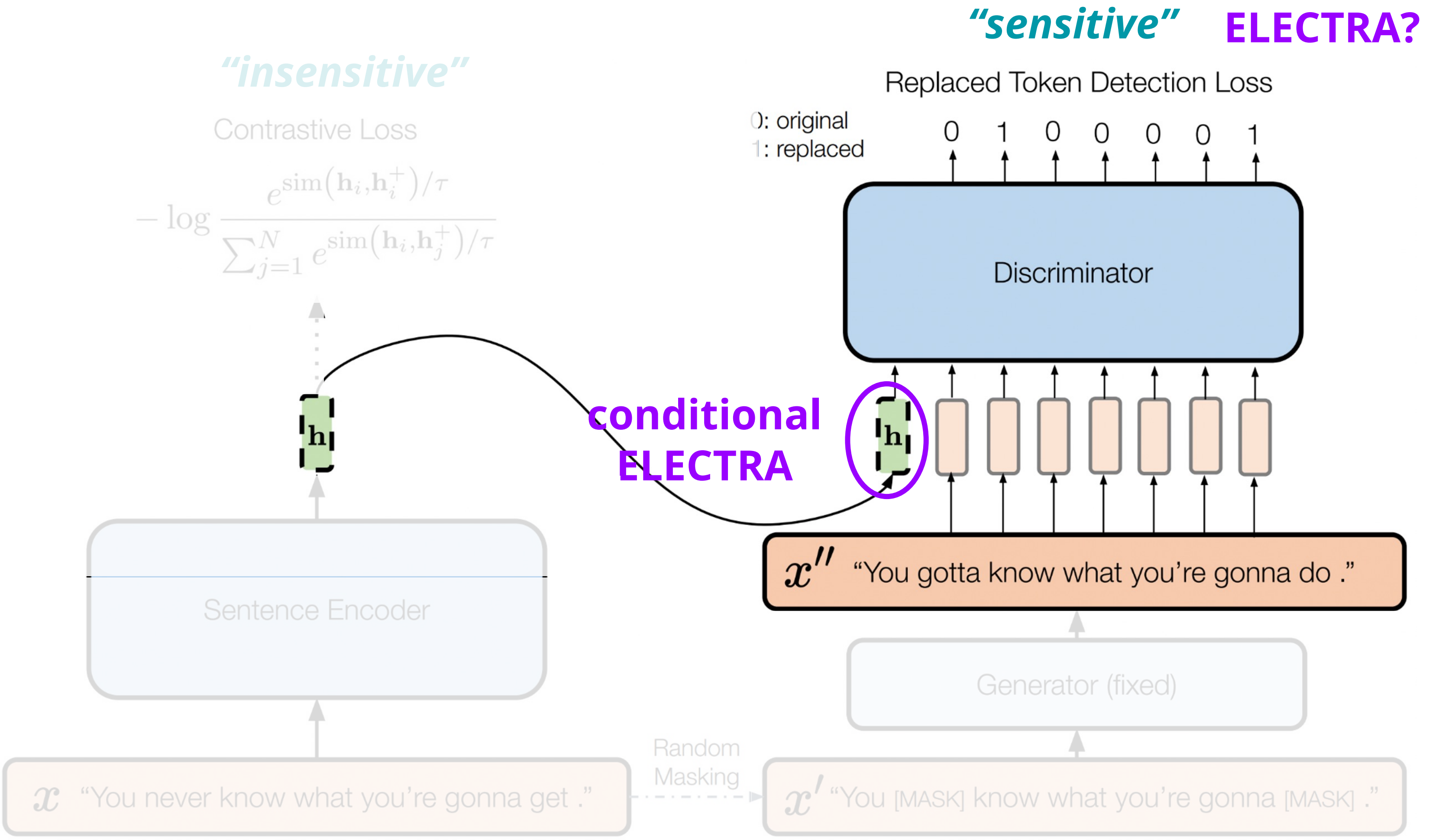


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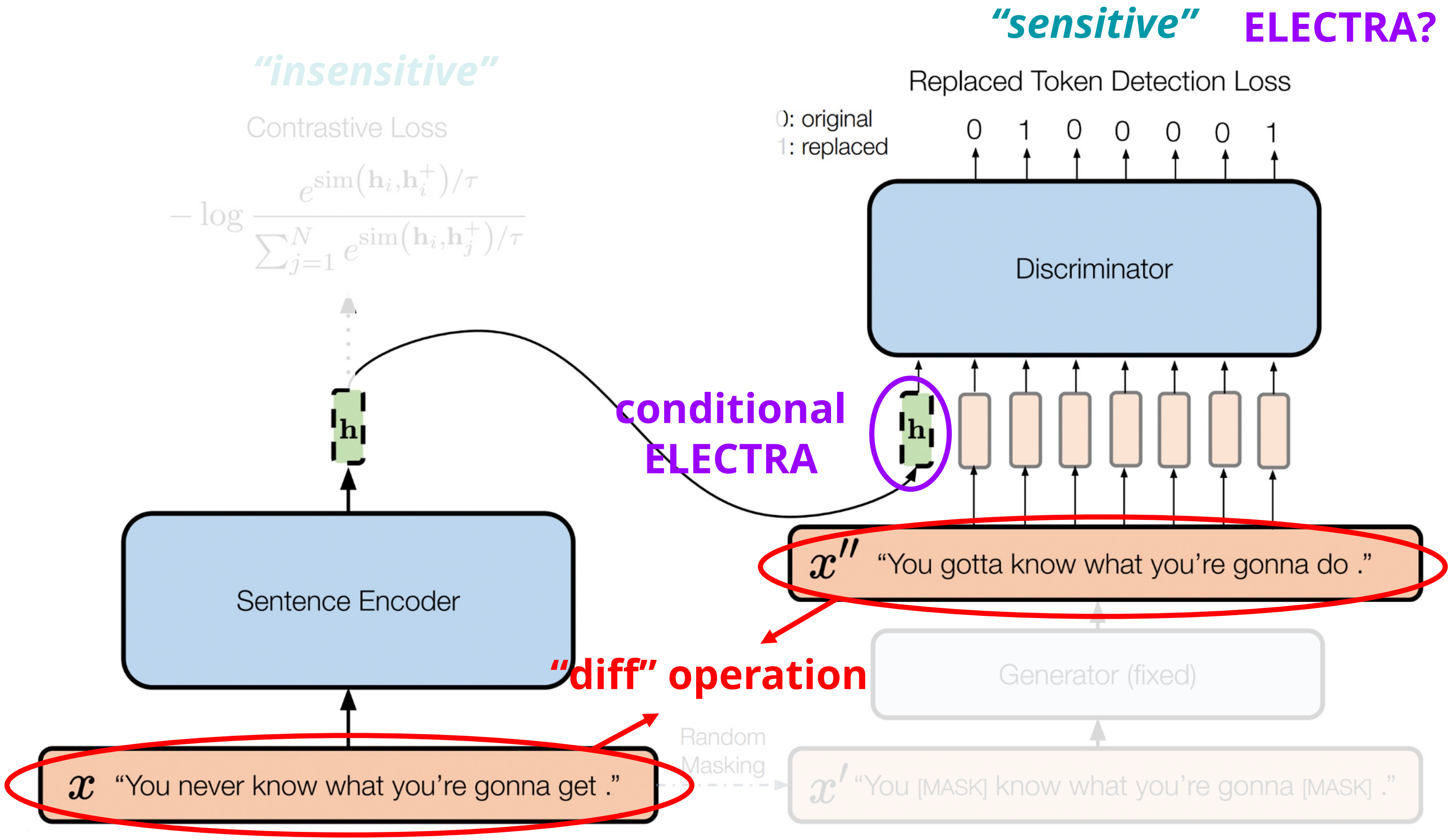


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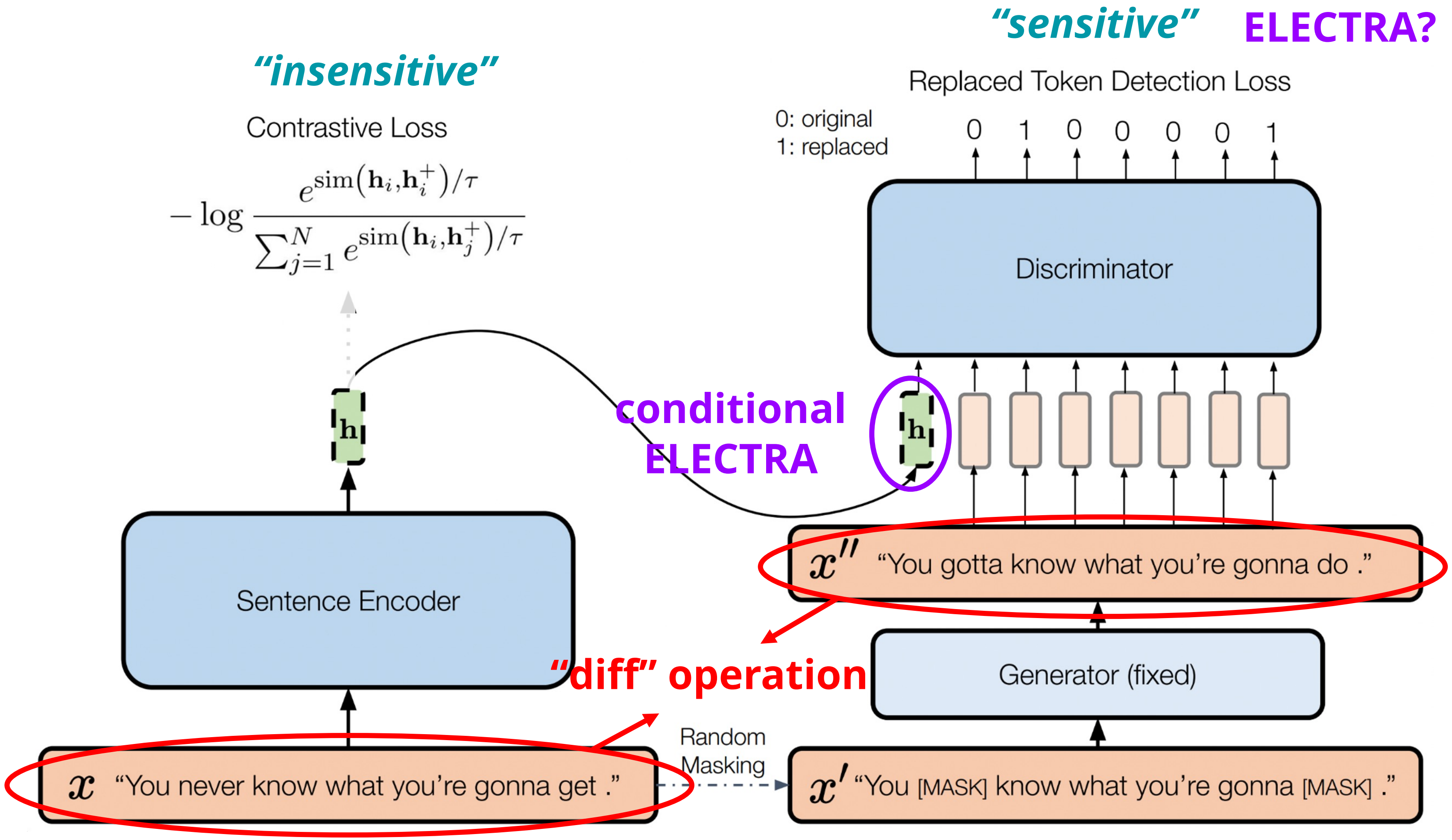


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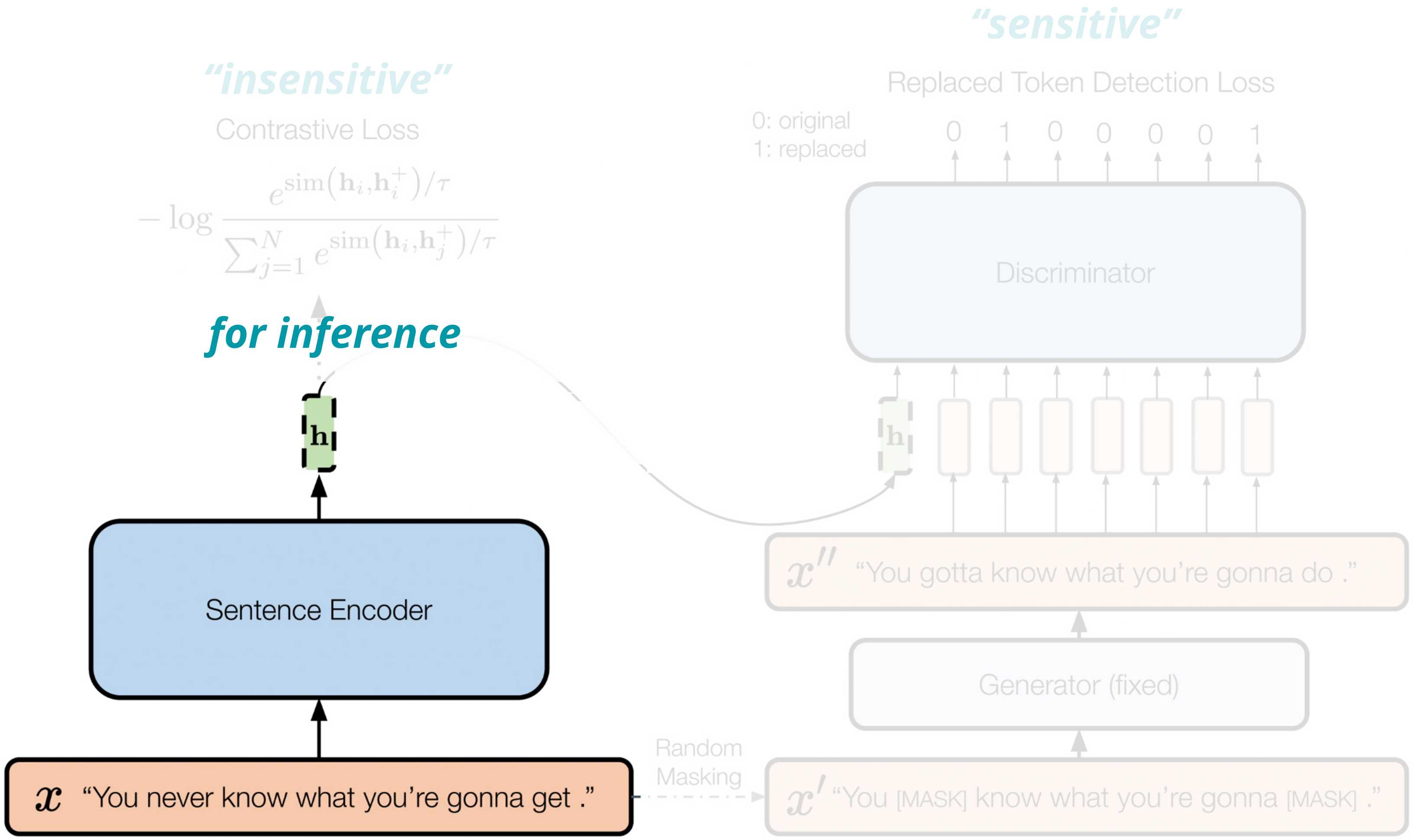


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# Results (STS)

| Model | STS12 | STS13 | STS14 | STS15 | STS16 | STS-B | SICK-R | Avg. |
|---|---|---|---|---|---|---|---|---|
| GloVe embeddings (avg.)♣ | 55.14 | 70.66 | 59.73 | 68.25 | 63.66 | 58.02 | 53.76 | 61.32 |
| $\text{BERT}_{\texttt{base}}$ (first-last avg.)◇ | 39.70 | 59.38 | 49.67 | 66.03 | 66.19 | 53.87 | 62.06 | 56.70 |
| $\text{BERT}_{\texttt{base}}$-flow◇ | 58.40 | 67.10 | 60.85 | 75.16 | 71.22 | 68.66 | 64.47 | 66.55 |
| $\text{BERT}_{\texttt{base}}$-whitening◇ | 57.83 | 66.90 | 60.90 | 75.08 | 71.31 | 68.24 | 63.73 | 66.28 |
| IS-$\text{BERT}_{\texttt{base}}$ ♡ | 56.77 | 69.24 | 61.21 | 75.23 | 70.16 | 69.21 | 64.25 | 66.58 |
| CMLM-$\text{BERT}_{\texttt{base}}$ ♠ (1TB data) | 58.20 | 61.07 | 61.67 | 73.32 | 74.88 | 76.60 | 64.80 | 67.22 |
| CT-$\text{BERT}_{\texttt{base}}$ ◇ | 61.63 | 76.80 | 68.47 | 77.50 | 76.48 | 74.31 | 69.19 | 72.05 |
| SG-OPT-$\text{BERT}_{\texttt{base}}$ † | 66.84 | 80.13 | 71.23 | 81.56 | 77.17 | 77.23 | 68.16 | 74.62 |
| SimCSE-$\text{BERT}_{\texttt{base}}$ ◇ | 68.40 | 82.41 | 74.38 | 80.91 | 78.56 | 76.85 | **72.23** | 76.25 |
| ∗ SimCSE-$\text{BERT}_{\texttt{base}}$(reproduce) | 70.82 | 82.24 | 73.25 | 81.38 | 77.06 | 77.24 | 71.16 | 76.16 |
| ∗ DiffCSE-$\text{BERT}_{\texttt{base}}$ | **72.28** | **84.43** | **76.47** | **83.90** | **80.54** | **80.59** | 71.23 | **78.49** |
| $\text{RoBERTa}_{\texttt{base}}$ (first-last avg.)◇ | 40.88 | 58.74 | 49.07 | 65.63 | 61.48 | 58.55 | 61.63 | 56.57 |
| $\text{RoBERTa}_{\texttt{base}}$-whitening◇ | 46.99 | 63.24 | 57.23 | 71.36 | 68.99 | 61.36 | 62.91 | 61.73 |
| DeCLUTR-$\text{RoBERTa}_{\texttt{base}}$ ◇ | 52.41 | 75.19 | 65.52 | 77.12 | 78.63 | 72.41 | 68.62 | 69.99 |
| SimCSE-$\text{RoBERTa}_{\texttt{base}}$ ◇ | **70.16** | 81.77 | 73.24 | 81.36 | 80.65 | 80.22 | 68.56 | 76.57 |
| ∗ SimCSE-$\text{RoBERTa}_{\texttt{base}}$(reproduce) | 68.60 | 81.36 | 73.16 | 81.61 | 80.76 | 80.58 | 68.83 | 76.41 |
| ∗ DiffCSE-$\text{RoBERTa}_{\texttt{base}}$ | 70.05 | **83.43** | **75.49** | **82.81** | **82.12** | **82.38** | **71.19** | **78.21** |

Chuang, Yung-Sung, et al. "DiffCSE: Difference-based Contrastive Learning for Sentence Embeddings. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. 2022.

# Retrieval Results

| **SimCSE-BERT$_{\texttt{base}}$** | **DiffCSE-BERT$_{\texttt{base}}$** |
|---|---|
| **Query**: This is not a problem. | |
| 1) This is a big problem. | 1) I don't see why this could be a problem. |
| 2) You have a problem. | 2) I don't see why that should be a problem. |
| 3) I don't see why that should be a problem. | 3) This is a big problem. |

Chuang, Yung-Sung, et al. "DiffCSE: Difference-based Contrastive Learning for Sentence Embeddings. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. 2022.

# Outline of Part 3

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   d. Dropout Augmentations
   e. Equivariant Contrastive Learning
   **f. Prompting**
   g. Ranking-based Methods
5. Conclusion

# PromptBERT

- Design/search good prompt templates to better extract sentence embeddings from BERT without fine-tuning
- Further fine-tuning with contrastive loss:
  - Using sentence vectors produced by two different templates as a positive pair

| Template | STS-B dev. |
|---|---|
| *Searching for relationship tokens* | |
| [X] [MASK] . | 39.34 |
| [X] is [MASK] . | 47.26 |
| [X] mean [MASK] . | 53.94 |
| [X] means [MASK] . | 63.56 |
| *Searching for prefix tokens* | |
| This [X] means [MASK] . | 64.19 |
| This sentence of [X] means [MASK] . | 68.97 |
| This sentence of “[X]” means [MASK] . | 70.19 |
| This sentence : “[X]” means [MASK] . | 73.44 |

Jiang, Ting, et al. "PromptBERT: Improving BERT Sentence Embeddings with Prompts." *arXiv preprint arXiv:2201.04337* (2022).

# PromptBERT

| Method | STS12 | STS13 | STS14 | STS15 | STS16 | STS-B | SICK-R | Avg. |
|---|---|---|---|---|---|---|---|---|
| *Unsupervised models* | | | | | | | | |
| IS-BERT$_{base}$ ¶ | 56.77 | 69.24 | 61.21 | 75.23 | 70.16 | 69.21 | 64.25 | 66.58 |
| ConSERT$_{base}$ ‡ | 64.64 | 78.49 | 69.07 | 79.72 | 75.95 | 73.97 | 67.31 | 72.74 |
| SimCSE-BERT$_{base}$ ‡ | 68.40 | 82.41 | 74.38 | 80.91 | 78.56 | 76.85 | **72.23** | 76.25 |
| PromptBERT$_{base}$ | **71.56**$_{\pm 0.18}$ | **84.58**$_{\pm 0.22}$ | **76.98**$_{\pm 0.26}$ | **84.47**$_{\pm 0.24}$ | **80.60**$_{\pm 0.21}$ | **81.60**$_{\pm 0.22}$ | 69.87$_{\pm 0.40}$ | **78.54**$_{\pm 0.15}$ |
| RoBERTa$_{base}$-whitening † | 46.99 | 63.24 | 57.23 | 71.36 | 68.99 | 61.36 | 62.91 | 61.73 |
| SimCSE-RoBERTa$_{base}$ † | 70.16 | 81.77 | 73.24 | 81.36 | 80.65 | 80.22 | 68.56 | 76.57 |
| PromptRoBERTa$_{base}$ | **73.94**$_{\pm 0.90}$ | **84.74**$_{\pm 0.36}$ | **77.28**$_{\pm 0.41}$ | **84.99**$_{\pm 0.25}$ | **81.74**$_{\pm 0.29}$ | **81.88**$_{\pm 0.37}$ | **69.50**$_{\pm 0.57}$ | **79.15**$_{\pm 0.25}$ |
| **DiffCSE (BERT-base)** | **72.28** | **84.43** | **76.47** | **83.90** | **80.54** | **80.59** | **71.23** | **78.49** |

Jiang, Ting, et al. "PromptBERT: Improving BERT Sentence Embeddings with Prompts." *arXiv preprint arXiv:2201.04337* (2022).

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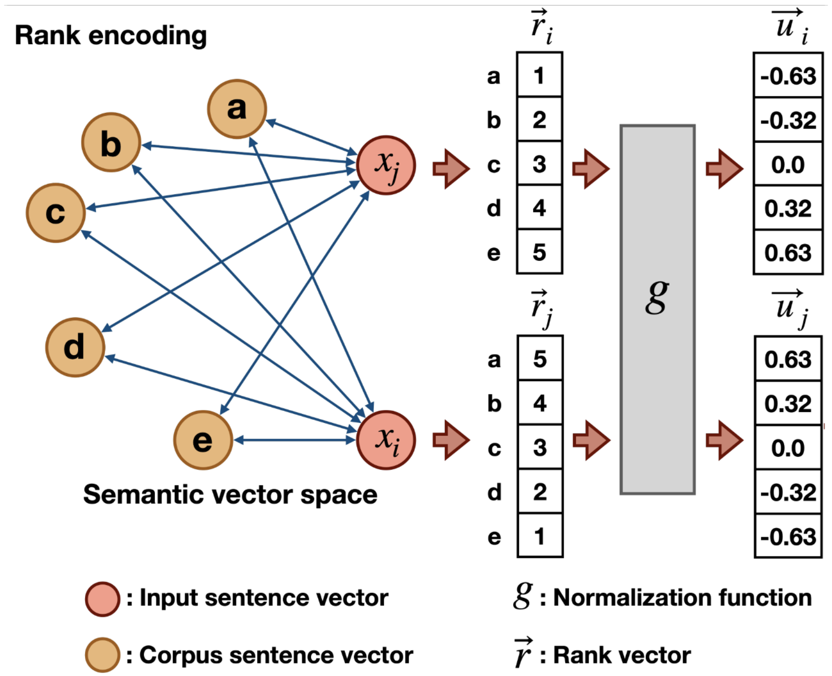
   f. Prompting
   **g. Ranking-based Methods**
5. Conclusion

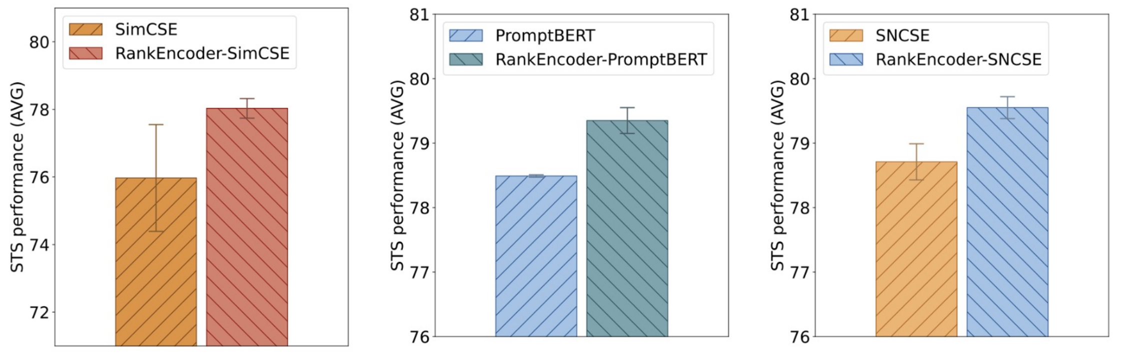
# RankEncoder

- Refine the vector space of existing models like SimCSE, PromptBERT
- Leverage ranking information from the whole corpus
- Train a new encoder to match the cosine similarity of rank vectors




Seonwoo, Yeon, et al. "Ranking-Enhanced Unsupervised Sentence Representation Learning." *arXiv preprint arXiv:2209.04333* (2022).

# RankEncoder

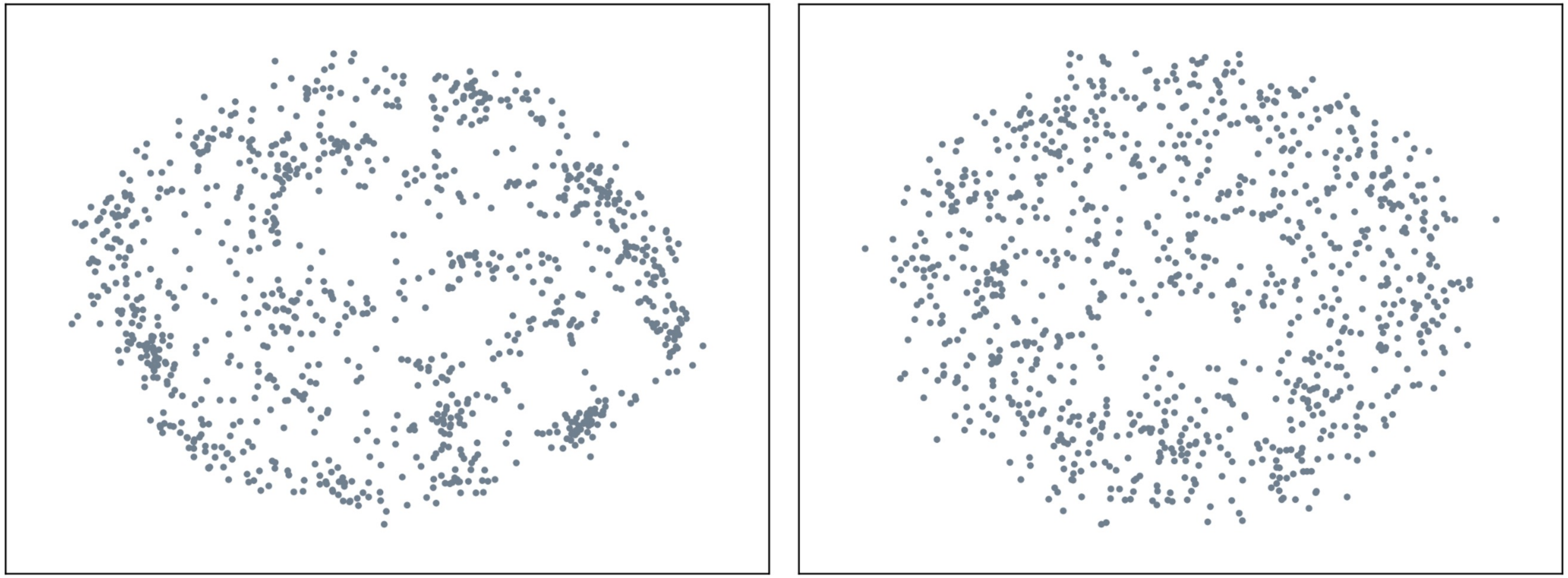



| Model | STS12 | STS13 | STS14 | STS15 | STS16 | STS-B | SICK-R | AVG |
|---|---|---|---|---|---|---|---|---|
| ConSERT (Yan et al., 2021) | 64.64 | 78.49 | 69.07 | 79.72 | 75.95 | 73.97 | 67.31 | 72.74 |
| SimCSE (Gao et al., 2021) | 68.40 | 82.41 | 74.38 | 80.91 | 78.56 | 76.85 | 72.23 | 76.25 |
| DCLR (Zhou et al., 2022) | 70.81 | 83.73 | 75.11 | 82.56 | 78.44 | 78.31 | 71.59 | 77.22 |
| ESimCSE (Wu et al., 2021) | 73.40 | 83.27 | 77.25 | 82.66 | 78.81 | 80.17 | 72.30 | 78.27 |
| DiffCSE (Chuang et al., 2022) | 72.28 | 84.43 | 76.47 | 83.90 | 80.54 | 80.59 | 71.23 | 78.49 |
| PromptBERT (Jiang et al., 2022) | 71.56 | 84.58 | 76.98 | **84.47** | **80.60** | **81.60** | 69.87 | 78.54 |
| SNCSE (Wang et al., 2022) | 70.67 | 84.79 | 76.99 | 83.69 | 80.51 | 81.35 | 74.77 | 78.97 |
| RankEncoder | **74.88** | **85.59** | **78.61** | 83.50 | 80.56 | 81.55 | **75.78** | **80.07** |

Seonwoo, Yeon, et al. "Ranking-Enhanced Unsupervised Sentence Representation Learning." *arXiv preprint arXiv:2209.04333* (2022).

# RankEncoder

- RankEncoder can be aware of the fine-grain interaction between the similar sentences in the corpus



(a) PromptBERT (b) RankEncoder

Seonwoo, Yeon, et al. "Ranking-Enhanced Unsupervised Sentence Representation Learning." *arXiv preprint arXiv:2209.04333* (2022).

# RankEncoder

- Better uniformity

| | Base Encoder $E$ | | |
|---|---|---|---|
| | SimCSE | PromptBERT | SNCSE |
| $E$ | -2.42 | -1.49 | -2.21 |
| RankEncoder$_E$ | -3.23 | -3.31 | -3.20 |

Seonwoo, Yeon, et al. "Ranking-Enhanced Unsupervised Sentence Representation Learning." *arXiv preprint arXiv:2209.04333* (2022).

# Conclusion

- We are closing the gap between unsupervised and supervised sentence representations:

| Model | STS12 | STS13 | STS14 | STS15 | STS16 | STS-B | SICK-R | Avg. |
|---|---|---|---|---|---|---|---|---|
| *Unsupervised models* | | | | | | | | |
| $*$ SimCSE-BERT$_{\texttt{base}}$ | **68.40** | **82.41** | **74.38** | **80.91** | **78.56** | **76.85** | **72.23** | **76.25** |
| **RankEncoder (BERT-base)** | **74.88** | **85.59** | **78.61** | **83.50** | **80.56** | **81.55** | **75.78** | **80.07** |
| *Supervised models* | | | | | | | | |
| $*$ SimCSE-BERT$_{\texttt{base}}$ | **75.30** | **84.67** | **80.19** | **85.40** | **80.82** | **84.25** | **80.39** | **81.57** |
| **PromptBERT (BERT-base)** | 75.48 | 85.59 | 80.57 | 85.99 | 81.08 | 84.56 | 80.52 | 81.97 |

- Contrastive learning should have more potential in NLP for using pre-trained language models in representation learning!

# Schedule

| | |
|---|---|
| 17:00 – 17:10 | **Part 1** Introduction [Hung-yi] |
| 17:10 – 17:40 | **Part 2** Why do PLMs work [Hung-yi] |
| 17:40 – 18:20 | **Part 3** How to use PLMs: Contrastive Learning for PLMs [Yung-Sung] |
| 18:20 – 18:30 | Q&A for Part 1+2+3 |
| 18:30 – 18:40 | Break |
| 18:40 – 19:05 | **Part 4** How to use PLMs: Parameter-efficient fine-tuning [Cheng-Han] |
| 19:05 – 19:50 | **Part 5** How to use PLMs: Using PLMs with different amounts of data [Cheng-Han] |
| 19:50 – 20:00 | Conclusion and Future work + Q&A |

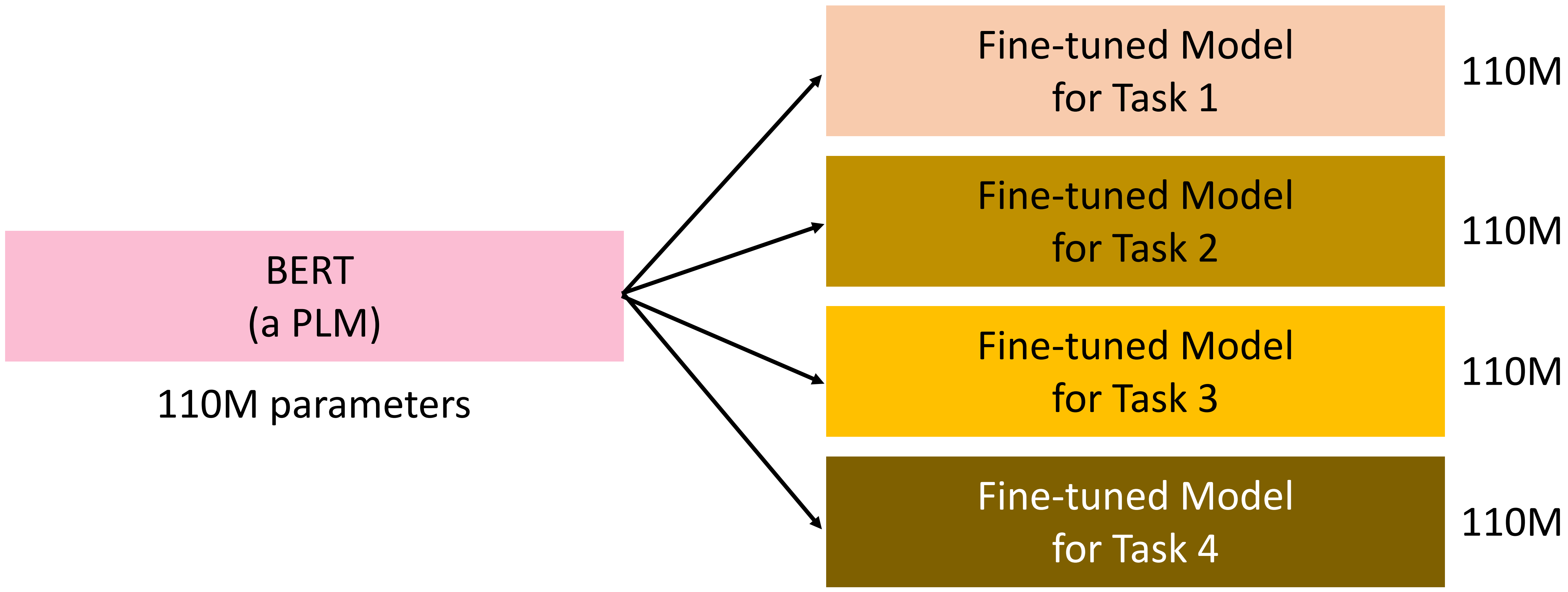
2022 AACL-IJCNLP

# Part 4:
# How to use PLMs:
# Parameter-efficient fine-tuning

Cheng-Han Chiang
**National Taiwan University**

# Parameter-Efficient Fine-tuning

- PLMs are gigantic
  - Need a copy for each downstream task

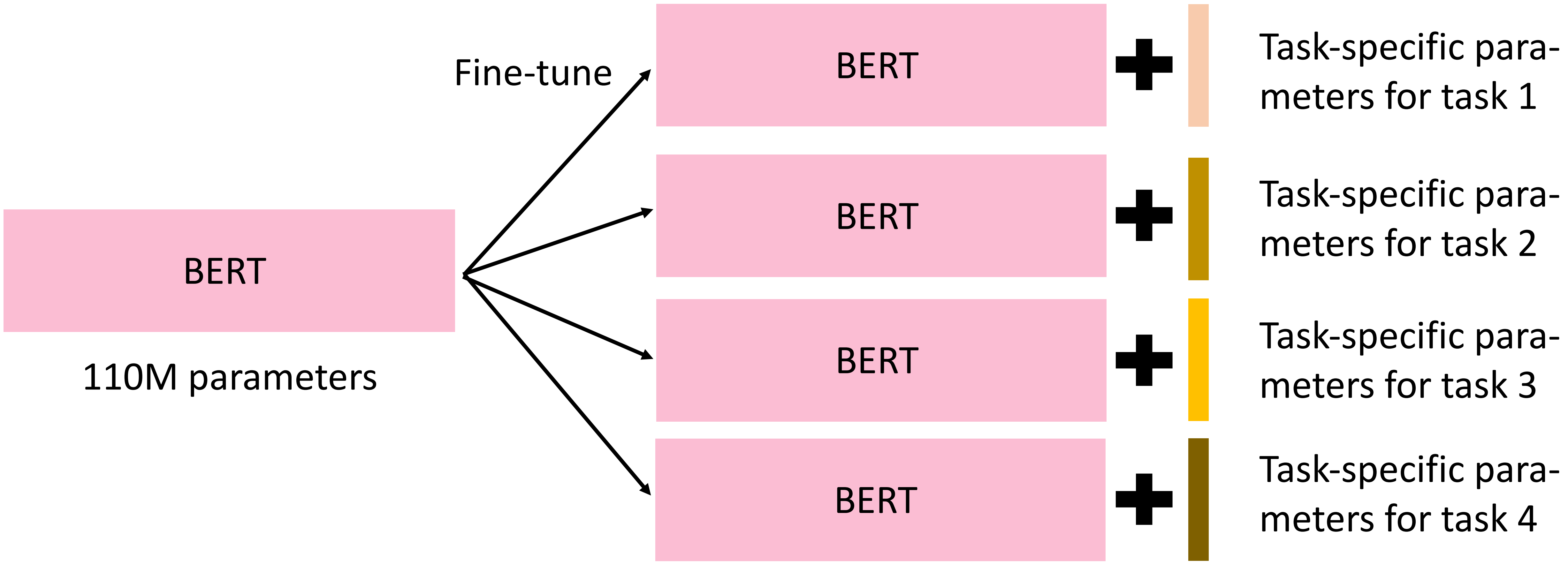


# Parameter-Efficient Fine-tuning

- Problem: PLMs are gigantic (in terms of numbers of parameters, model size, and the storage needed to store the model)
- Solution: Reduce the number of parameters by parameter-efficient fine-tuning

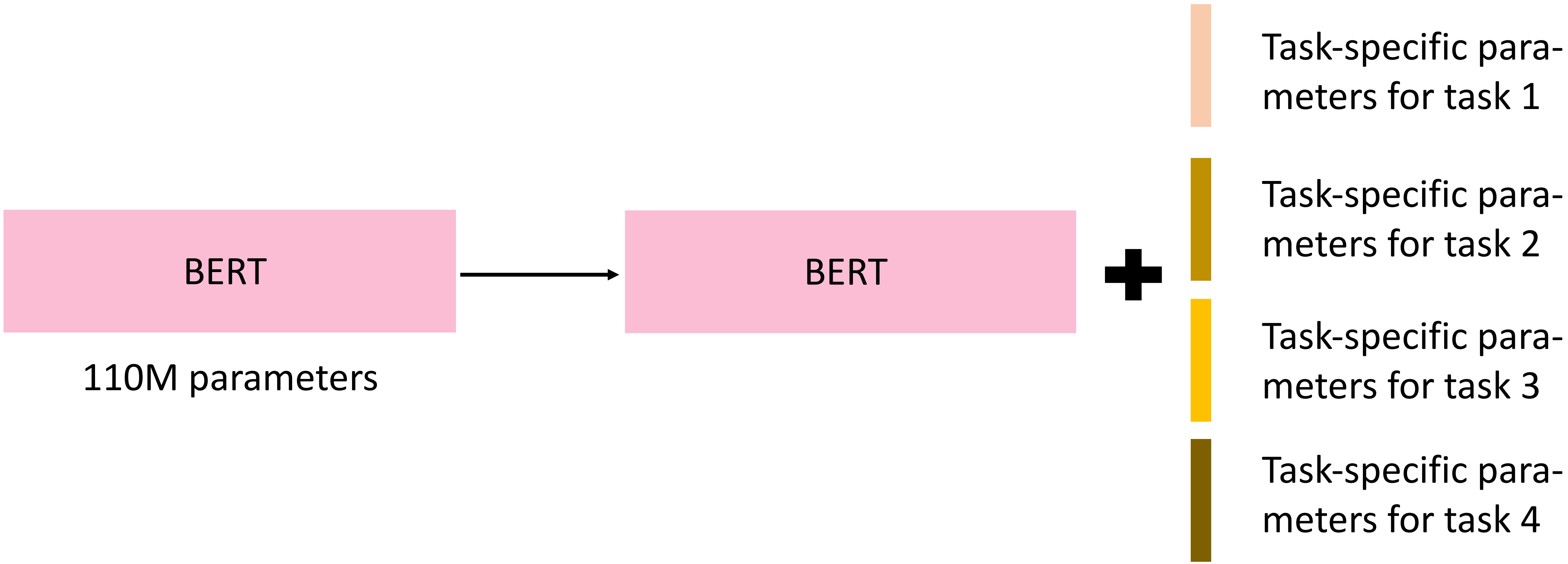
# Parameter-Efficient Fine-tuning

- Use a small amount of parameters  for each downstream task



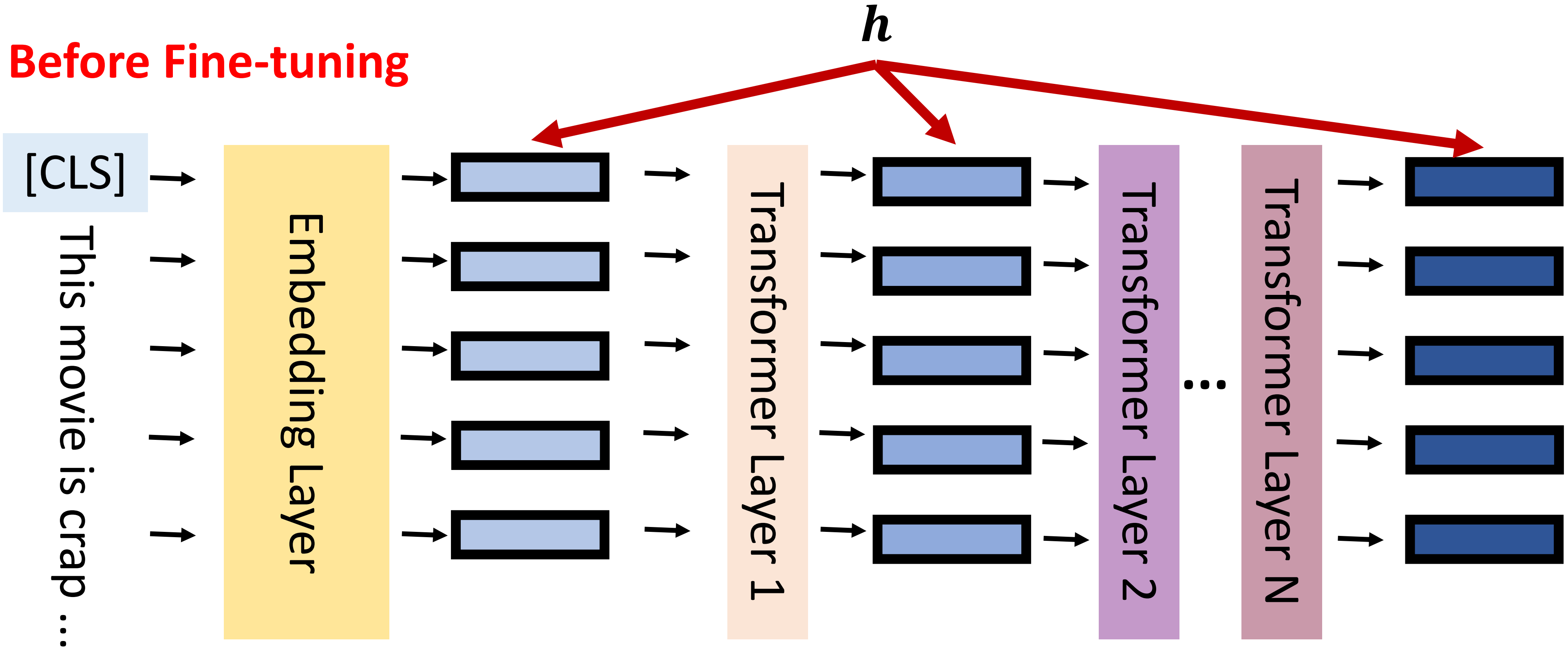
# Parameter-Efficient Fine-tuning

- Use a small amount of parameters  for each downstream task



# Parameter-Efficient Fine-tuning

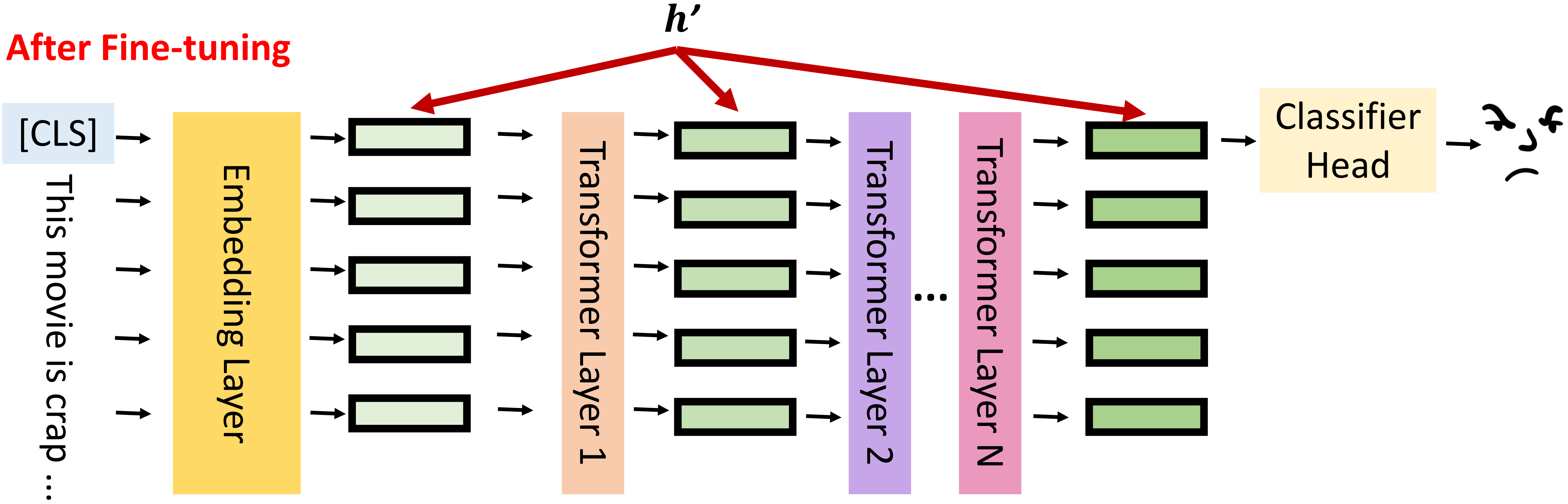
- What is standard fine-tuning really doing?
  - Modify the <u>*hidden representations*</u> ($\boldsymbol{h}$) of the PLM such that it can perform well on downstream task




He, Junxian, et al. "Towards a Unified View of Parameter-Efficient Transfer Learning." *International Conference on Learning Representations*. 2022.

# Parameter-Efficient Fine-tuning

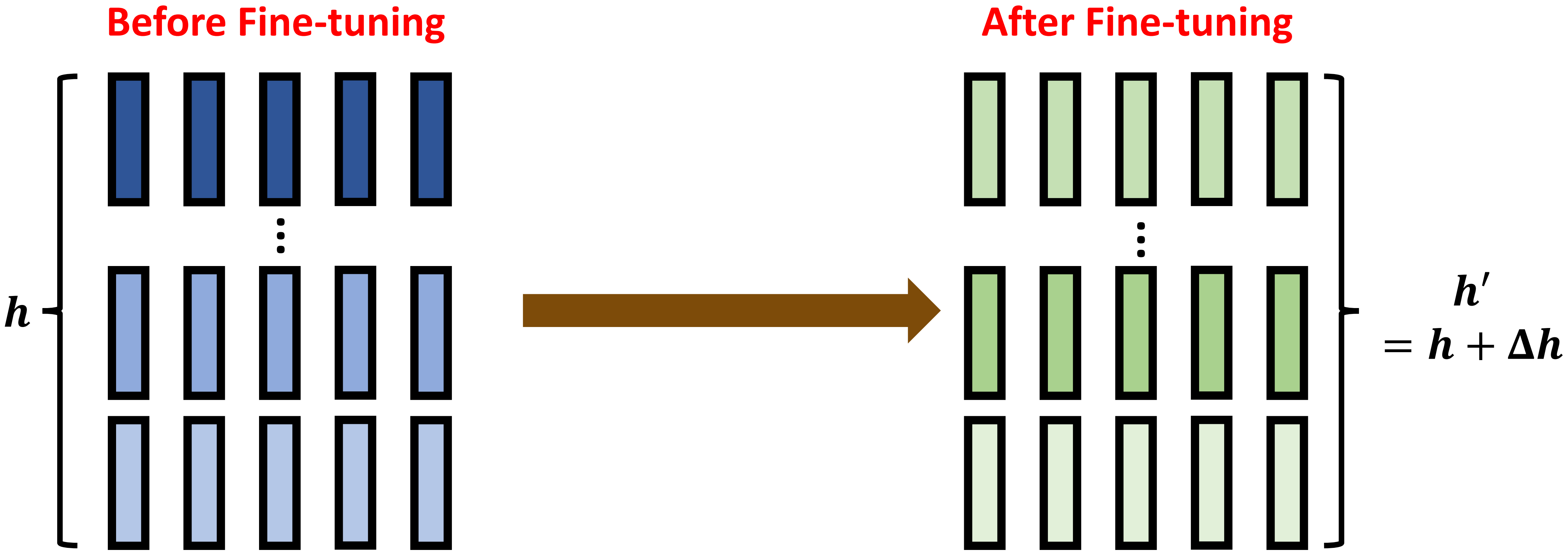
- What is standard fine-tuning really doing?
  - Modify the ***hidden representations*** (***h***) of the PLM such that it can perform well on downstream task




He, Junxian, et al. "Towards a Unified View of Parameter-Efficient Transfer Learning." *International Conference on Learning Representations*. 2022.

# Parameter-Efficient Fine-tuning

- Fine-tuning = modifying the hidden representation based on a PLM




$\boldsymbol{h}$:hidden representation calculated by the original PLM

$\boldsymbol{h}' = \boldsymbol{h} + \Delta\boldsymbol{h}$

$\boldsymbol{h}'$:hidden representation calculated by the fine-tuned model

He, Junxian, et al. "Towards a Unified View of Parameter-Efficient Transfer Learning." *International Conference on Learning Representations*. 2022.

# Part 4:

# How to use PLMs:

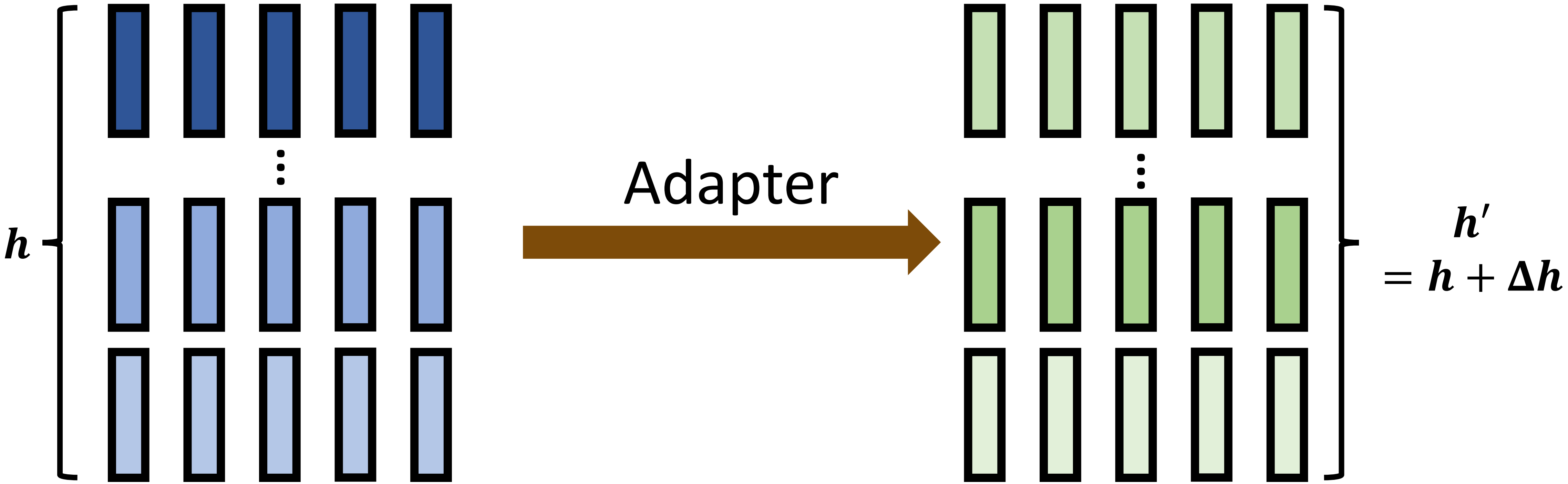
# Parameter-efficient fine-tuning

## 4-1 Adapter

# Parameter-Efficient Fine-tuning: Adapter

- Use special submodules to modify hidden representations!

**Before Fine-tuning** **After Fine-tuning**




$\boldsymbol{h}$:hidden representation calculated by the original PLM

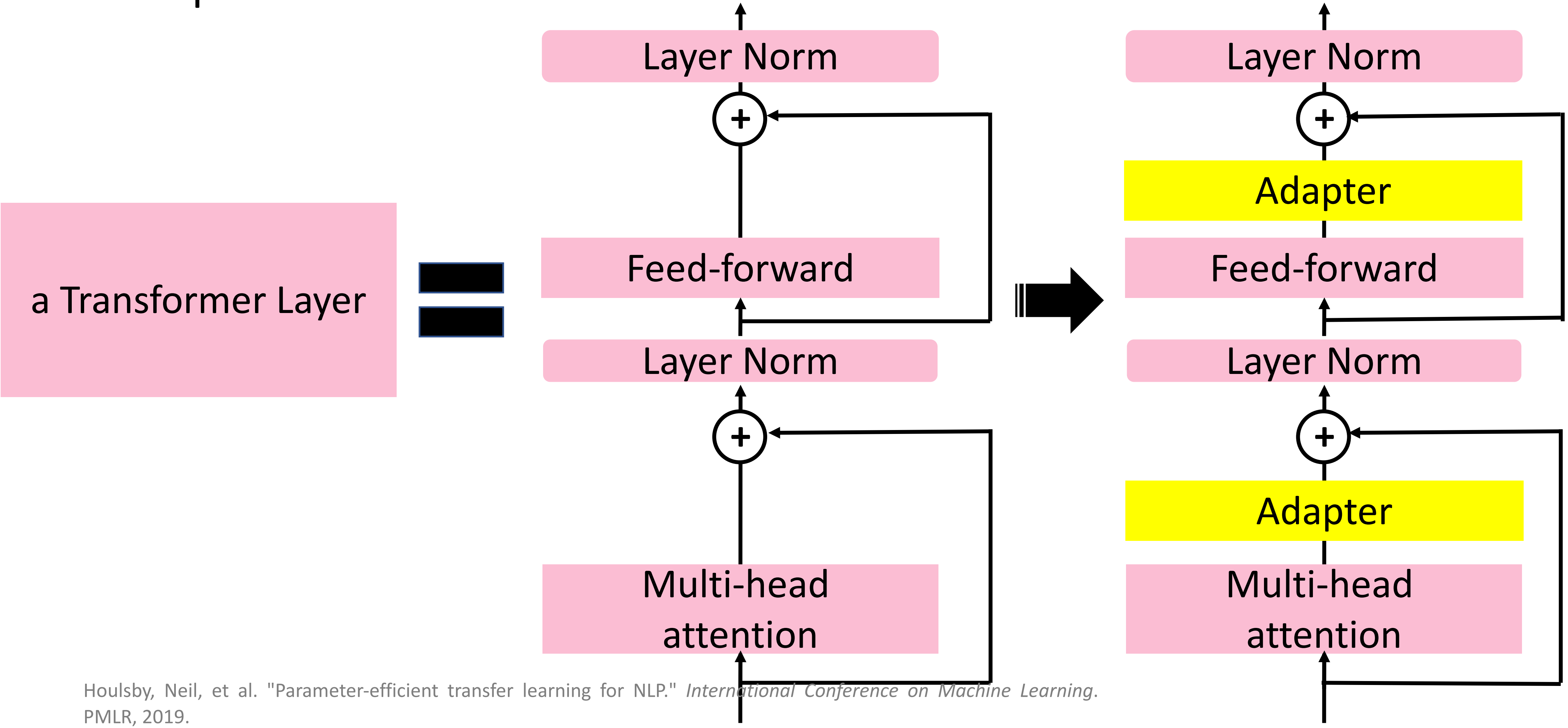
$\boldsymbol{h}' = \boldsymbol{h} + \boldsymbol{\Delta h}$

$\boldsymbol{h}'$:hidden representation calculated by the fine-tuned model

He, Junxian, et al. "Towards a Unified View of Parameter-Efficient Transfer Learning." *International Conference on Learning Representations*. 2022.

# Parameter-Efficient Fine-tuning: Adapter

- Adapters: small trainable submodules inserted in transformers

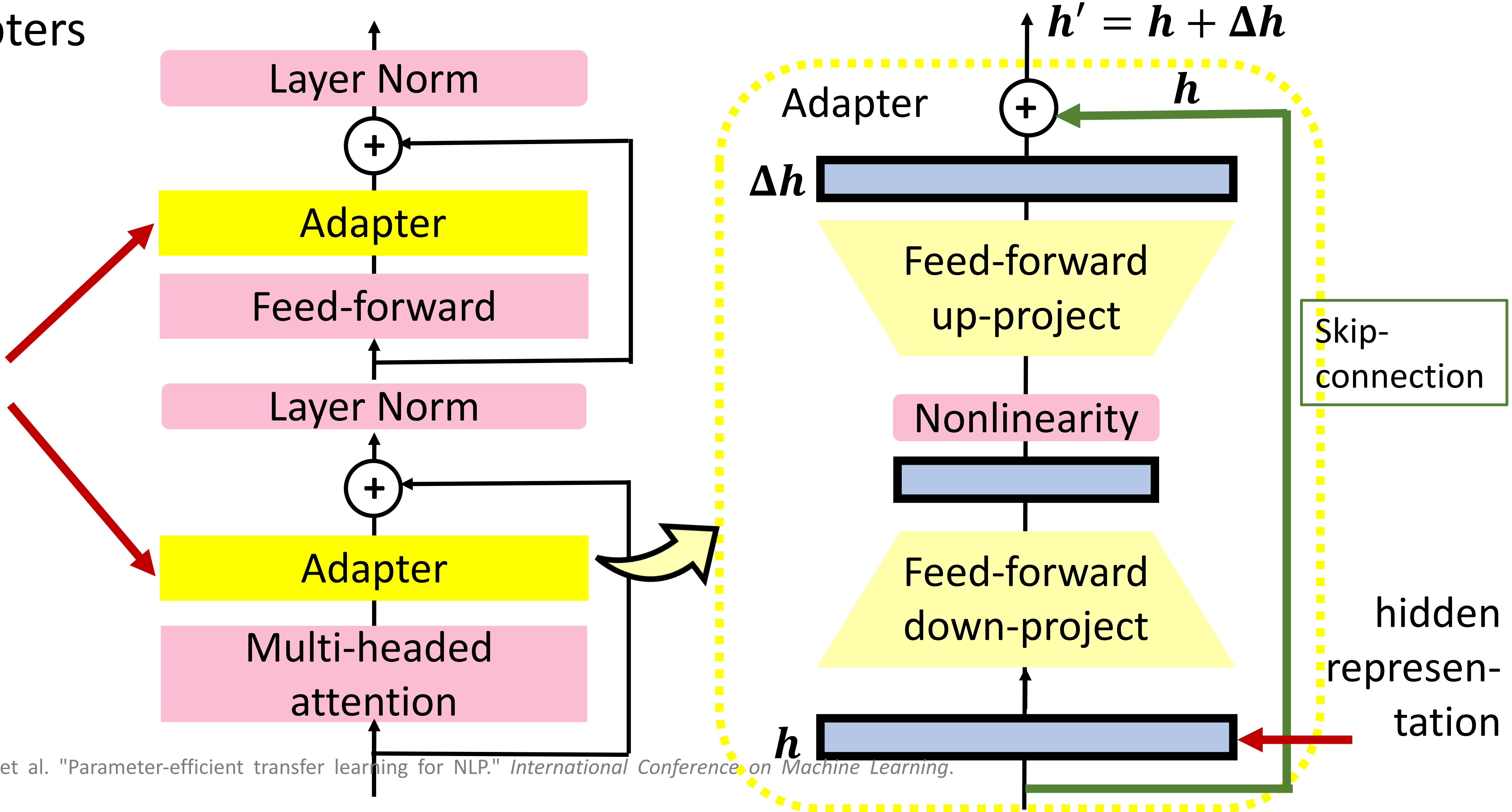



Houlsby, Neil, et al. "Parameter-efficient transfer learning for NLP." *International Conference on Machine Learning*. PMLR, 2019.

# Parameter-Efficient Fine-tuning: Adapter

- Adapters

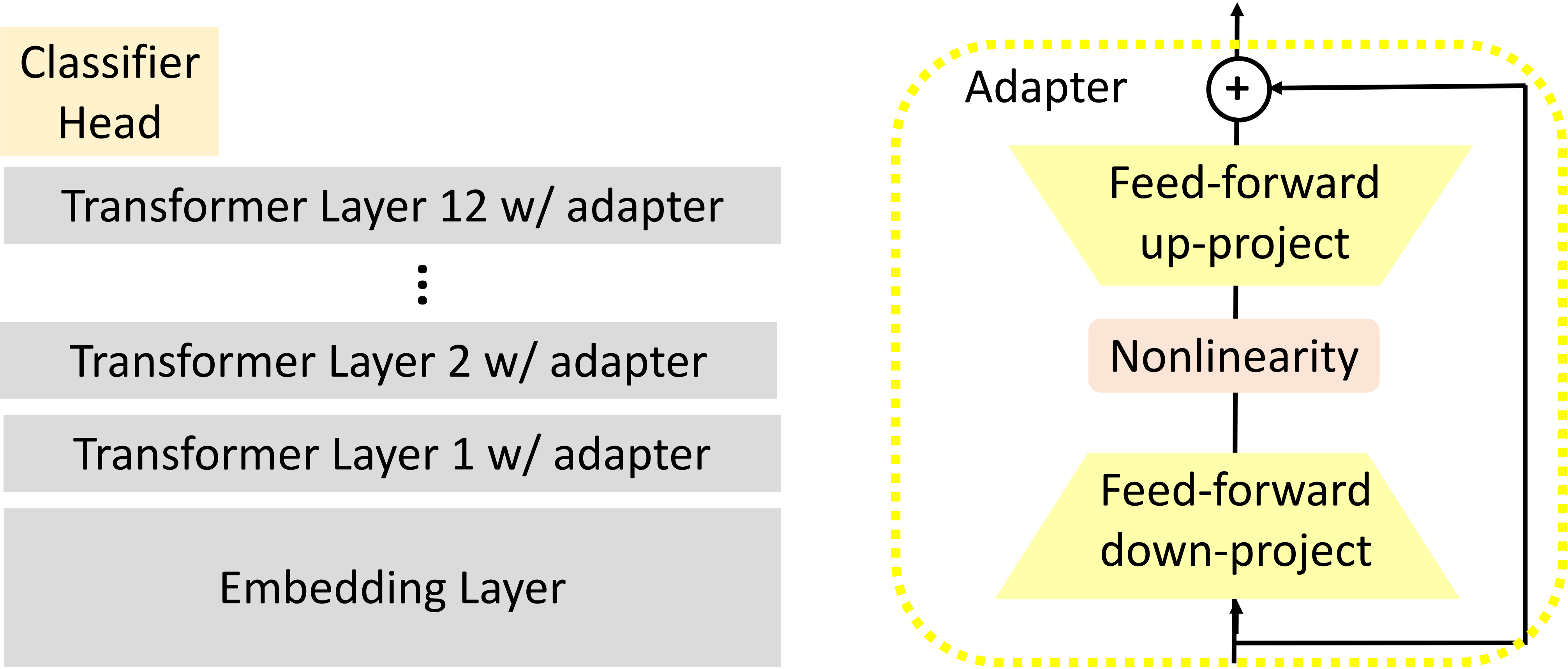
Inside of the transformer layer, only adapters are updated




Houlsby, Neil, et al. "Parameter-efficient transfer learning for NLP." *International Conference on Machine Learning*. PMLR, 2019.

# Parameter-Efficient Fine-tuning: Adapter

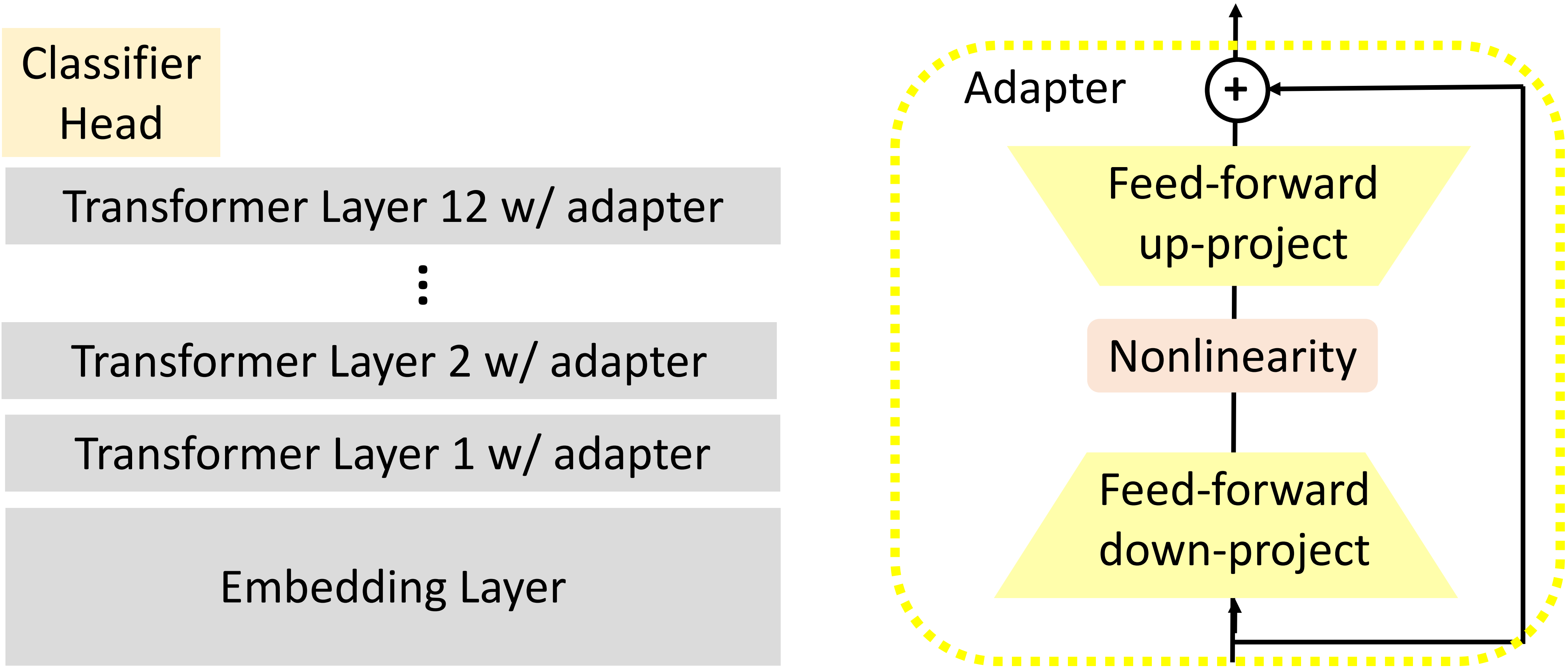
- Adapters: During fine-tuning, only update the adpaters and the classifier head




Houlsby, Neil, et al. "Parameter-efficient transfer learning for NLP." *International Conference on Machine Learning*. PMLR, 2019.

# Parameter-Efficient Fine-tuning: Adapter

- Adapters: All downstream tasks share the PLM; the adapters in each layer and the classifier heads are the task-specific modules




Houlsby, Neil, et al. "Parameter-efficient transfer learning for NLP." *International Conference on Machine Learning*. PMLR, 2019.

Part 4:

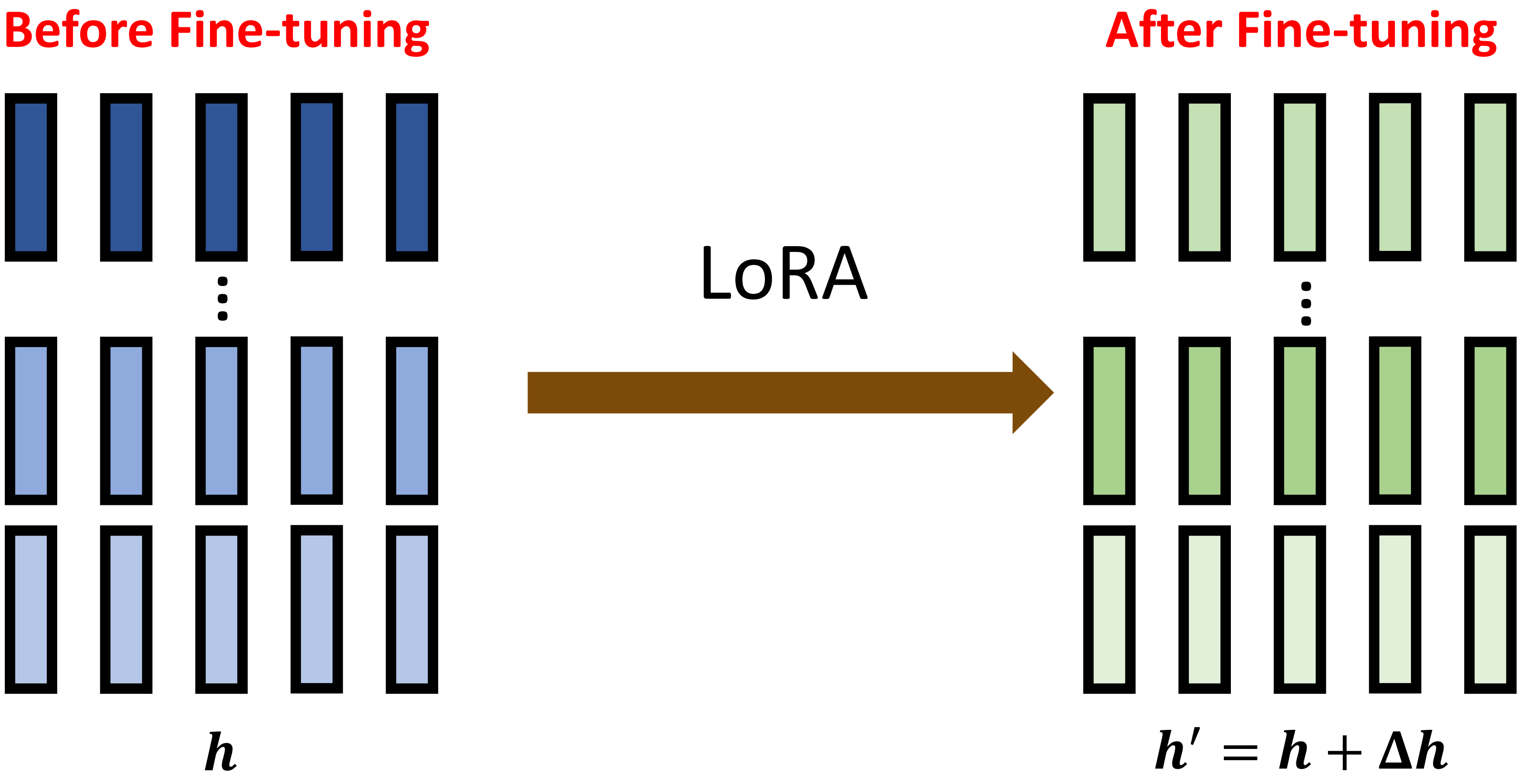
How do PLMs work:

Parameter-efficient fine-tuning

4-2 LoRA

# Parameter-Efficient Fine-tuning: LoRA

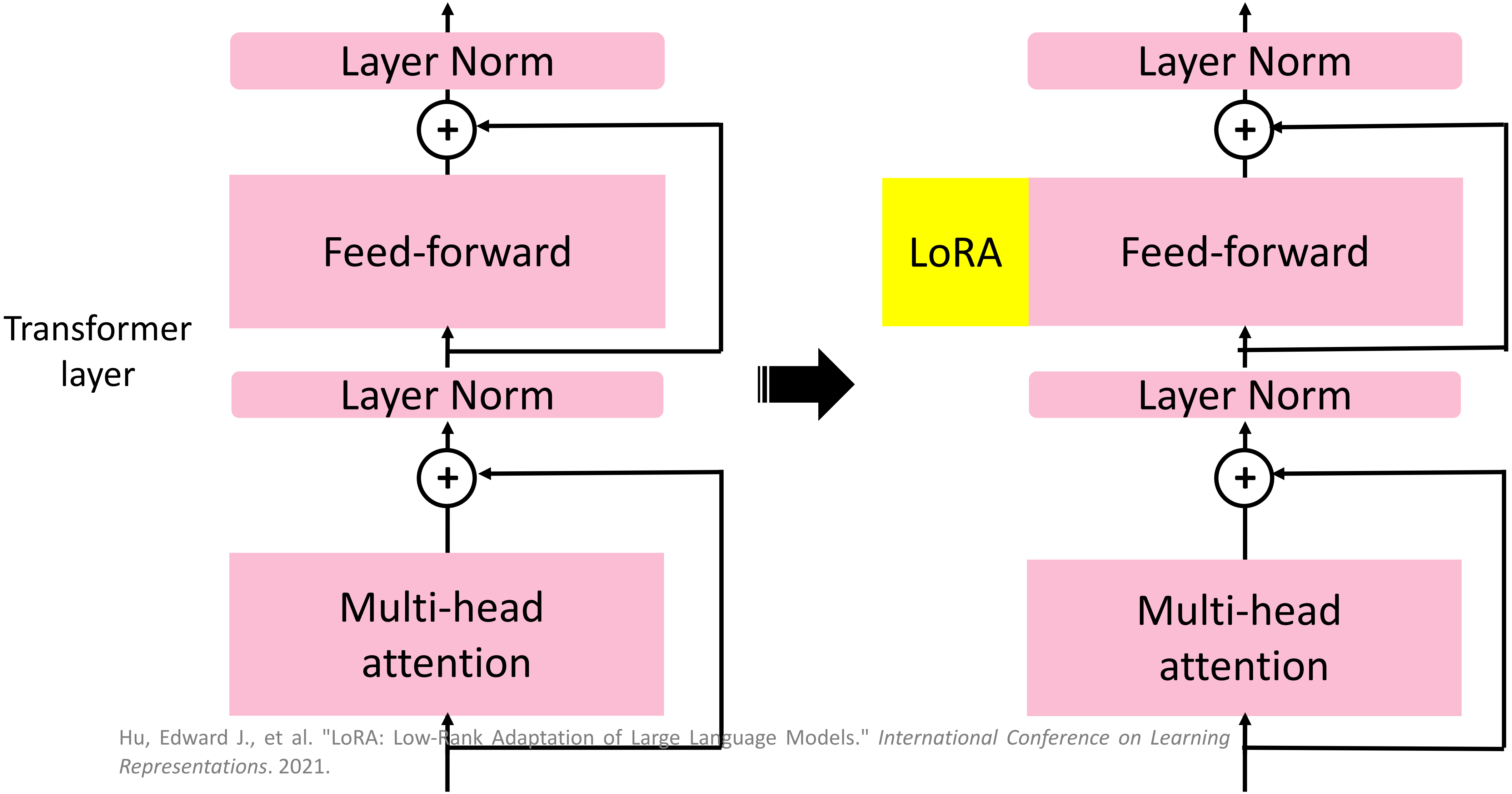
- Use special submodules to modify hidden representations!




He, Junxian, et al. "Towards a Unified View of Parameter-Efficient Transfer Learning." *International Conference on Learning Representations*. 2022.

# Parameter-Efficient Fine-tuning: LoRA

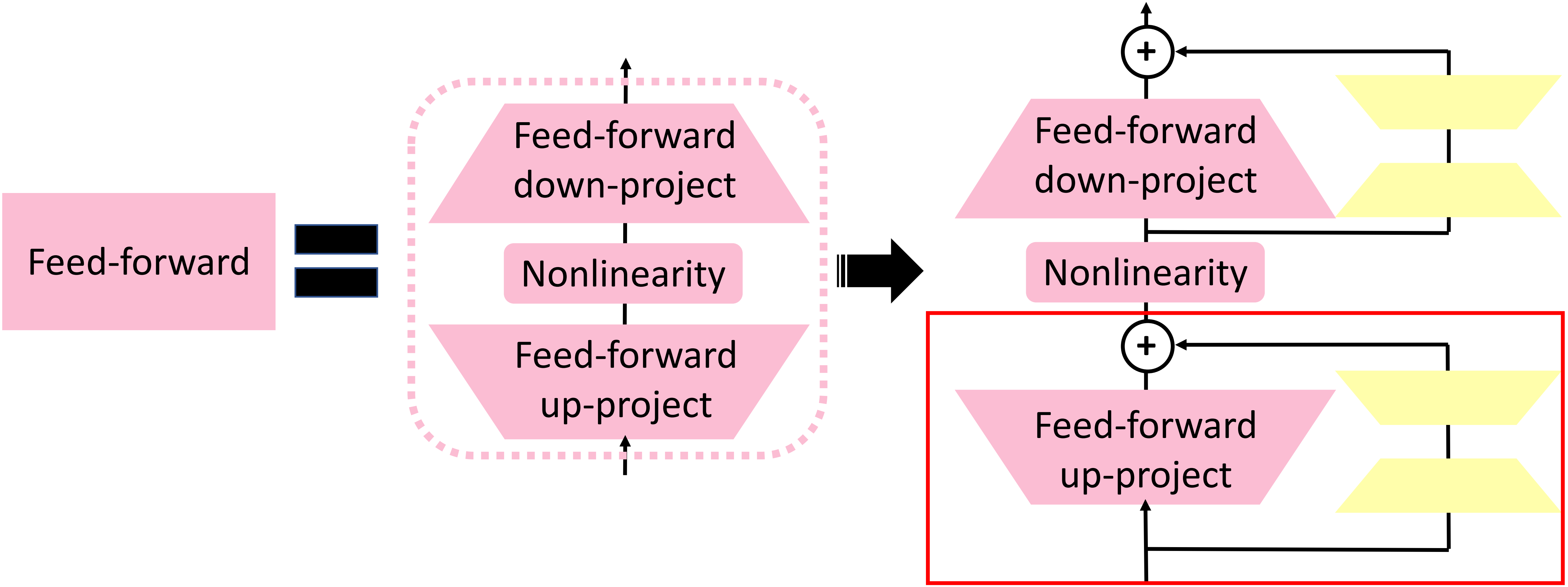
- LoRA: Low-Rank Adaptation of Large Language Models




Hu, Edward J., et al. "LoRA: Low-Rank Adaptation of Large Language Models." *International Conference on Learning Representations*. 2021.

# Parameter-Efficient Fine-tuning: LoRA

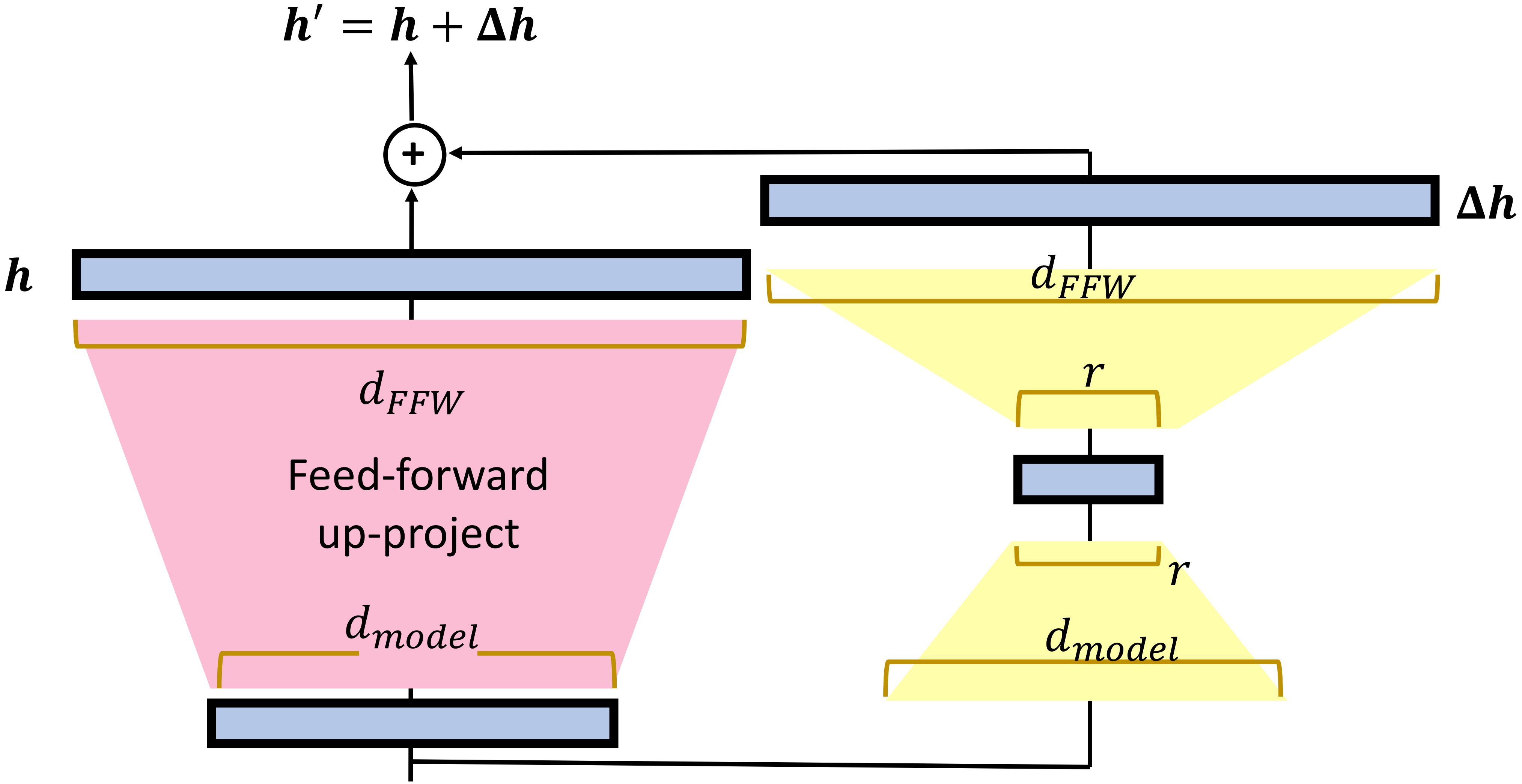
- LoRA




Hu, Edward J., et al. "LoRA: Low-Rank Adaptation of Large Language Models." *International Conference on Learning Representations*. 2021.

# Parameter-Efficient Fine-tuning: LoRA

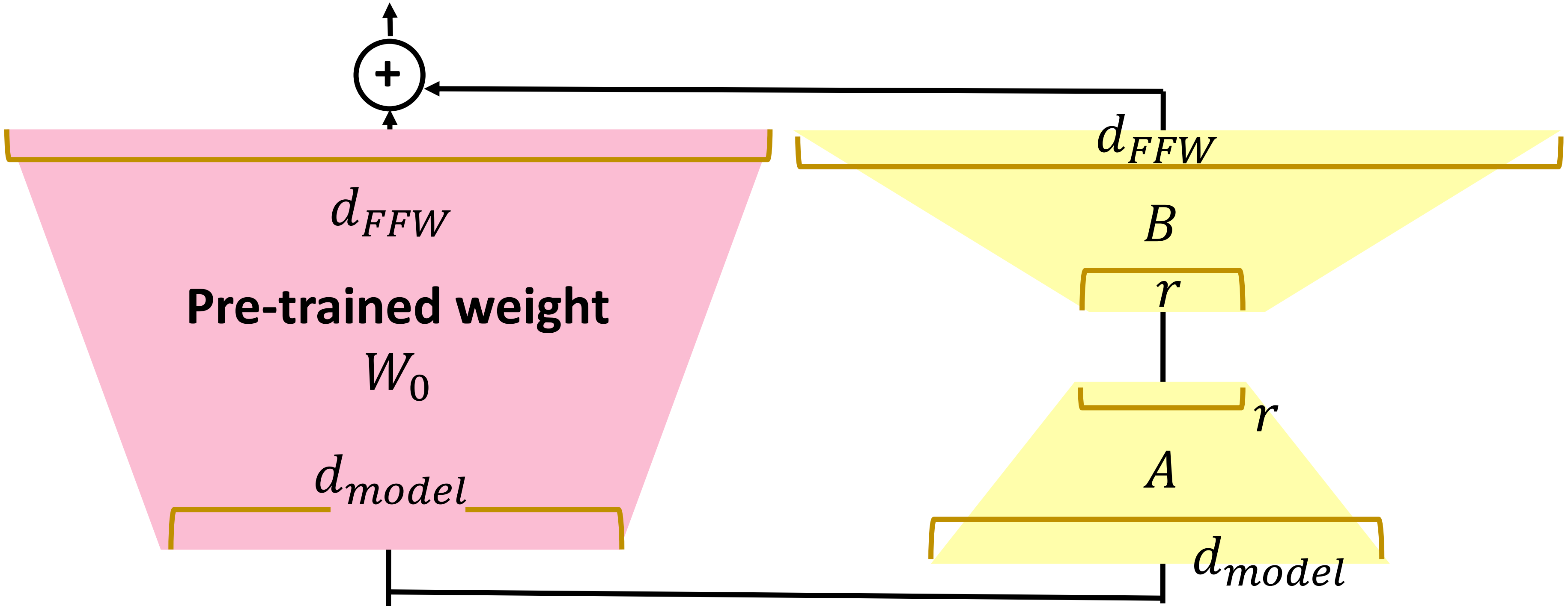
- LoRA




Hu, Edward J., et al. "LoRA: Low-Rank Adaptation of Large Language Models." *International Conference on Learning Representations*. 2021.

# Parameter-Efficient Fine-tuning: LoRA

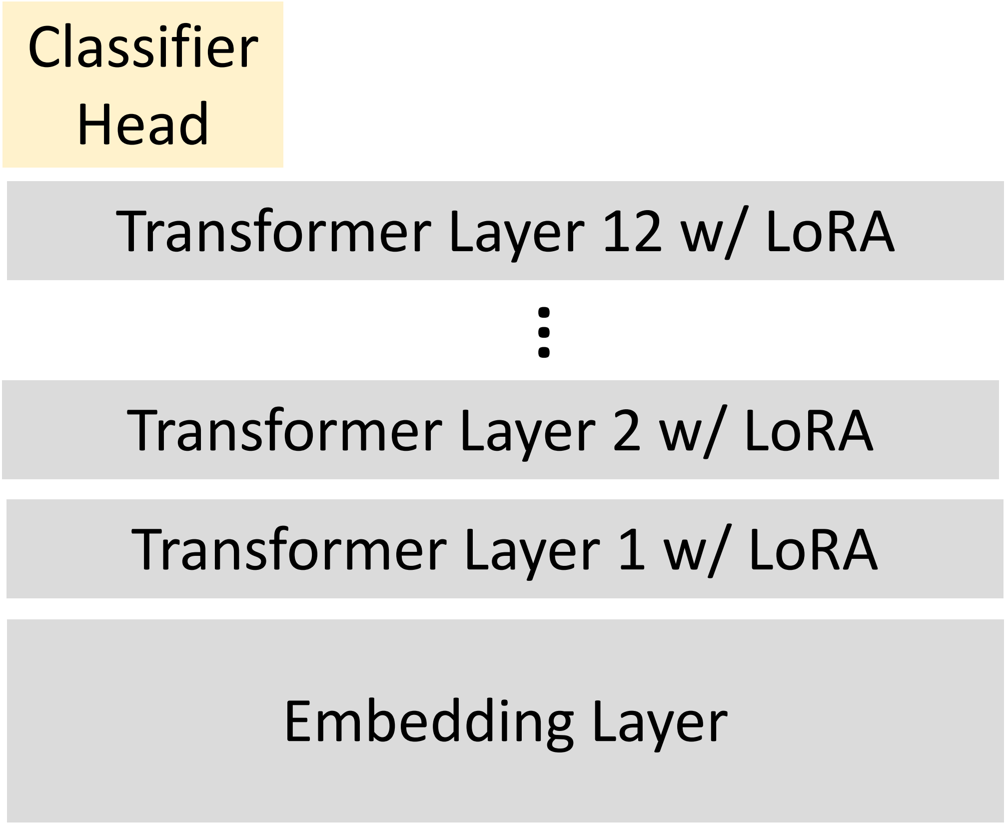
- **Lo**w-**R**ank **A**daptation of Large Language Models
- Motivation: Downstream fine-tunings have low intrinsic dimension
- Weight after fine-tuning $= W_0$ (pre-trained weight) $+\Delta W$ (updates to the weight)
- Hypothesis: The updates to the weight ($\Delta W$) also gave a low intrinsic rank
- Fine-tuned weight $= W_0 + \Delta W = W_0 + BA$, rank $r \ll \min(d_{FFW}, d_{model})$

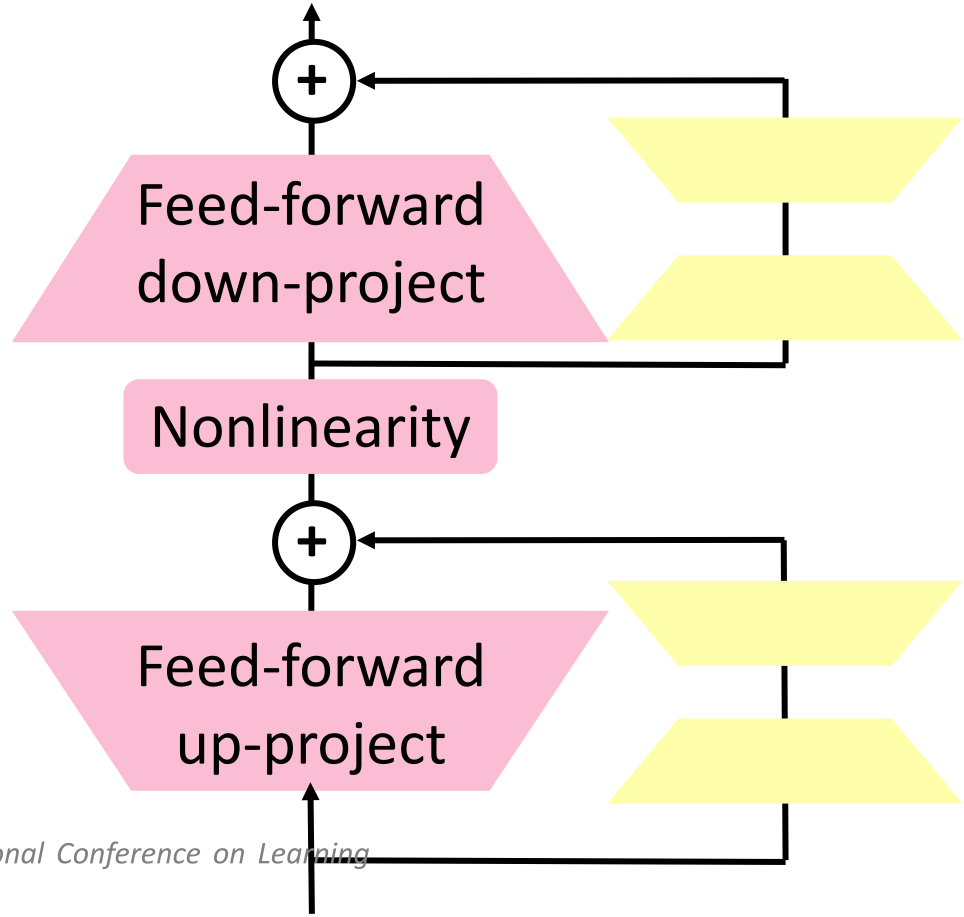



Hu, Edward J., et al. "LoRA: Low-Rank Adaptation of Large Language Models." *International Conference on Learning Representations*. 2021.

# Parameter-Efficient Fine-tuning: LoRA

- LoRA: All downstream tasks share the PLM; the LoRA in each layer and the classifier heads are the task-specific modules



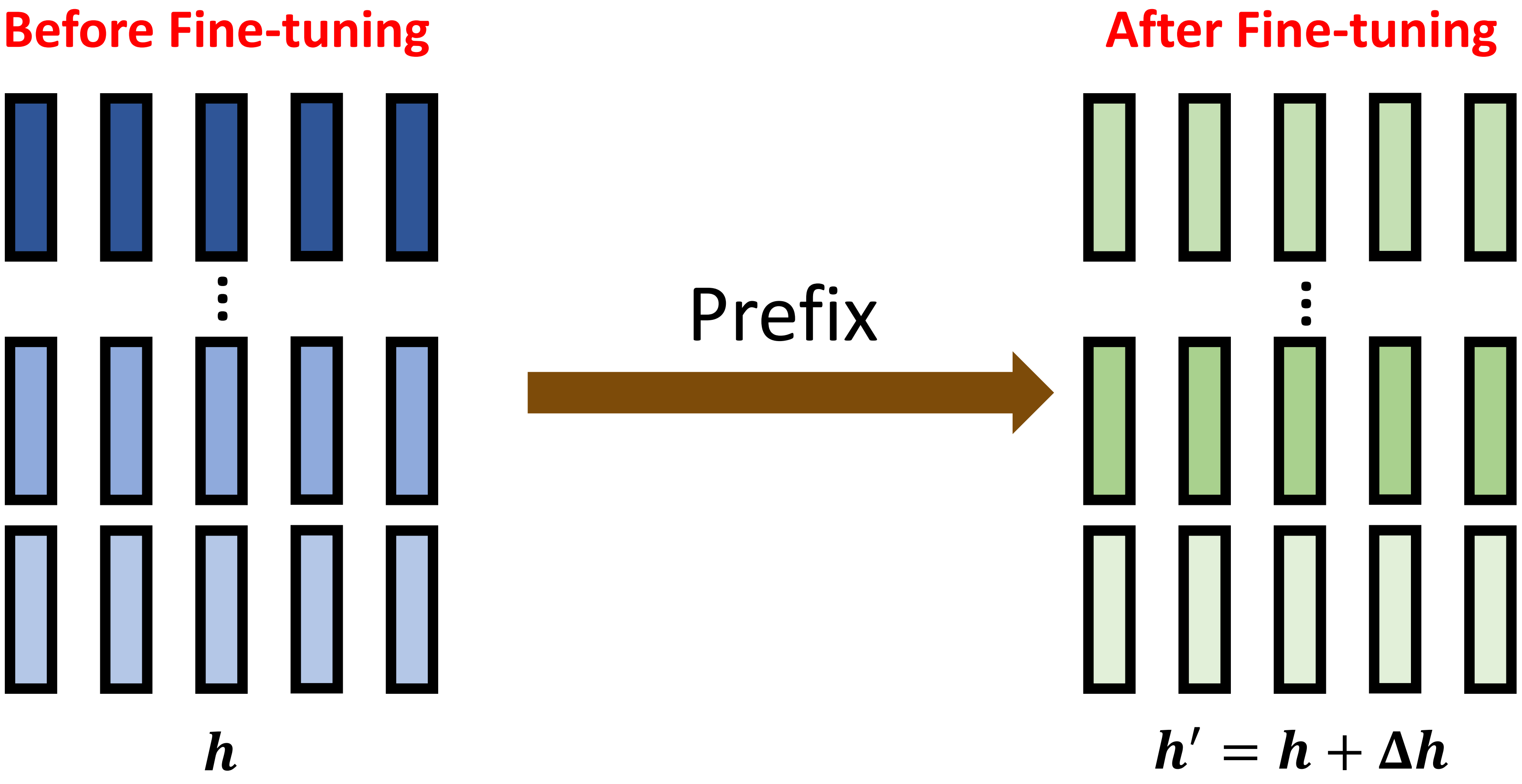




Hu, Edward J., et al. "LoRA: Low-Rank Adaptation of Large Language Models." *International Conference on Learning Representations*. 2021.

# Part 4:
# How do PLMs work:
# Parameter-efficient fine-tuning
## 4-3 Prefix tuning

# Parameter-Efficient Fine-tuning: Prefix Tuning

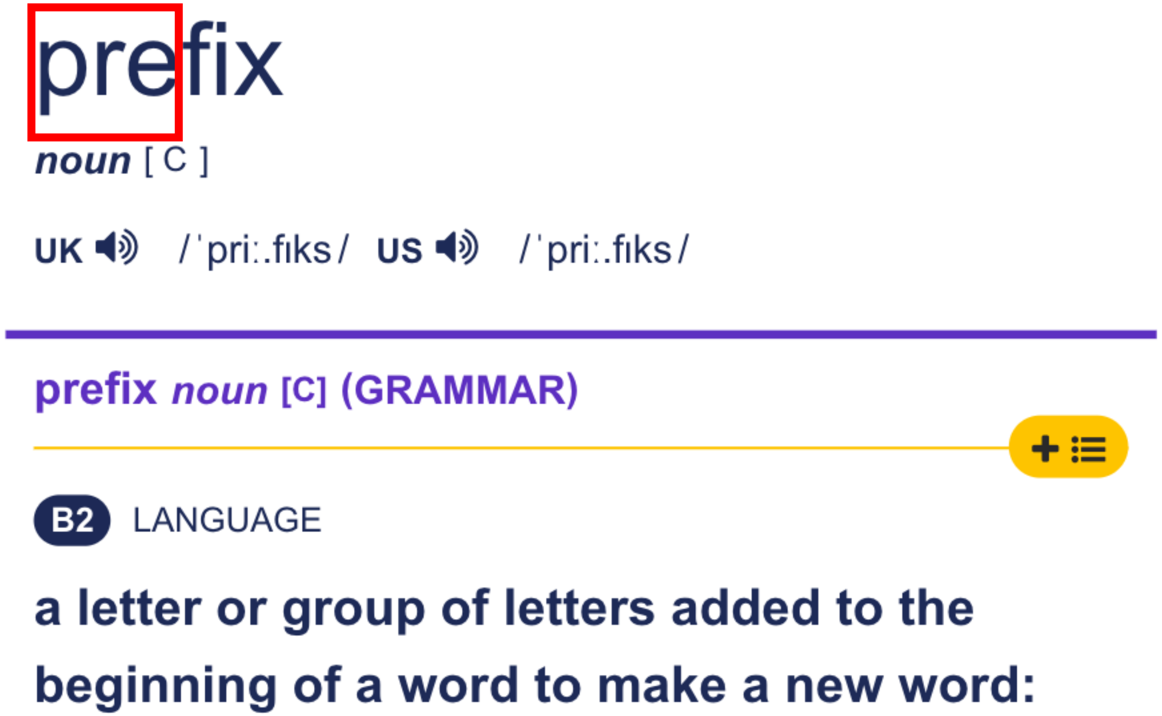
- Use special submodules to modify hidden representations!




He, Junxian, et al. "Towards a Unified View of Parameter-Efficient Transfer Learning." *International Conference on Learning Representations*. 2022.

# Parameter-Efficient Fine-tuning: Prefix Tuning

- What is “*prefix*”


prefix

*noun* [ C ]

UK /ˈpriː.fɪks/ US /ˈpriː.fɪks/

**prefix** ***noun*** **[C] (GRAMMAR)**

B2 LANGUAGE

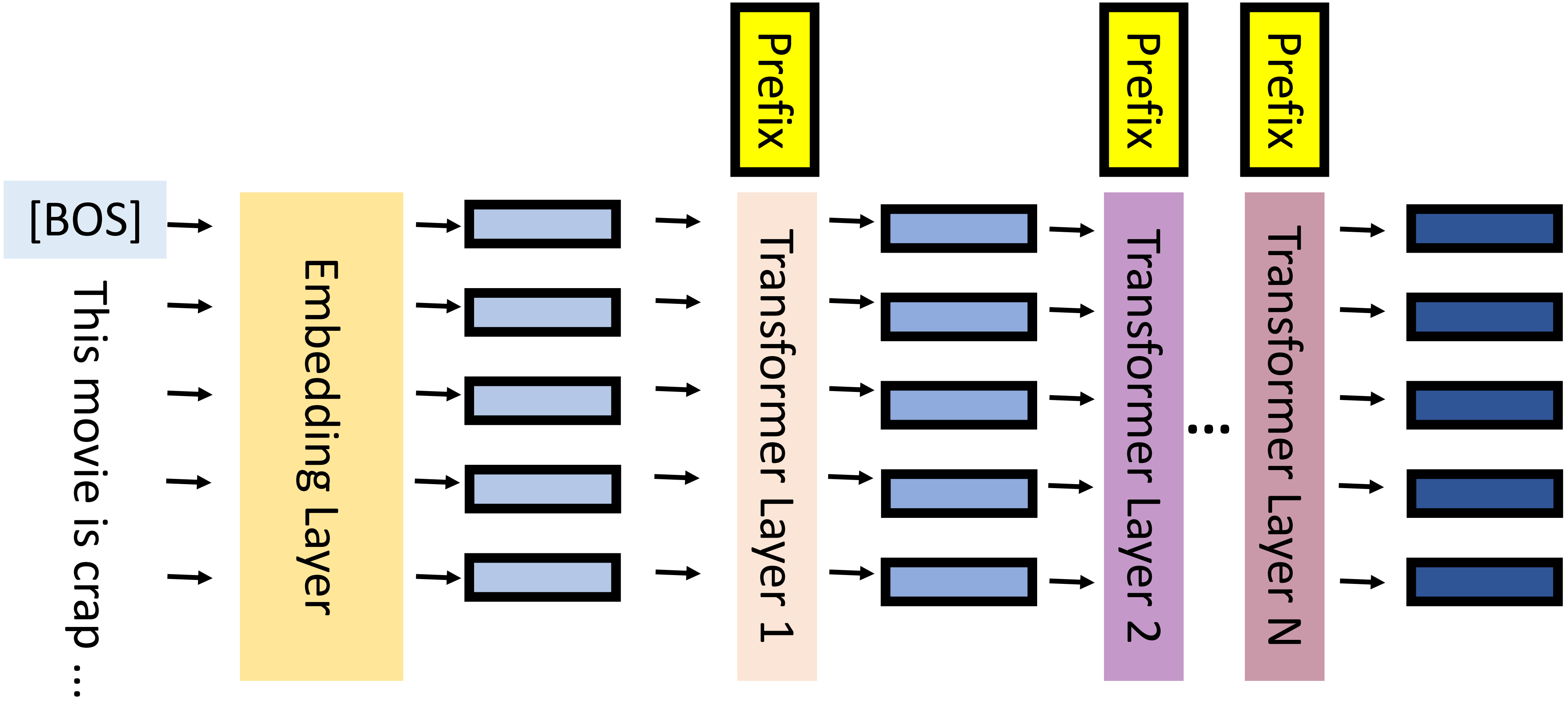
**a letter or group of letters added to the beginning of a word to make a new word:**

- Something that is put in front of another something

https://dictionary.cambridge.org/zht/%E8%A9%9E%E5%85%B8/%E8%8B%B1%E8%AA%9E/prefix

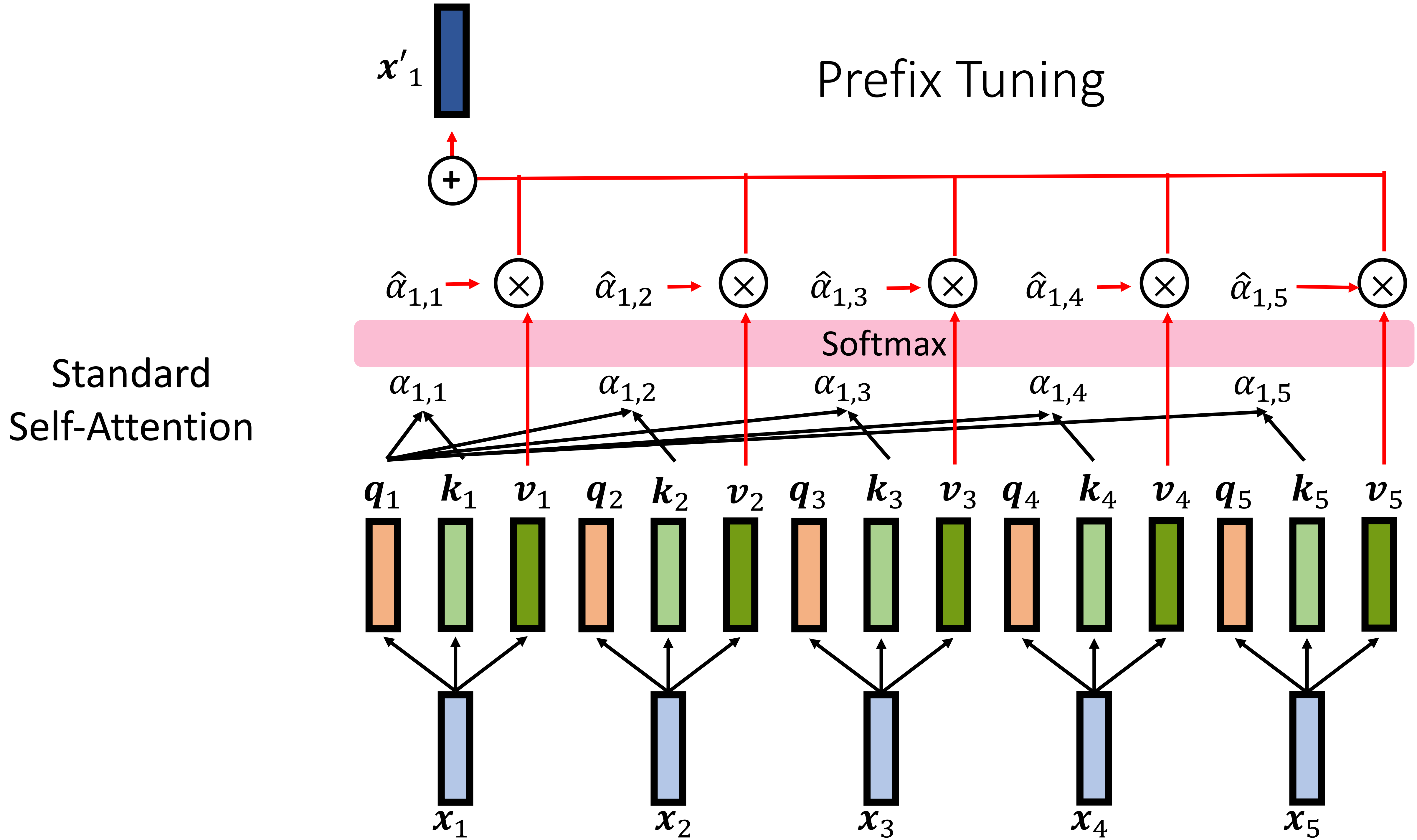
# Parameter-Efficient Fine-tuning: Prefix Tuning

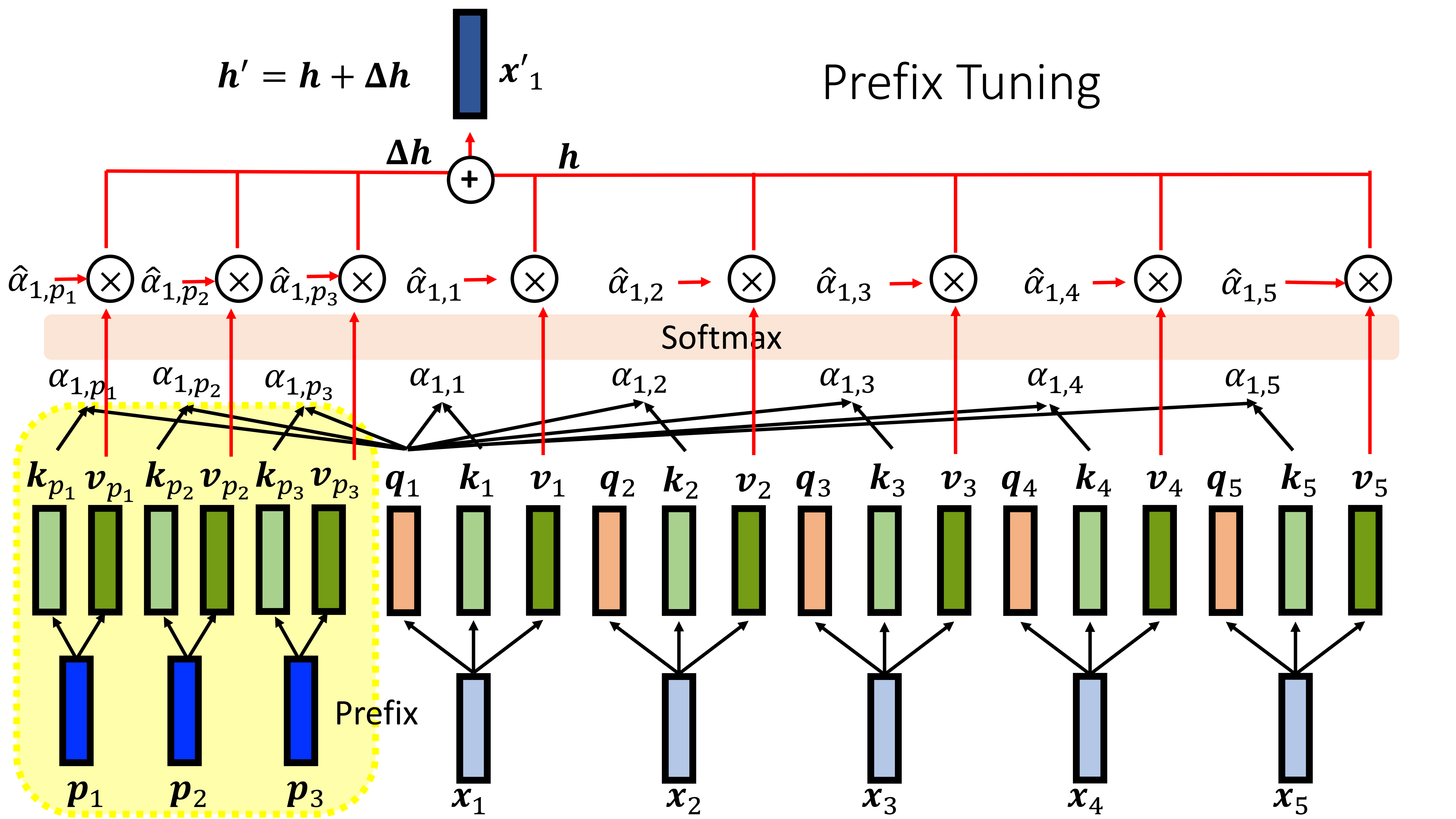
- **Prefix Tuning: Insert trainable prefix in each layer**




Li, Xiang Lisa, and Percy Liang. "Prefix-Tuning: Optimizing Continuous Prompts for Generation." *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. 2021.

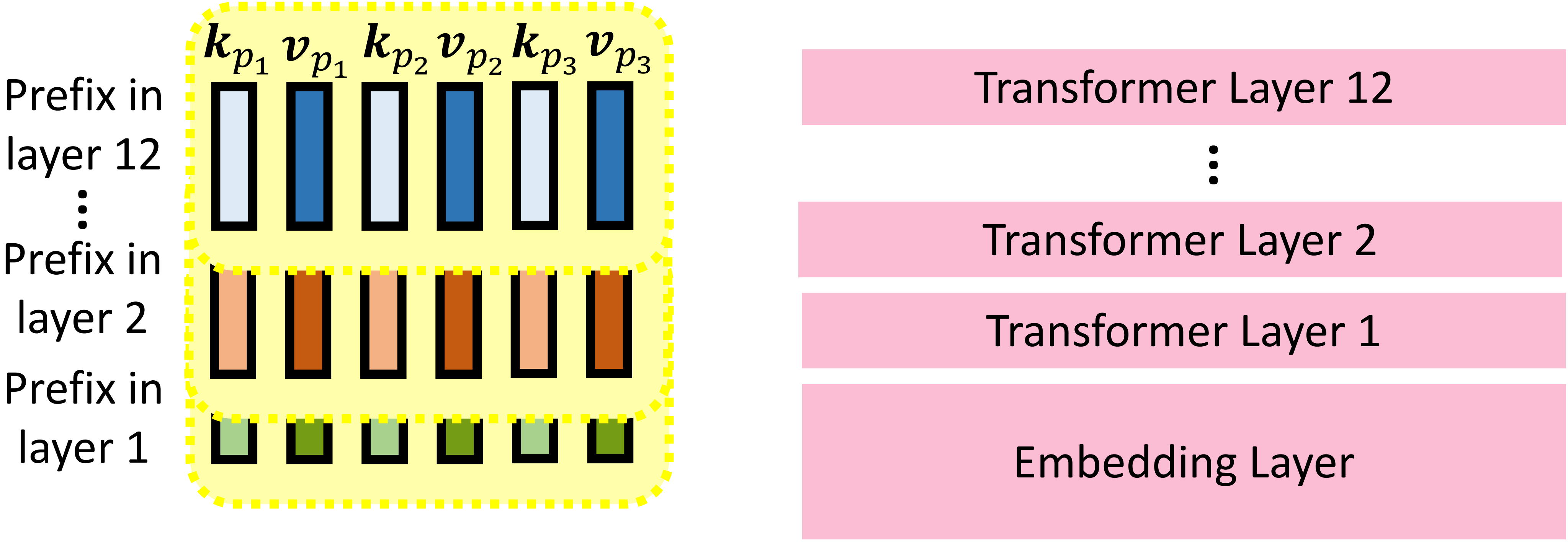
# Prefix Tuning




Prefix Tuning
$h' = h + \Delta h$
$x'_1$
$\Delta h$
$h$
$\hat{\alpha}_{1,p_1}$ $\hat{\alpha}_{1,p_2}$ $\hat{\alpha}_{1,p_3}$ $\hat{\alpha}_{1,1}$ $\hat{\alpha}_{1,2}$ $\hat{\alpha}_{1,3}$ $\hat{\alpha}_{1,4}$ $\hat{\alpha}_{1,5}$
Softmax
$\alpha_{1,p_1}$ $\alpha_{1,p_2}$ $\alpha_{1,p_3}$ $\alpha_{1,1}$ $\alpha_{1,2}$ $\alpha_{1,3}$ $\alpha_{1,4}$ $\alpha_{1,5}$
$k_{p_1}$ $v_{p_1}$ $k_{p_2}$ $v_{p_2}$ $k_{p_3}$ $v_{p_3}$ $q_1$ $k_1$ $v_1$ $q_2$ $k_2$ $v_2$ $q_3$ $k_3$ $v_3$ $q_4$ $k_4$ $v_4$ $q_5$ $k_5$ $v_5$
Prefix
$p_1$ $p_2$ $p_3$ $x_1$ $x_2$ $x_3$ $x_4$ $x_5$

# Parameter-Efficient Fine-tuning: Prefix Tuning

- Prefix Tuning: Only the prefix (key and value) are updated during fine-tuning

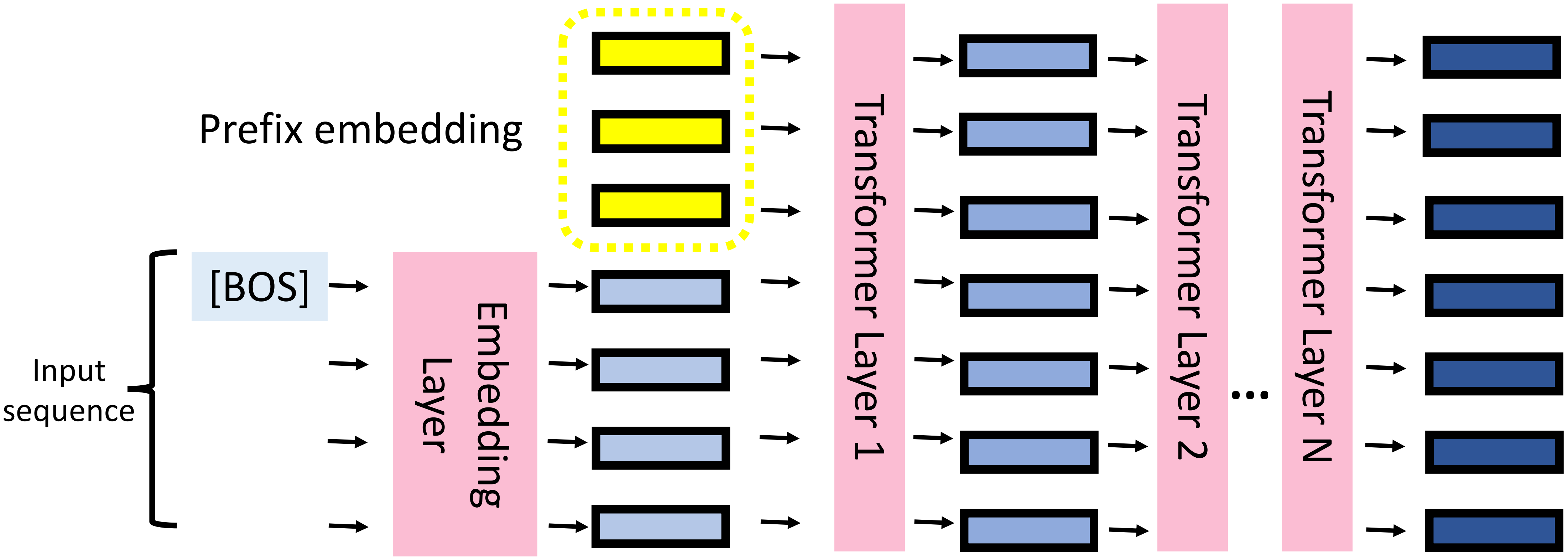



Li, Xiang Lisa, and Percy Liang. "Prefix-Tuning: Optimizing Continuous Prompts for Generation." *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. 2021.

# Part 4:
# How do PLMs work:
# Parameter-efficient fine-tuning
## 4-4 (Soft) Prompt tuning

# Parameter-Efficient Fine-tuning: Soft Prompting

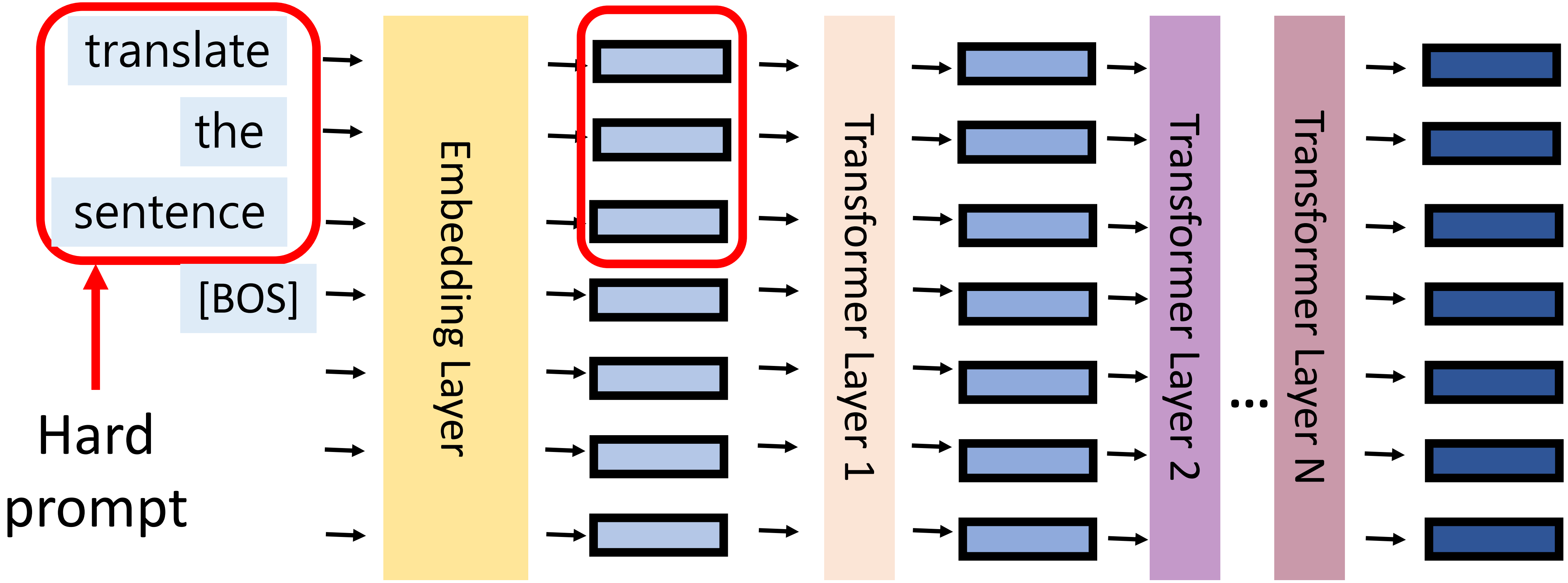
- Soft Prompting
  - Prepend the prefix embedding at the input layer




Lester, Brian, Rami Al-Rfou, and Noah Constant. "The Power of Scale for Parameter-Efficient Prompt Tuning." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

# Parameter-Efficient Fine-tuning: Soft Prompting

- Soft Prompting can be considered as the ***soften*** version of prompting
  - (Hard) prompting: add words in the input sentence



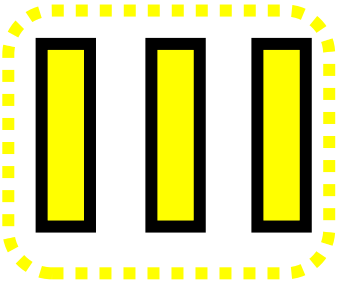

Lester, Brian, Rami Al-Rfou, and Noah Constant. "The Power of Scale for Parameter-Efficient Prompt Tuning." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

# Parameter-Efficient Fine-tuning: Soft Prompting

- Hard Prompts: words (that are originally in the vocabulary)

Translate the sentence

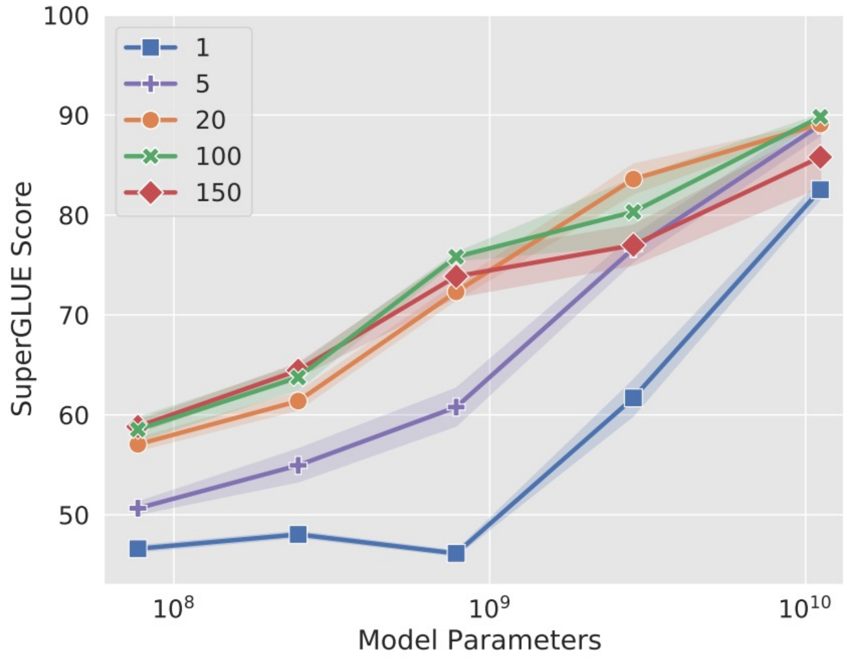
- Soft Prompts: vectors (can be initialized from some word embeddings)



Lester, Brian, Rami Al-Rfou, and Noah Constant. "The Power of Scale for Parameter-Efficient Prompt Tuning." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

# Parameter-Efficient Fine-tuning: Soft Prompting

- How to determine the length of the soft prompt embedding
  - The prompt needs to be long enough
  - Increasing the prompt length shows diminishing performance gain when the length is long enough



(a) Prompt length

Lester, Brian, Rami Al-Rfou, and Noah Constant. "The Power of Scale for Parameter-Efficient Prompt Tuning." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

# Parameter-Efficient Fine-tuning: Soft Prompting

- How to initialize the soft prompt embedding?
  - Random initialization
  - Sample from the word embedding of top 5000 frequent words
  - Class label in the downstream task

(b) Prompt initialization

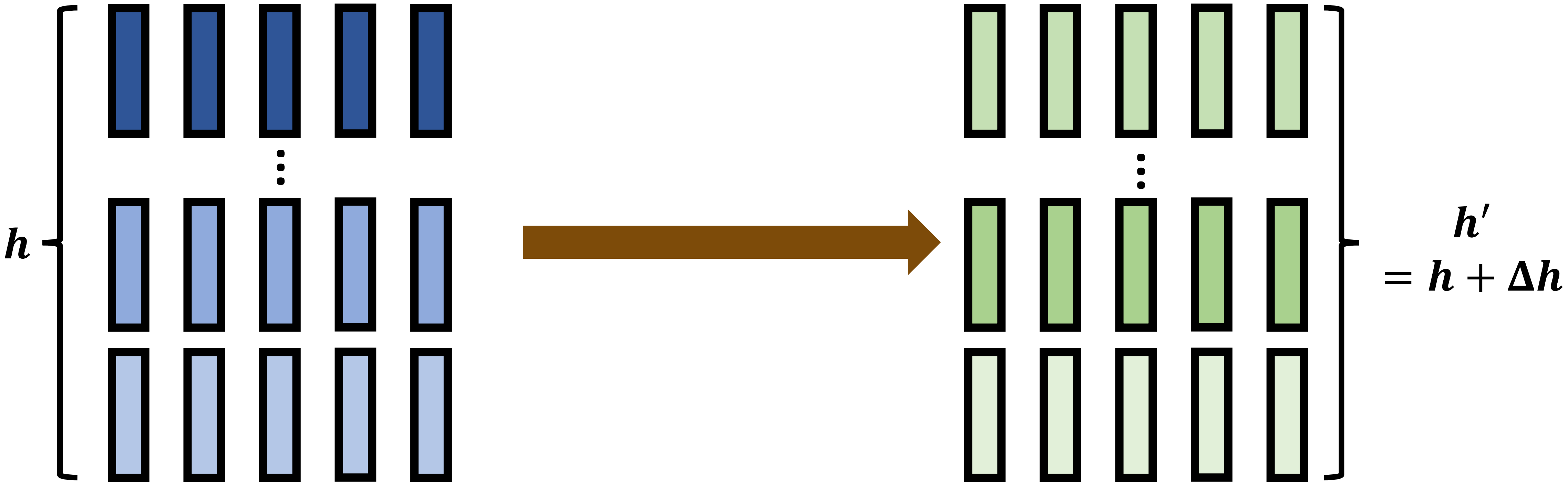
Lester, Brian, Rami Al-Rfou, and Noah Constant. "The Power of Scale for Parameter-Efficient Prompt Tuning." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

# Part 4:
# How do PLMs work:
# Parameter-efficient fine-tuning
## 4-5 Short summary

# Parameter-Efficient Fine-tuning

- Fine-tuning = modifying the hidden representation based on a PLM

**Before Fine-tuning** **After Fine-tuning**




$\boldsymbol{h}$:hidden representation calculated by the original PLM

$\boldsymbol{h}' = \boldsymbol{h} + \boldsymbol{\Delta h}$

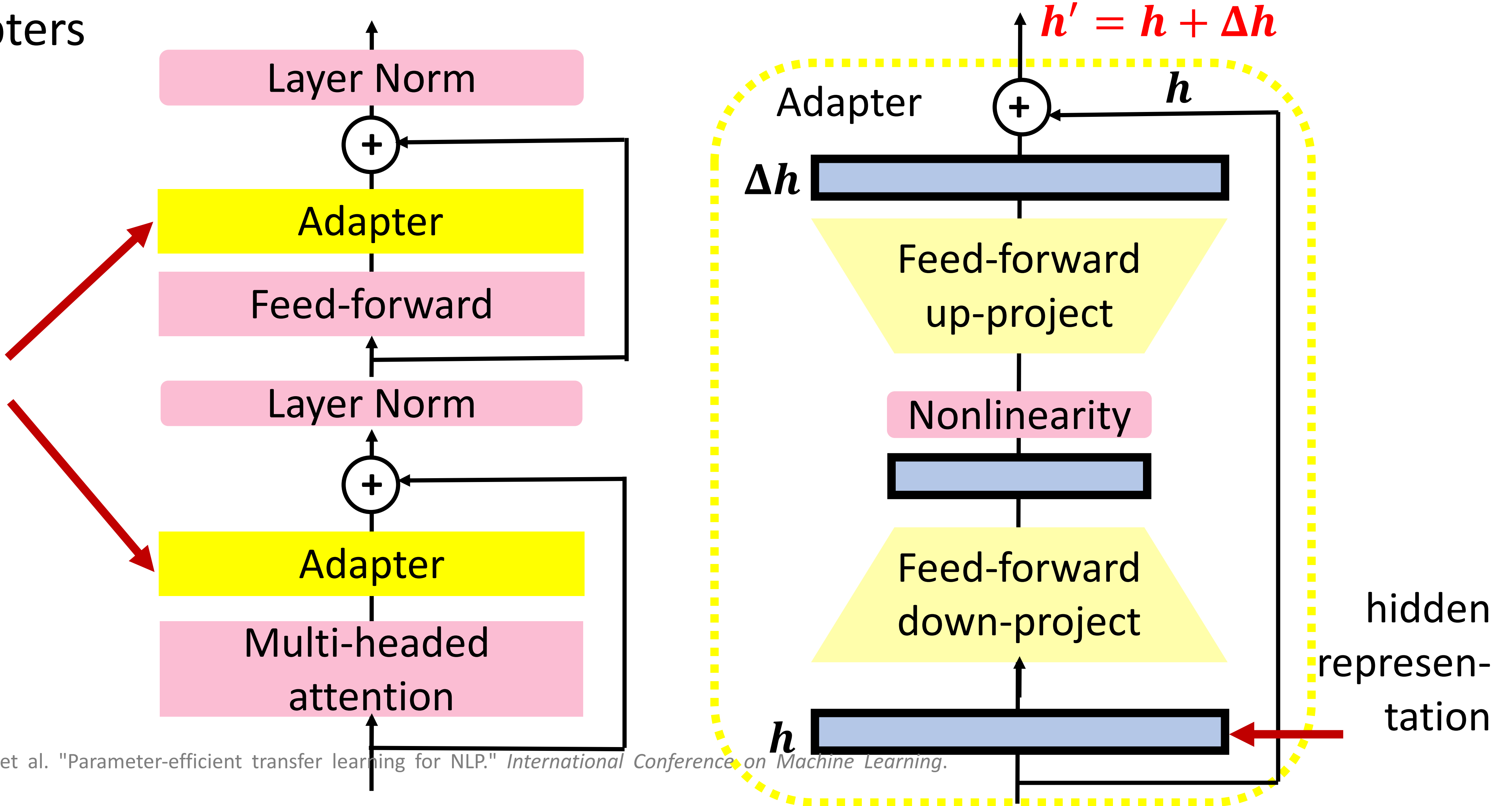
$\boldsymbol{h}'$:hidden representation calculated by the fine-tuned model

He, Junxian, et al. "Towards a Unified View of Parameter-Efficient Transfer Learning." *International Conference on Learning Representations*. 2022.

# Parameter-Efficient Fine-tuning: Adapter

- Adapters

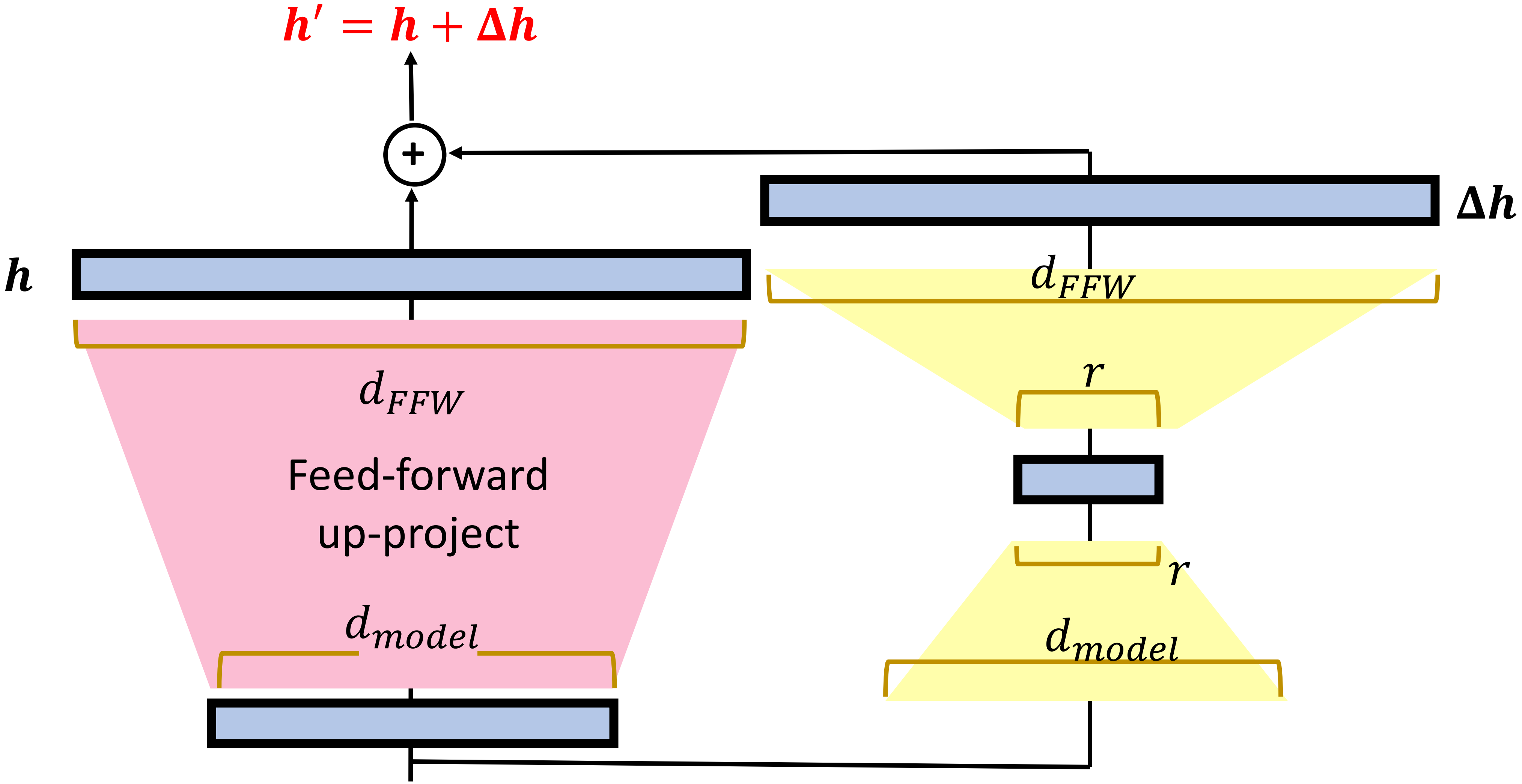
Inside of the transformer layer, only adapters are updated




Houlsby, Neil, et al. "Parameter-efficient transfer learning for NLP." *International Conference on Machine Learning*. PMLR, 2019.

# Parameter-Efficient Fine-tuning: LoRA

- LoRA

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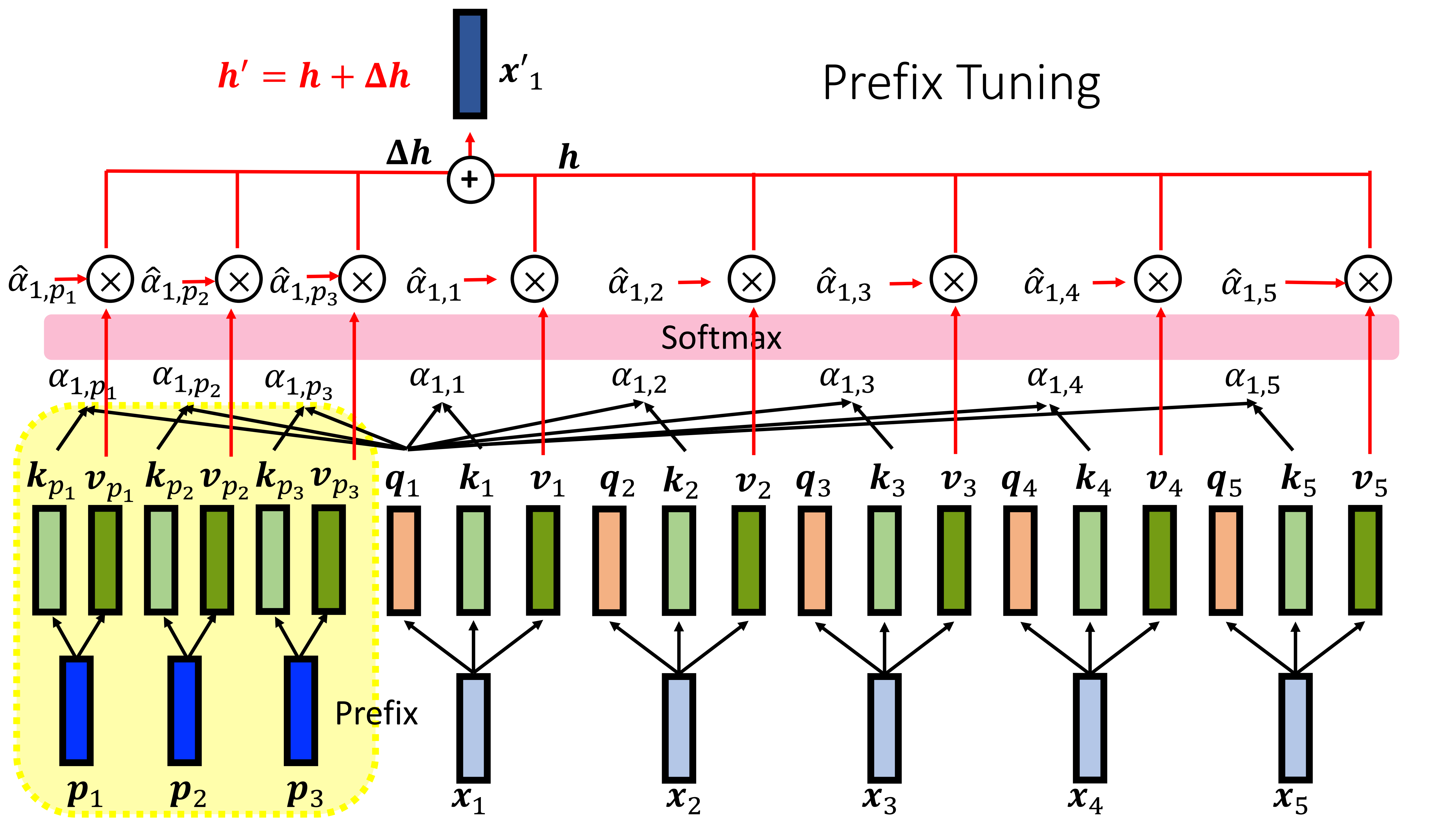
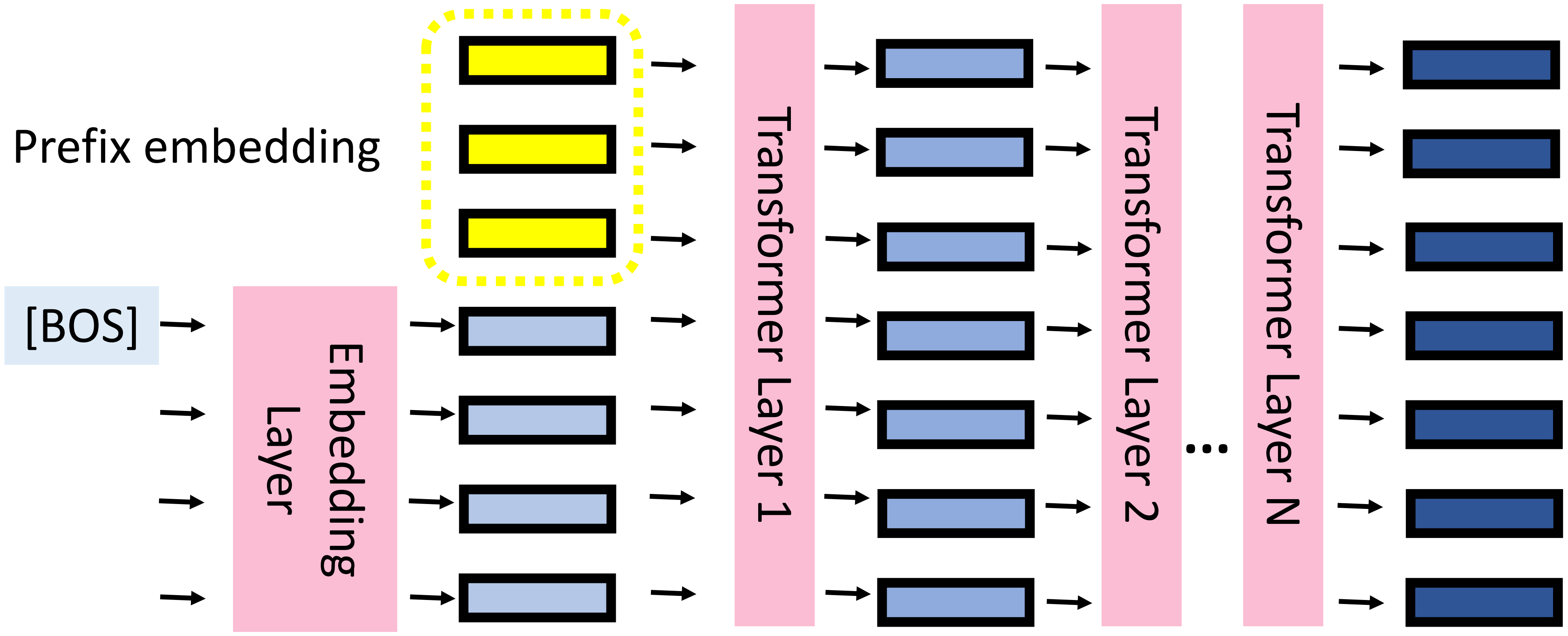


Prefix Tuning
h′ = h + Δh
x′1
Δh
h
α̂1,p1 α̂1,p2 α̂1,p3 α̂1,1 α̂1,2 α̂1,3 α̂1,4 α̂1,5
Softmax
α1,p1 α1,p2 α1,p3 α1,1 α1,2 α1,3 α1,4 α1,5
kp1 vp1 kp2 vp2 kp3 vp3
q1 k1 v1 q2 k2 v2 q3 k3 v3 q4 k4 v4 q5 k5 v5
Prefix
p1 p2 p3
x1 x2 x3 x4 x5

# Parameter-Efficient Fine-tuning: Soft Prompting

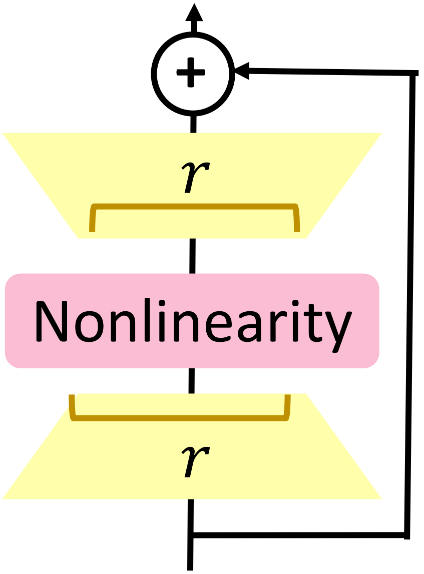
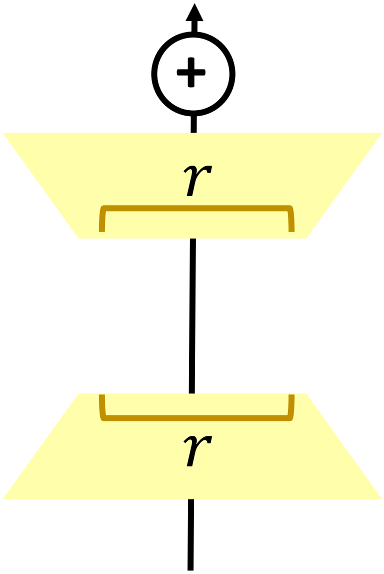
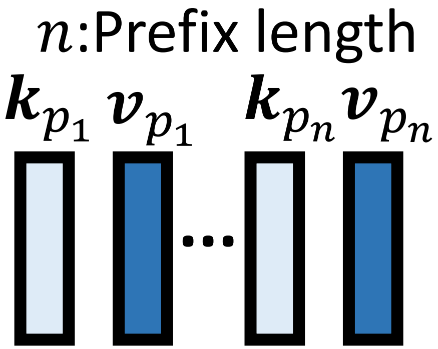
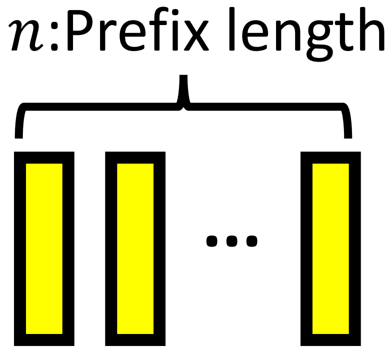
- Soft Prompting
  - Prepend the prefix embedding at the input layer




Lester, Brian, Rami Al-Rfou, and Noah Constant. "The Power of Scale for Parameter-Efficient Prompt Tuning." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

# Parameter-Efficient Fine-tuning

- **Benefit 1: Drastically decreases the task-specific parameters**

| | Adapter | LoRA | Prefix Tuning | Soft Prompt |
|---|---|---|---|---|
| Task-specific parameters* | $\Theta(d_{model} r L)$ | $\Theta(d_{model} r L)$ | $\Theta(d_{model} n L)$ | $\Theta(d_{model} n)$ |
| Percent Trainable | <5% | <0.1% | <0.1% | <0.05% |
| Trainable parameters Illustration |   |   |   |   |

*not including the classifier head

# Parameter-Efficient Fine-tuning

- Benefit 2: Less easier to overfit on training data; better out-of-domain performance

| | Dataset | Domain | Standard | Soft Prompt | $\Delta$ =Soft Prompt - Standard |
|---|---|---|---|---|---|
| Training dataset | SQuAD | Wiki | 94.9 ±0.2 | 94.8 ±0.1 | −0.1 |
| OOD test dataset | TextbookQA | Book | 54.3 ±3.7 | **66.8** ±2.9 | +12.5 |
| | BioASQ | Bio | 77.9 ±0.4 | **79.1** ±0.3 | +1.2 |
| | RACE | Exam | 59.8 ±0.6 | **60.7** ±0.5 | +0.9 |
| | RE | Wiki | 88.4 ±0.1 | **88.8** ±0.2 | +0.4 |
| | DuoRC | Movie | **68.9** ±0.7 | 67.7 ±1.1 | −1.2 |
| | DROP | Wiki | **68.9** ±1.7 | 67.1 ±1.9 | −1.8 |

Lester, Brian, Rami Al-Rfou, and Noah Constant. "The Power of Scale for Parameter-Efficient Prompt Tuning." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

# Parameter-Efficient Fine-tuning

- Benefit 3: Fewer parameters to fine-tune, making them good candidates when training with small dataset

| Dataset (Train set size) | low-resource | | | | high-resource | | | |
|---|---|---|---|---|---|---|---|---|
| | CHEMPROT (4169) | ACL-ARC (1688) | SCIERC (3219) | HYP. (515) | RCT (180k) | AGNEWS (115k) | HELPFUL. (115k) | IMDB (20k) |
| **RoBERTa**-full model | $81.7_{0.8}$ | $65.0_{3.6}$ | $78.5_{1.8}$ | $88.9_{3.3}$ | $87.0_{0.1}$ | $93.7_{0.2}$ | $\mathbf{69.1}_{0.6}$ | $95.2_{0.1}$ |
| **RoBERTa**-adapter, r=256 | $\mathbf{82.9}_{0.6}$ | $\mathbf{67.5}_{4.3}$ | $\mathbf{80.8}_{0.7}$ | $\mathbf{90.4}_{4.2}$ | $87.1_{0.1}$ | $93.8_{0.1}$ | $69.0_{0.4}$ | $\mathbf{95.7}_{0.1}$ |

He, Ruidan, et al. "On the Effectiveness of Adapter-based Tuning for Pretrained Language Model Adaptation." *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. 2021.

# Parameter-Efficient Fine-tuning

- Which parameter-efficient fine-tuning should one select?
  - No one-size-fit-all

| | Method | SST-2 | MRPC | CoLA | RTE | QNLI | STS-B | MNLI | QQP | Avg. |
|---|---|---|---|---|---|---|---|---|---|---|
| | Best Performance on GLUE Dev | | | | | | | | | |
| Full-model | Fine-tuning | 91.63 | 90.94 | **62.08** | 66.43 | 89.95 | **89.76** | **83.23** | **87.35** | 82.67 |
| Parameter-efficient fine-tuning | Adapter | **91.86** | 89.86 | 61.51 | 71.84 | **90.55** | 88.63 | 83.14 | 86.78 | **83.02** |
| | Prefix-tuning | 90.94 | **91.29** | 55.37 | **76.90** | 90.39 | 87.19 | 81.15 | 83.30 | 82.07 |
| | LoRA | 91.51 | 90.03 | 60.47 | 71.48 | 89.93 | 85.65 | 82.51 | 85.98 | 82.20 |

**Boldface**: best performance
Underline: second best performance

Mao, Yuning, et al. "UniPELT: A Unified Framework for Parameter-Efficient Language Model Tuning." *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 2022.

# Schedule

17:00 – 17:10 **Part 1** Introduction [Hung-yi]
17:10 – 17:40 **Part 2** Why do PLMs work [Hung-yi]
17:40 – 18:20 **Part 3** How to use PLMs: Contrastive Learning for PLMs [Yung-Sung]
18:20 – 18:30 Q&A for Part 1+2+3

18:30 – 18:40 Break

18:40 – 19:05 **Part 4** How to use PLMs: Parameter-efficient fine-tuning [Cheng-Han]
19:05 – 19:50 **Part 5** How to use PLMs: Using PLMs with different amounts of data [Cheng-Han]
19:50 – 20:00 Conclusion and Future work + Q&A

2022 AACL-IJCNLP

# Part 5:
# How do PLMs work:
# Using PLMs with different amounts of data

Cheng-Han Chiang

**National Taiwan University**

# Using PLMs with different amounts of data

- Our goal: fine-tune a model for a target downstream task using a PLM
  - Traditionally, we assume that we have sufficient amount of data for the target task

Target task dataset
(labeled)

# Using PLMs with different amounts of data

- Our goal: fine-tune a model for a target downstream task using a PLM
  - Sometimes, we have additional labeled dataset for other datasets

Target task dataset
(labeled)

Datasets of other tasks
(labeled)

# Using PLMs with different amounts of data

- Our goal: fine-tune a model for a target downstream task using a PLM
  - Sometimes, labeled data for the target task is scarce

Target task dataset
(labeled)

# Using PLMs with different amounts of data

- Our goal: fine-tune a model for a target downstream task using a PLM
  - Sometimes, we only have a few labeled data for the target task, and we have unlabeled dataset related to the target task

Target task dataset (labeled)

Target task dataset (Unlabeled)

# Using PLMs with different amounts of data

- Our goal: fine-tune a model for a target downstream task using a PLM
  - Sometimes, we have no labeled data for the target task

Target task dataset
(labeled)

# Using PLMs with different amounts of data

- Our goal: fine-tune a model for a target downstream task using a PLM
  - How to use PLMs with different amount of data?

Target task dataset
(labeled)

Datasets of other tasks
(labeled)

Data related to target task
(Unlabeled)

# Part 5:

# How do PLMs work:

# Using PLMs with different amounts of data

## 5-1: Intermediate-task fine-tuning:
## using labeled data from other tasks

# Intermediate-task fine-tuning

- Goal: Obtain a model for task (target task)
  - Standard supervised learning

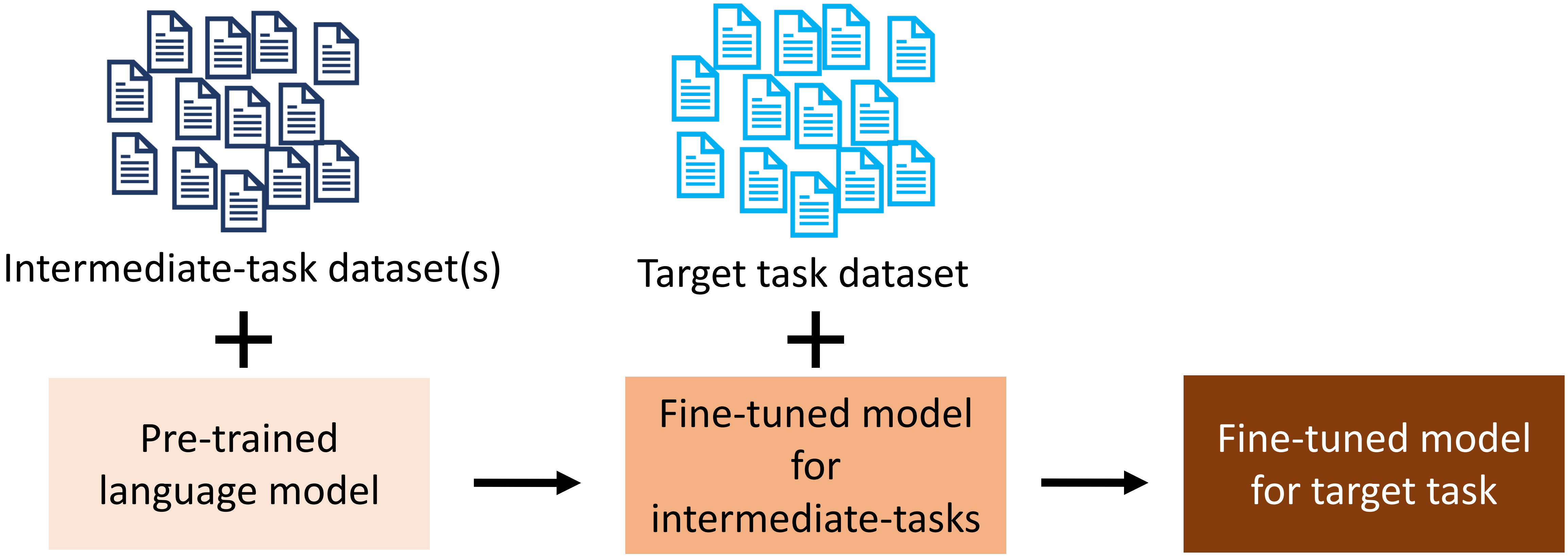
Target task dataset

+

Pre-trained language model → Fine-tuned model for target task

# Intermediate-task fine-tuning

- Goal: Obtain a model for task (target task)
  - Intermediate-task fine-tuning: transfer the knowledge from a model fine-tuned on other tasks (intermediate-tasks)




Vu, Tu, et al. "Exploring and Predicting Transferability across NLP Tasks." *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 2020.

# Intermediate-task fine-tuning

- What kind of intermediate tasks can help target task?
  - This paper studies the transferability of 33 datasets, which can be categorized into three types: classification (CR), question answering (QA), and sequence labeling (SL)

| **Task** | | |
|---|---|---|
| *text classification/regression (CR)* | *question answering (QA)* | *sequence labeling (SL)* |
| SNLI (Bowman et al., 2015) | SQuAD-2 (Rajpurkar et al., 2018) | ST (Bjerva et al., 2016) |
| MNLI (Williams et al., 2018) | NewsQA (Trischler et al., 2017) | CCG (Hockenmaier and Steedman, 2007) |
| QQP (Iyer et al., 2017) | HotpotQA (Yang et al., 2018) | Parent (Liu et al., 2019a) |
| QNLI (Wang et al., 2019b) | SQuAD-1 (Rajpurkar et al., 2016) | GParent (Liu et al., 2019a) |
| SST-2 (Socher et al., 2013) | DuoRC-p (Saha et al., 2018) | GGParent (Liu et al., 2019a) |
| SciTail (Khot et al., 2018) | DuoRC-s (Saha et al., 2018) | POS-PTB (Marcus et al., 1993) |
| CoLA (Warstadt et al., 2019) | DROP (Dua et al., 2019) | GED (Yannakoudakis et al., 2011) |
| STS-B (Cer et al., 2017) | WikiHop (Welbl et al., 2018) | NER (Tjong Kim Sang and De Meulder, 2003) |
| MRPC (Dolan and Brockett, 2005) | BoolQ (Clark et al., 2019) | POS-EWT (Silveira et al., 2014) |
| RTE (Dagan et al., 2005, et seq.) | ComQA (Abujabal et al., 2019) | Conj (Ficler and Goldberg, 2016) |
| WNLI (Levesque, 2011) | CQ (Bao et al., 2016) | Chunk (Tjong Kim Sang and Buchholz, 2000) |

Vu, Tu, et al. "Exploring and Predicting Transferability across NLP Tasks." *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 2020.

# Intermediate-task fine-tuning

- What kind of intermediate tasks can help target task?
  - $p_t$: the performance of directly fine-tuning on target task $t$
  - $p_{s \to t}$: the performance of transferring from intermediate-task $s$ to a target task $t$

Target task (CR)

Intermediate-task (CR)

| Task | CoLA | SST-2 | MRPC | STS-B | QQP | MNLI | QNLI | RTE | WNLI | SNLI | SciTail |
|---|---|---|---|---|---|---|---|---|---|---|---|
| CoLA | 51.0 | 92.2 | 86.6 | 86.4 | **87.5** | 84.2 | 91.4 | 60.3 | **54.9** | 90.5 | 93.8 |
| SST-2 | 54.2 | 91.9 | 84.2 | 86.9 | 87.0 | 84.1 | 91.3 | 56.0 | 53.5 | 90.9 | 93.5 |
| MRPC | 51.0 | 92.3 | 84.0 | 87.1 | 87.1 | 84.4 | 91.3 | 61.7 | 47.9 | 90.9 | 93.5 |
| STS-B | 48.8 | 91.9 | 87.3 | 85.9 | 86.4 | 84.0 | 90.4 | 65.0 | 35.2 | 90.9 | 92.1 |
| QQP | 49.4 | 92.0 | **87.7** | 88.5 | 87.3 | 84.2 | 90.7 | 61.7 | 36.6 | 90.9 | 92.9 |
| MNLI | 50.0 | **93.5** | 87.6 | 87.0 | 87.1 | 84.2 | **91.5** | **77.6** | 40.8 | **91.2** | **95.6** |
| QNLI | 49.9 | 92.5 | 86.6 | **88.6** | 86.6 | 84.4 | 91.4 | 70.4 | 38.0 | 91.1 | 94.5 |
| RTE | 52.1 | 92.1 | 83.9 | 87.0 | 86.8 | 84.4 | 91.3 | 60.6 | 50.7 | 91.0 | 93.5 |
| WNLI | **54.5** | 91.7 | 84.2 | 84.8 | 87.0 | 84.2 | 91.4 | 60.6 | 45.1 | 90.9 | 93.6 |
| SNLI | 54.2 | 93.1 | $\boxed{86.8}$ | 87.5 | 86.9 | **84.6** | 90.4 | **77.6** | 39.4 | 90.7 | 95.2 |
| SciTail | 50.8 | 91.9 | 82.2 | 88.1 | 86.6 | 84.3 | 91.0 | 69.3 | 46.5 | 91.0 | 93.9 |

$p_{s \to t}$

$p_{s \to t}$

$p_t$

Vu, Tu, et al. "Exploring and Predicting Transferability across NLP Tasks." *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 2020.

# Intermediate-task fine-tuning

- What kind of intermediate tasks can help target task?
  - $p_t$: the performance of directly fine-tuning on target task $t$
  - $p_{s \to t}$: the performance of transferring from intermediate-task $s$ to a target task $t$

Target task (CR)

Intermediate-task (CR)

| Task | CoLA | SST-2 | MRPC | STS-B | QQP | MNLI | QNLI | RTE | WNLI | SNLI | SciTail |
|---|---|---|---|---|---|---|---|---|---|---|---|
| CoLA | 51.0 | 92.2 | 86.6 | 86.4 | **87.5** | 84.2 | 91.4 | 60.3 | $\boxed{\textbf{54.9}}$ | 90.5 | 93.8 |
| SST-2 | 54.2 | 91.9 | 84.2 | 86.9 | 87.0 | 84.1 | 91.3 | 56.0 | 53.5 | 90.9 | 93.5 |
| MRPC | 51.0 | 92.3 | 84.0 | 87.1 | 87.1 | 84.4 | 91.3 | 61.7 | 47.9 | 90.9 | 93.5 |
| STS-B | 48.8 | 91.9 | 87.3 | 85.9 | 86.4 | 84.0 | 90.4 | 65.0 | 35.2 | 90.9 | 92.1 |
| QQP | 49.4 | 92.0 | **87.7** | 88.5 | 87.3 | 84.2 | 90.7 | 61.7 | 36.6 | 90.9 | 92.9 |
| MNLI | 50.0 | **93.5** | 87.6 | 87.0 | 87.1 | 84.2 | **91.5** | **77.6** | 40.8 | **91.2** | **95.6** |
| QNLI | 49.9 | 92.5 | 86.6 | **88.6** | 86.6 | 84.4 | 91.4 | 70.4 | 38.0 | 91.1 | 94.5 |
| RTE | 52.1 | 92.1 | 83.9 | 87.0 | 86.8 | 84.4 | 91.3 | 60.6 | 50.7 | 91.0 | 93.5 |
| WNLI | **54.5** | 91.7 | 84.2 | 84.8 | 87.0 | 84.2 | 91.4 | 60.6 | 45.1 | 90.9 | 93.6 |
| SNLI | 54.2 | 93.1 | 86.8 | 87.5 | 86.9 | **84.6** | 90.4 | **77.6** | 39.4 | 90.7 | 95.2 |
| SciTail | 50.8 | 91.9 | 82.2 | 88.1 | 86.6 | 84.3 | 91.0 | 69.3 | 46.5 | 91.0 | 93.9 |

Vu, Tu, et al. "Exploring and Predicting Transferability across NLP Tasks." *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 2020.

# Intermediate-task fine-tuning

- What kind of intermediate tasks can help target task?
  - The relative transfer gain is defined as $g_{s\rightarrow t} = \frac{p_{s\rightarrow t} - p_t}{p_t}$
  - Same type of tasks is the most beneficial

| FULL → FULL | | | |
|---|---|---|---|
| ↓src,tgt→ | CR | QA | SL |
| CR | $\boxed{6.3 \ (11)}$ | 3.4 (10) | 0.3 (10) |
| QA | 3.2 (10) | 9.5 (11) | 0.3 (9) |
| SL | 5.3 (8) | 2.5 (10) | 0.5 (11) |

A summary of our transfer results for each combination of the three task classes in the three data regimes. Each cell represents the relative gain of the *best* source task in the source class (row) for a given target task, averaged across all of target tasks in the target class (column). In parentheses, we additionally report the number of target tasks (out of 11) for which at least one source task results in a positive transfer gain. The diagonal cells indicate in-class transfer.

Vu, Tu, et al. "Exploring and Predicting Transferability across NLP Tasks." *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 2020.

# Intermediate-task fine-tuning

- Does the dataset size affect the transferability of intermediate tasks?
  - Limited dataset size: **1K training samples** only
  - Intermediate-task transfer is beneficial even when the intermediate-task or the target task has limited data

Intermediate (src)→ target

| FULL → LIMITED | | | |
|---|---|---|---|
| ↓src,tgt→ | CR | QA | SL |
| CR | 56.9 (11) | 36.8 (10) | 2.0 (10) |
| QA | 44.3 (11) | 63.3 (11) | 5.3 (11) |
| SL | 45.6 (11) | 39.2 (6) | 20.9 (11) |
| **LIMITED → LIMITED** | | | |
| ↓src,tgt→ | CR | QA | SL |
| CR | 23.7 (11) | 7.3 (11) | 1.1 (11) |
| QA | 37.3 (11) | 49.3 (11) | 4.2 (11) |
| SL | 29.3 (10) | 30.0 (8) | 10.2 (11) |

Vu, Tu, et al. "Exploring and Predicting Transferability across NLP Tasks." *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 2020.

# Intermediate-task fine-tuning

- When fine-tuning the whole model, we will have a full-sized model for each intermediate task

13B Fine-tuned Model for Intermediate-Task A

13B Fine-tuned Model for Intermediate-Task B

13B Fine-tuned Model for Intermediate-Task C

13B Fine-tuned Model for Intermediate-Task D

Full model (T5-13B) fine-tuning

# Intermediate-task fine-tuning

- When fine-tuning with soft prompt tuning, we only need to transfer the prompt embedding instead of the whole model

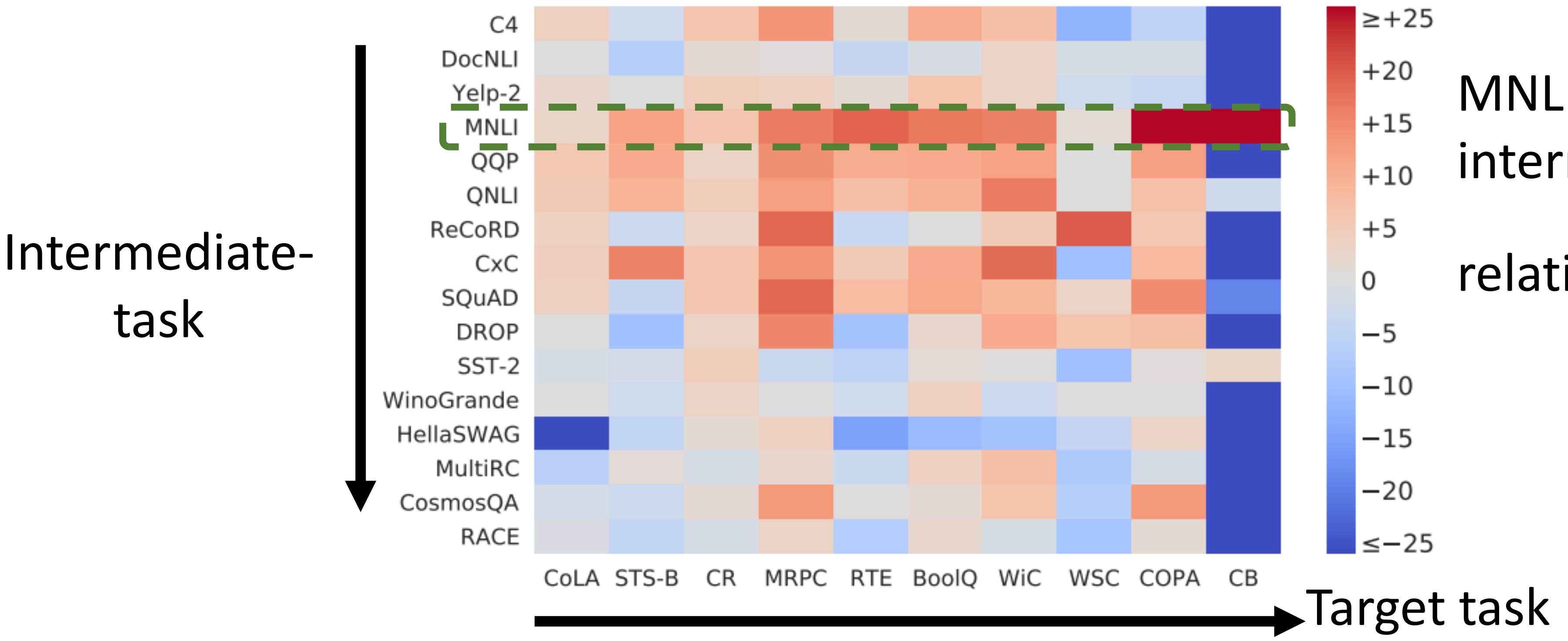
| | | | |
|---|---|---|---|
| 13B | Fine-tuned Model for Intermediate-Task A | Prompt for Intermediate-Task A | 204K |
| 13B | Fine-tuned Model for Intermediate-Task B | Prompt for Intermediate-Task B | 204K |
| 13B | Fine-tuned Model for Intermediate-Task C | Prompt for Intermediate-Task C | 204K |
| 13B | Fine-tuned Model for Intermediate-Task D | Prompt for Intermediate-Task D | 204K |

0.00184%

Full model (T5-13B) fine-tuning → Prefix tuning

# Intermediate-task fine-tuning

- **Soft Prompt Transfer (SPoT)**: Using soft prompts for transferring
  - SPoT yields positive transfer in many cases



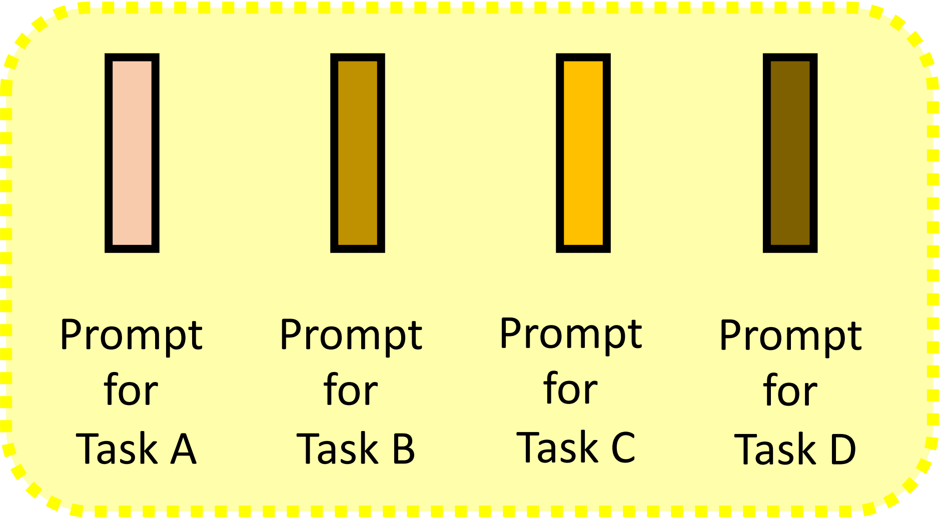

MNLI is a good intermediate-task

relative transfer gain

Vu, Tu, et al. "SPoT: Better Frozen Model Adaptation through Soft Prompt Transfer." *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 2022.

# Intermediate-task fine-tuning

- **S**oft **Pro**mpt **T**ransfer (**SPoT**): The soft prompt of a task can be used as the task embedding of that task.



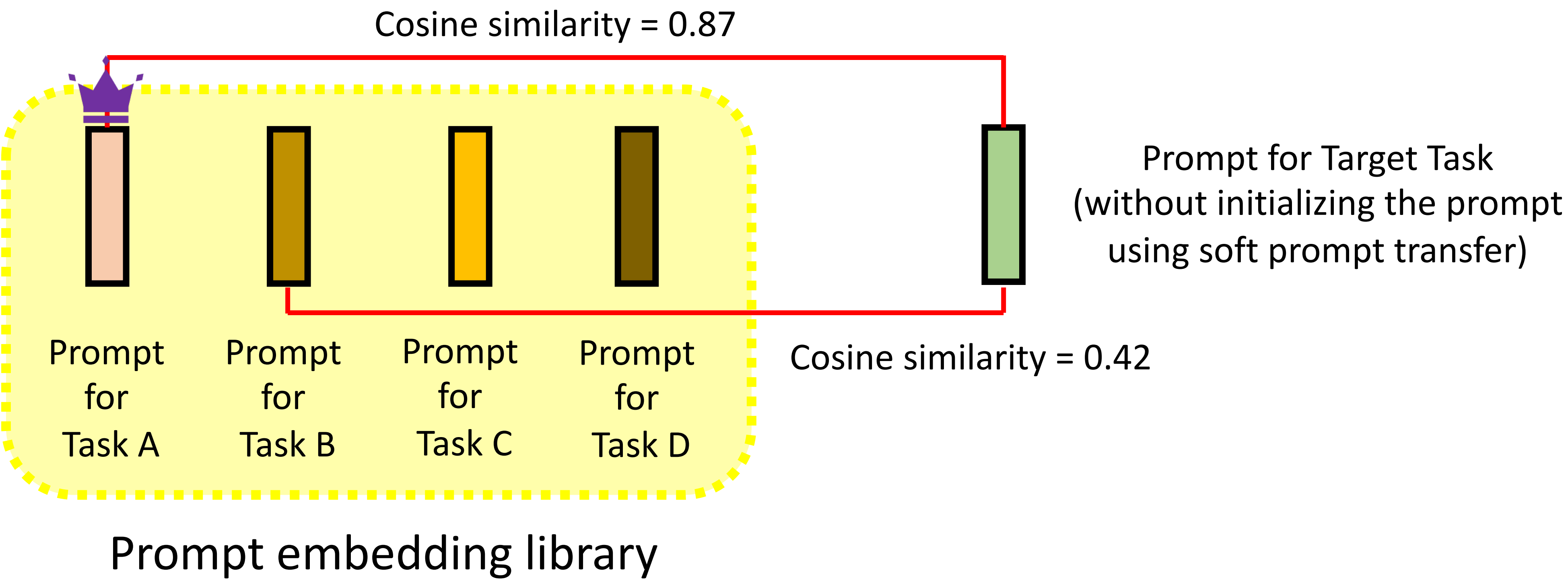

Prompt embedding library

Prompt embedding = Task embedding

Vu, Tu, et al. "SPoT: Better Frozen Model Adaptation through Soft Prompt Transfer." *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 2022.

# Intermediate-task fine-tuning

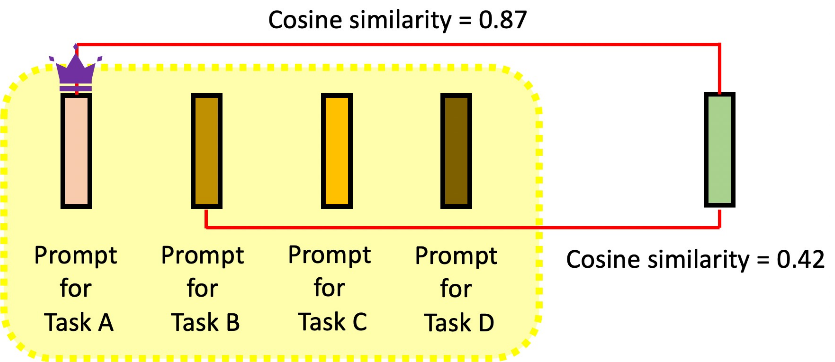
- **S**oft **P**r**o**mpt **T**ransfer (**SPoT**): Given a novel task, we can first train only using the novel task, and find a intermediate task whose task embedding is most similar to the novel task and use it to transfer




Vu, Tu, et al. "SPoT: Better Frozen Model Adaptation through Soft Prompt Transfer." *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 2022.

# Intermediate-task fine-tuning

- **Soft Prompt Transfer (SPoT)**: Selecting the best intermediate-task soft prompt




Prompt embedding library

| | Method | Change Abs. | Change Rel. | Avg. score (16 target tasks) |
|---|---|---|---|---|
| w/o SPoT: | BASELINE | - | - | $74.7_{0.7}$ |
| Oracle SPoT: | BRUTE-FORCE SEARCH ($k = 48$) | | | |
| | ORACLE | $6.0_{0.5}$ | $26.5_{1.1}$ | $80.7_{0.0}$ |
| | COSINE SIMILARITY | | | |
| | BEST OF TOP-$k$ | | | |
| | $k = 1$ | $1.5_{0.5}$ | $11.7_{1.1}$ | $76.2_{0.1}$ |
| | $k = 3$ | $2.7_{0.6}$ | $16.6_{1.1}$ | $77.4_{0.3}$ |
| | $k = 6$ | $3.8_{0.1}$ | $20.0_{1.1}$ | $78.5_{0.5}$ |
| | $k = 9$ | $4.5_{0.4}$ | $22.2_{1.1}$ | $79.2_{0.1}$ |
| | $k = 12$ | $5.0_{0.9}$ | $23.6_{2.2}$ | $79.7_{0.4}$ |
| | $k = 15$ | $5.4_{0.8}$ | $24.9_{1.8}$ | $80.1_{0.3}$ |

Vu, Tu, et al. "SPoT: Better Frozen Model Adaptation through Soft Prompt Transfer." *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 2022.

# Part 5:

# How do PLMs work:

# Using PLMs with different amounts of data

## 5-1.1: Multi-task fine-tuning:
## using labeled data from other tasks

# Multi-task fine-tuning

- Fine-tune the PLM using the auxiliary task datasets and the target task dataset simultaneously


How to weight the loss of different tasks?

Chen, Shuxiao, et al. "Weighted Training for Cross-Task Learning." *International Conference on Learning Representations*. 2022.

# Part 5:

# How do PLMs work:

# Using PLMs with different amounts of data

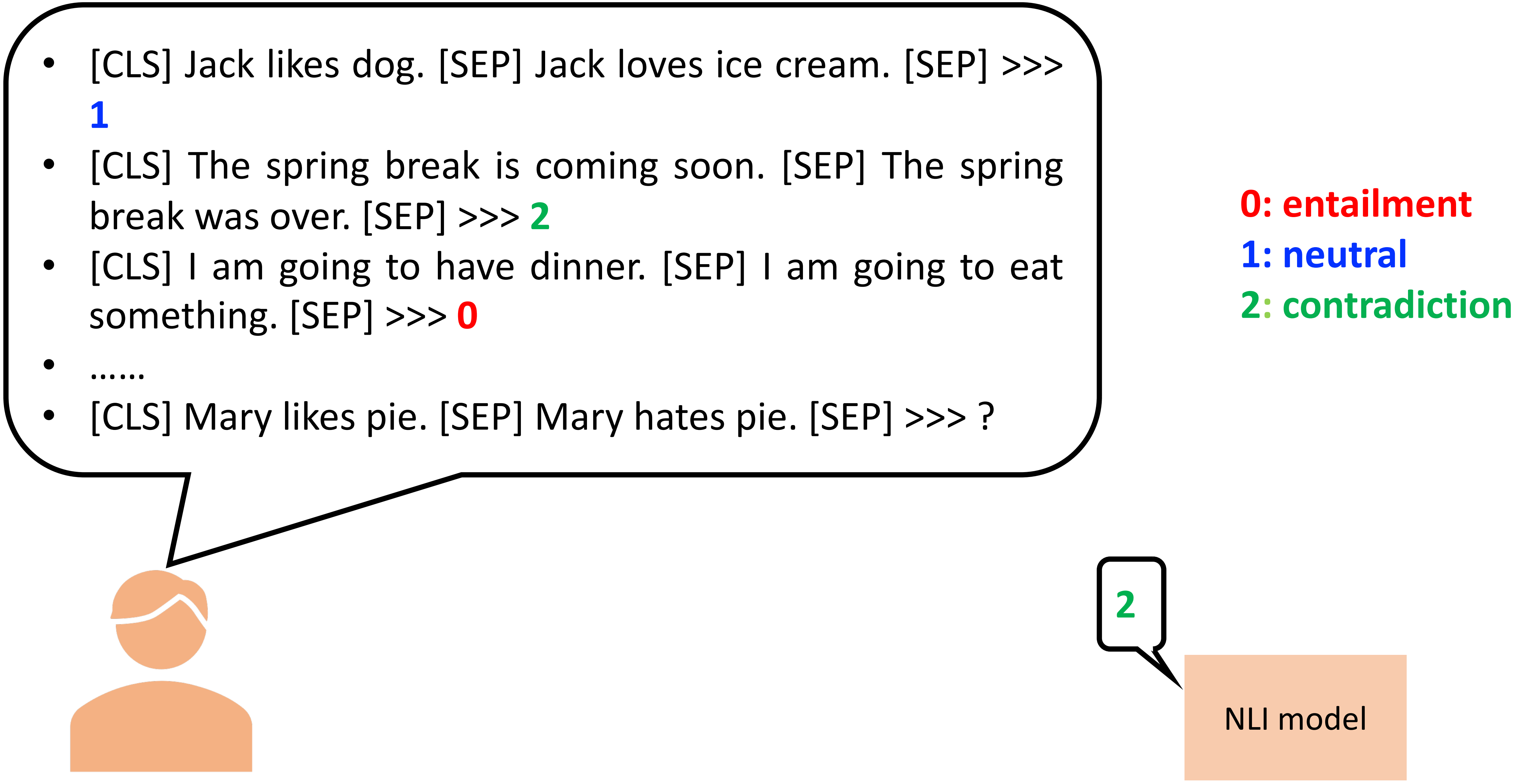
## 5-2: Prompt tuning for few-shot learning

# Prompt tuning for few-shot learning

- Standard fine-tuning mostly assumes a large amount of labeled data

Pre-trained Language Model
(Fine-tuning)

| MNLI-(m/mm) | QQP | QNLI | SST-2 | CoLA | STS-B | MRPC | RTE | |
|---|---|---|---|---|---|---|---|---|
| 392k | 363k | 108k | 67k | 8.5k | 5.7k | 3.5k | 2.5k | **(size of training set)** |



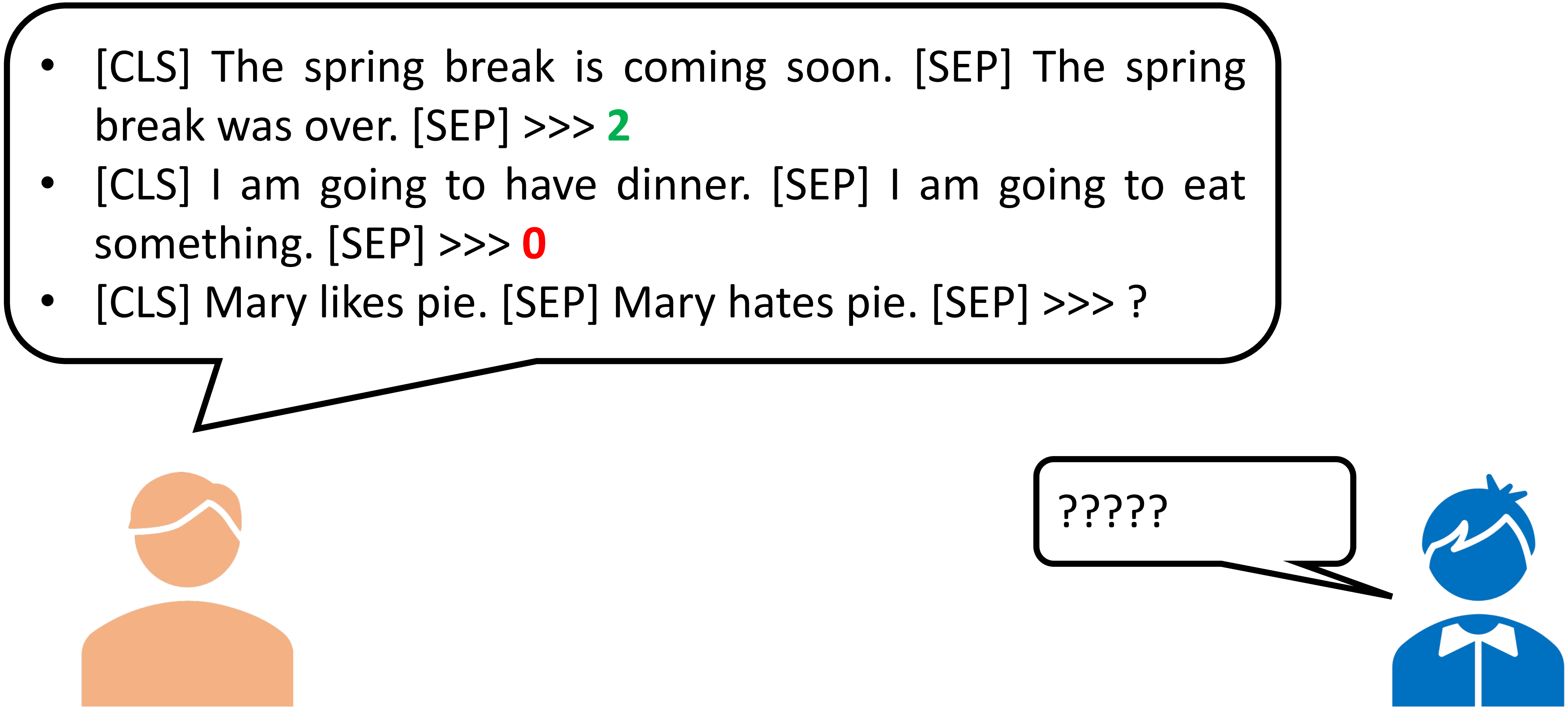

**Natural language inference (NLI)**: premise + hypothesis

# Prompt tuning for few-shot learning

- **Data scarcity** in downstream tasks is very common
- Few-shot learning: We have some labeled training data
  - ”Some” ≈ less than a hundred

Target task dataset
(labeled)

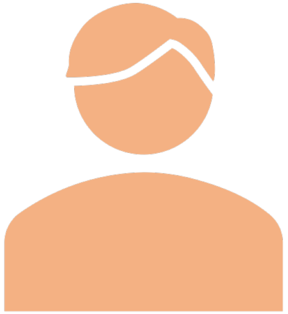
Pre-trained Language Model




**Natural language inference (NLI)**: premise + hypothesis

# Prompt tuning for few-shot learning

- [CLS] The spring break is coming soon. Is it true that the spring break was over? >>> **no**
- [CLS] I am going to have dinner. Is it true that I am going to eat something? >>> **yes**
- [CLS] Mary likes pie. Is it true that Mary hates pie. [SEP] >>> ?




**Natural language inference (NLI)**: premise + hypothesis

# Prompt tuning for few-shot learning

- By converting the data points in the dataset into **natural language prompts**, the model may be easier to know what it should do

- [CLS] The spring break is coming soon. [SEP] The spring break was over. [SEP] >>> **contradiction**
- [CLS] I am going to have dinner. [SEP] I am going to eat something. [SEP] >>> **entailment**
- [CLS] Mary likes pie. [SEP] Mary hates pie. [SEP] >>> ?

- [CLS] The spring break is coming soon. Is it true that the spring break was over? >>> **no**
- [CLS] I am going to have dinner. Is it true that I am going to eat something? >>> **yes**
- [CLS] Mary likes pie. Is it true that Mary hates pie. [SEP] >>> ?

# Prompt tuning for few-shot learning

- Format the downstream task as a language modelling task with pre-defined templates into natural language **prompts**

*verb (used with object)*

5 to move or induce to action:
*What prompted you to say that?*

6 to occasion or incite; inspire:
*What prompted his resignation?*

*noun*

11 the act of prompting.

https://www.dictionary.com/browse/prompt

# Prompt tuning for few-shot learning

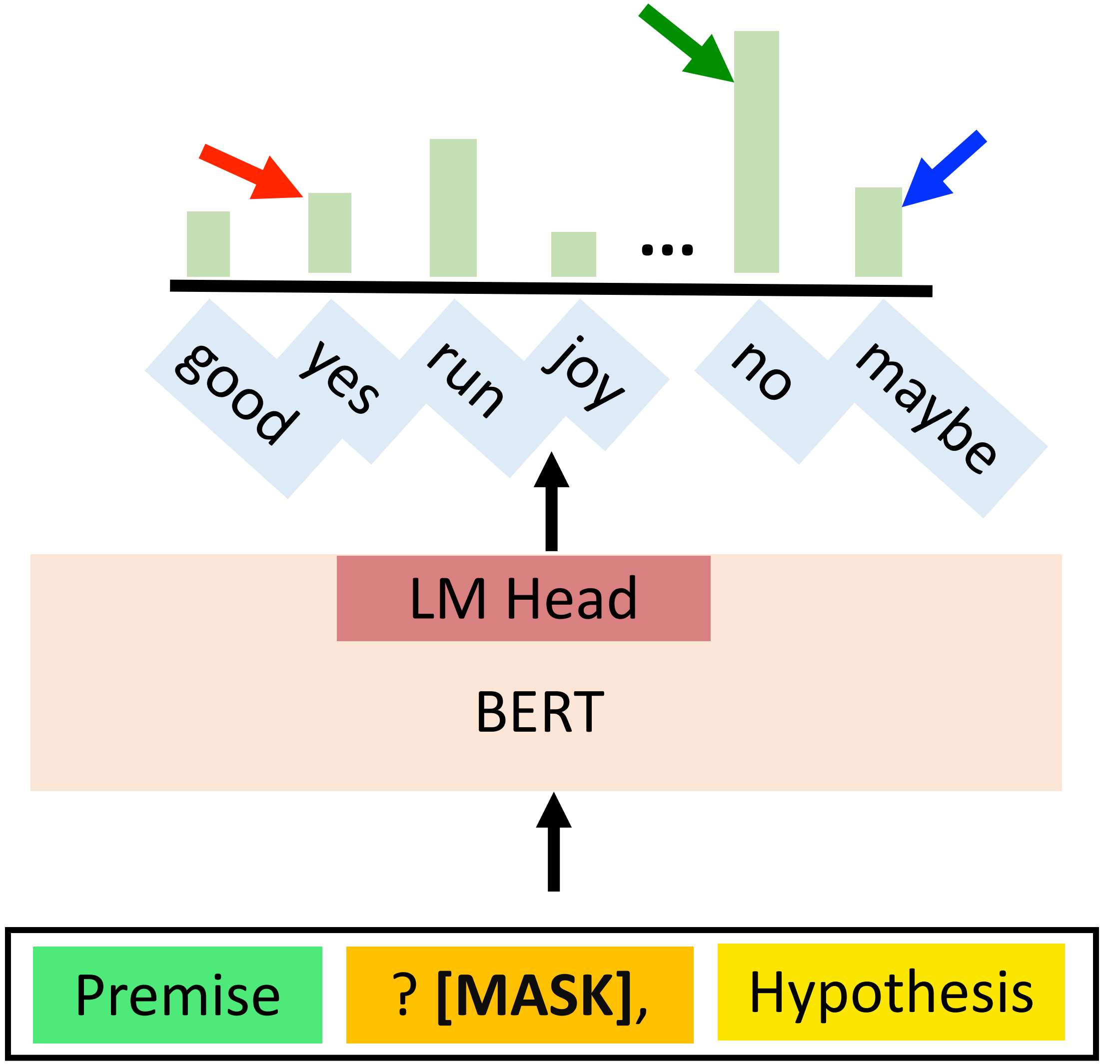
- What you need in prompt tuning
    1. A prompt template
    2. A PLM
    3. A verbalizer

| | |
|---|---|
| **Premise** | Mary likes pie. |
| **Hypothesis** | Mary hates pie. |
| **Label** | 2 |


```
"label" : [
  0 : "entailment"
  1 : "neutral"
  2 : "contradiction"
]
```


→ yes / maybe / no

Prompt template:



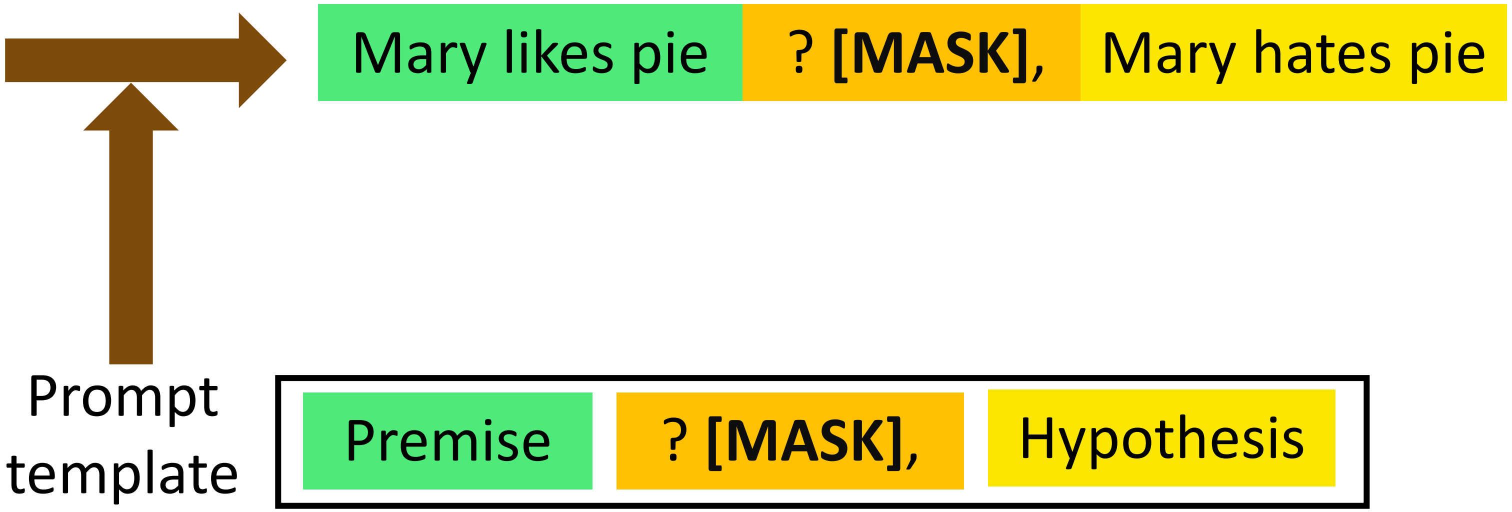

Schick, Timo, and Hinrich Schütze. "Exploiting Cloze-Questions for Few-Shot Text Classification and Natural Language Inference." *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*. 2021.

# Prompt tuning for few-shot learning

- What you need in prompt tuning
    1. A prompt template: convert data points into a natural language prompt

| | |
|---|---|
| **Premise** | Mary likes pie |
| **Hypothesis** | Mary hates pie |
| **Label** | 2 |

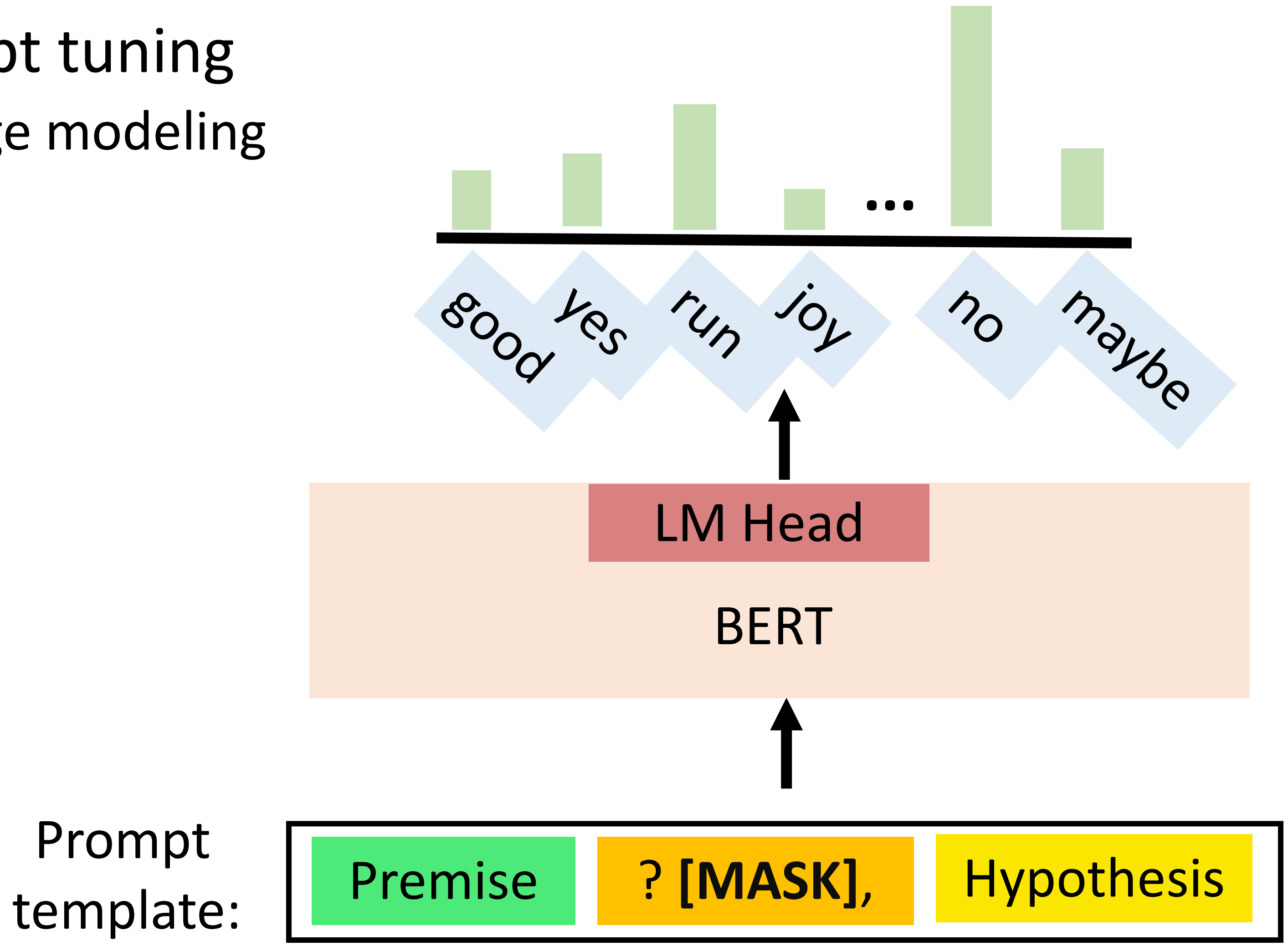
```
"label" : [
  0 : "entailment"
  1 : "neutral"
  2 : "contradiction"
]
```




Schick, Timo, and Hinrich Schütze. "Exploiting Cloze-Questions for Few-Shot Text Classification and Natural Language Inference." *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*. 2021.

# Prompt tuning for few-shot learning

- What you need in prompt tuning
  2. A PLM: perform language modeling

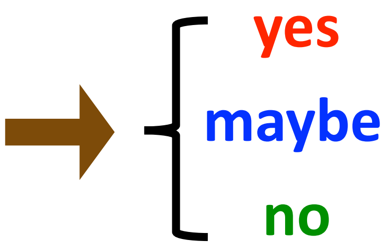


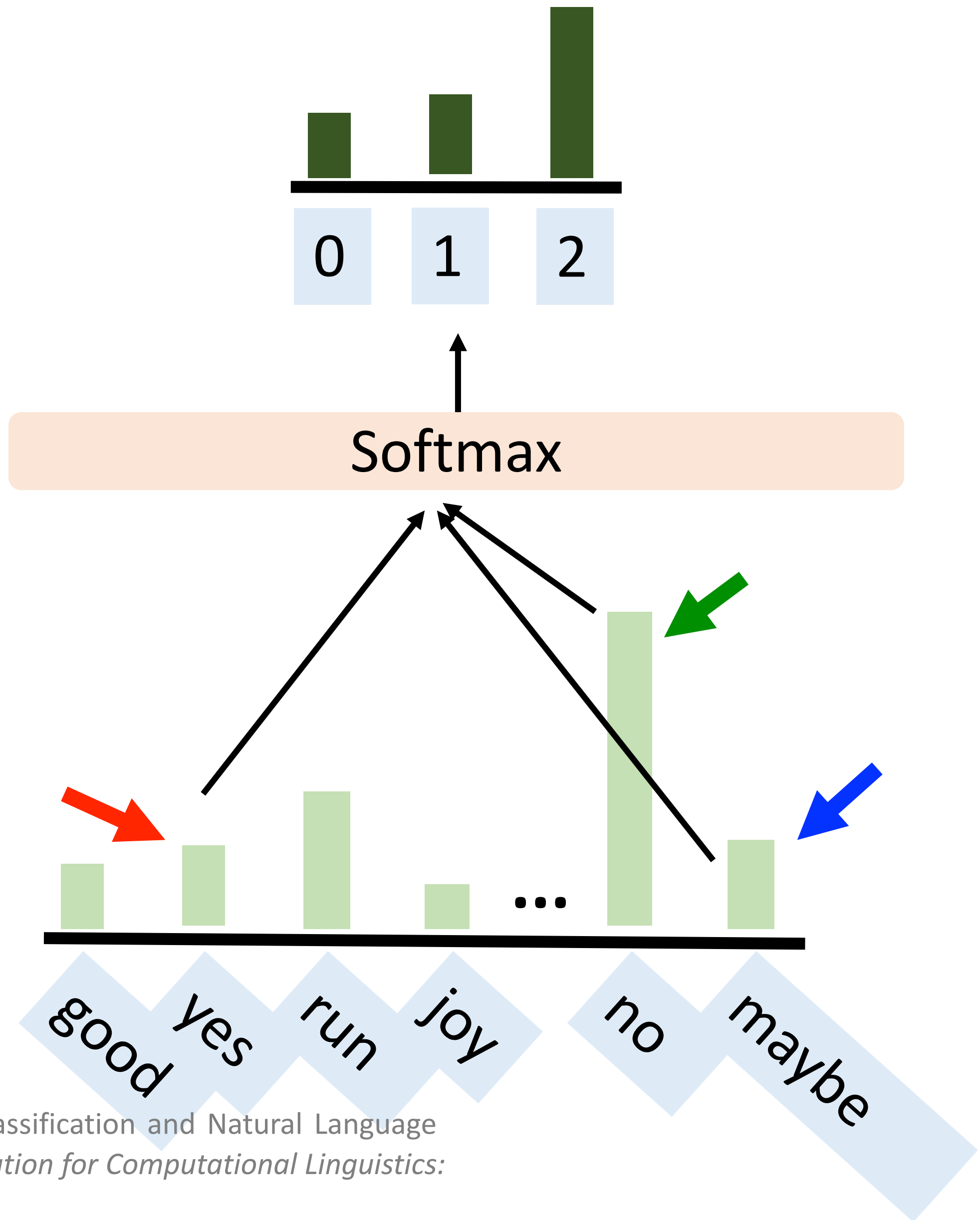

Schick, Timo, and Hinrich Schütze. "Exploiting Cloze-Questions for Few-Shot Text Classification and Natural Language Inference." *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*. 2021.

# Prompt tuning for few-shot learning

- What you need in prompt tuning
  3. A verbalizer: A mapping between the label and the vocabulary
     - Which vocabulary should represents the class “entailment”

```
"label" : [
  0 : "entailment"
  1 : "neutral"
  2 : "contradiction"
]
```



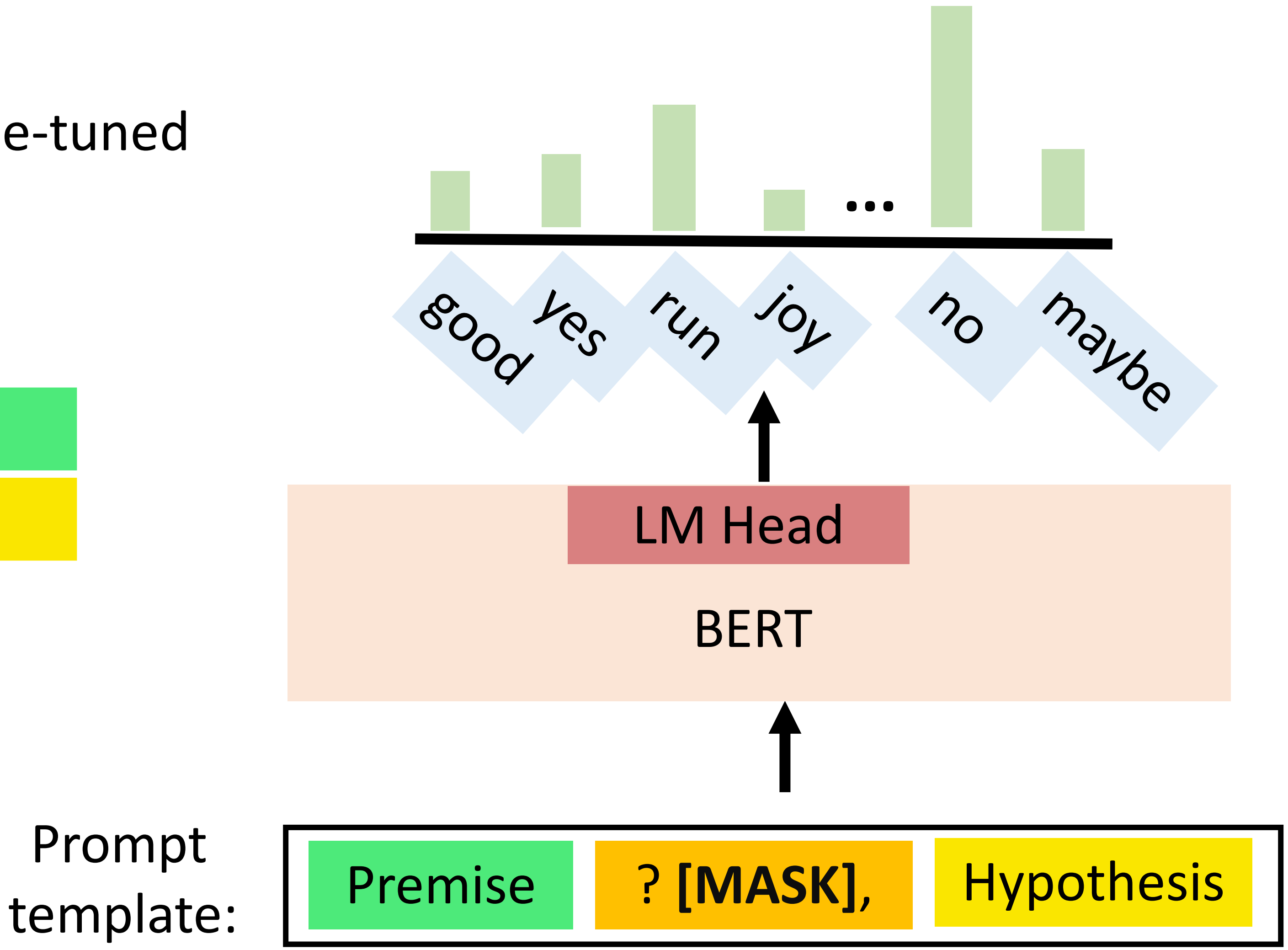

Schick, Timo, and Hinrich Schütze. "Exploiting Cloze-Questions for Few-Shot Text Classification and Natural Language Inference." *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*. 2021.

# Prompt tuning for few-shot learning

- Prompt tuning
  - The whole PLM will be fine-tuned

| | |
|---|---|
| **Premise** | Mary likes pie. |
| **Hypothesis** | Mary hates pie. |
| **Label** | 2 |

```
"label" : [
  0 : "entailment"
  1 : "neutral"
  2 : "contradiction"
]
```

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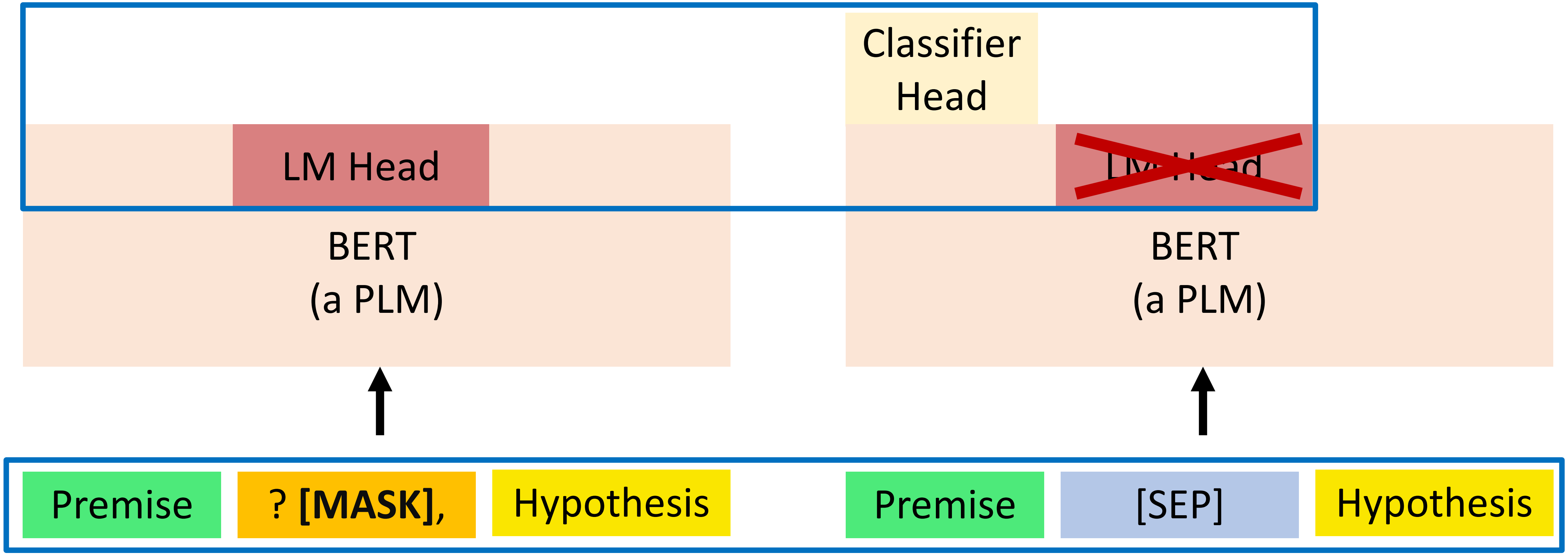
# Prompt tuning for few-shot learning

- Prompt tuning
- Standard fine-tuning

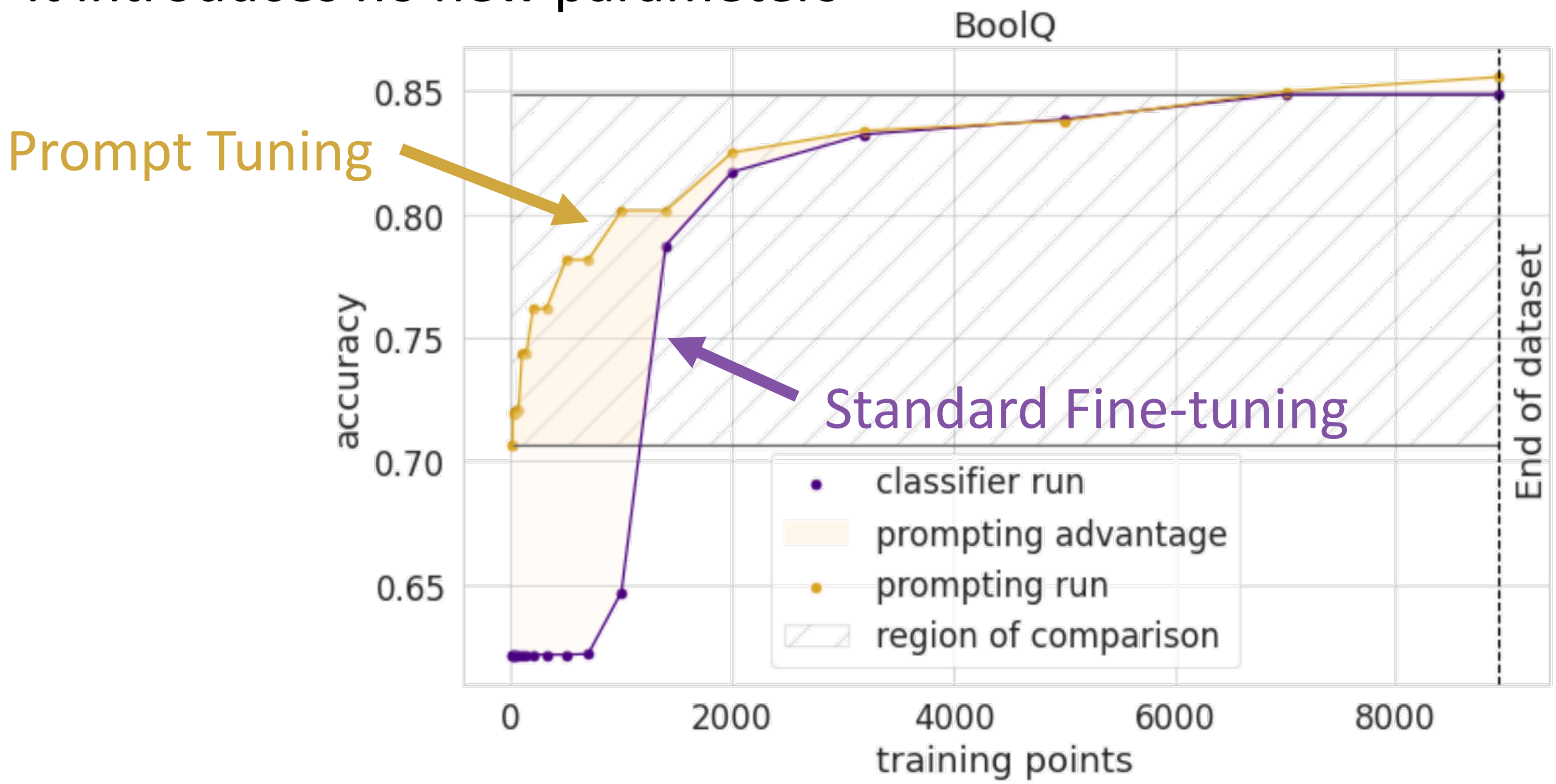



* I omit the [CLS] at the beginning and the [SEP] at the end

Schick, Timo, and Hinrich Schütze. "Exploiting Cloze-Questions for Few-Shot Text Classification and Natural Language Inference." *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*. 2021.

# Prompt tuning for few-shot learning

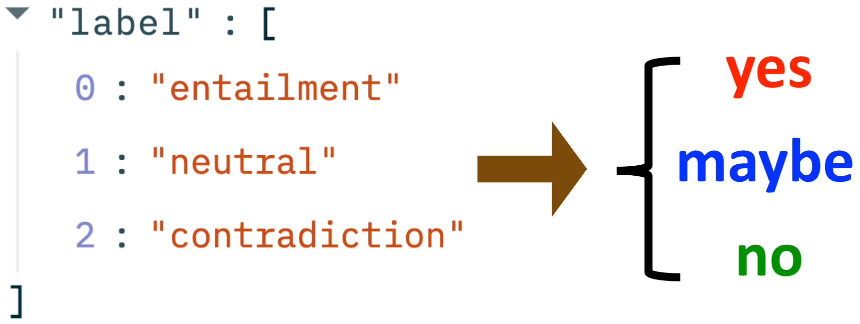
- Prompt tuning has better performance under data scarcity because
  - It incorporates human knowledge
  - It introduces no new parameters




Le Scao, Teven, and Alexander M. Rush. "How many data points is a prompt worth?." *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. 2021.

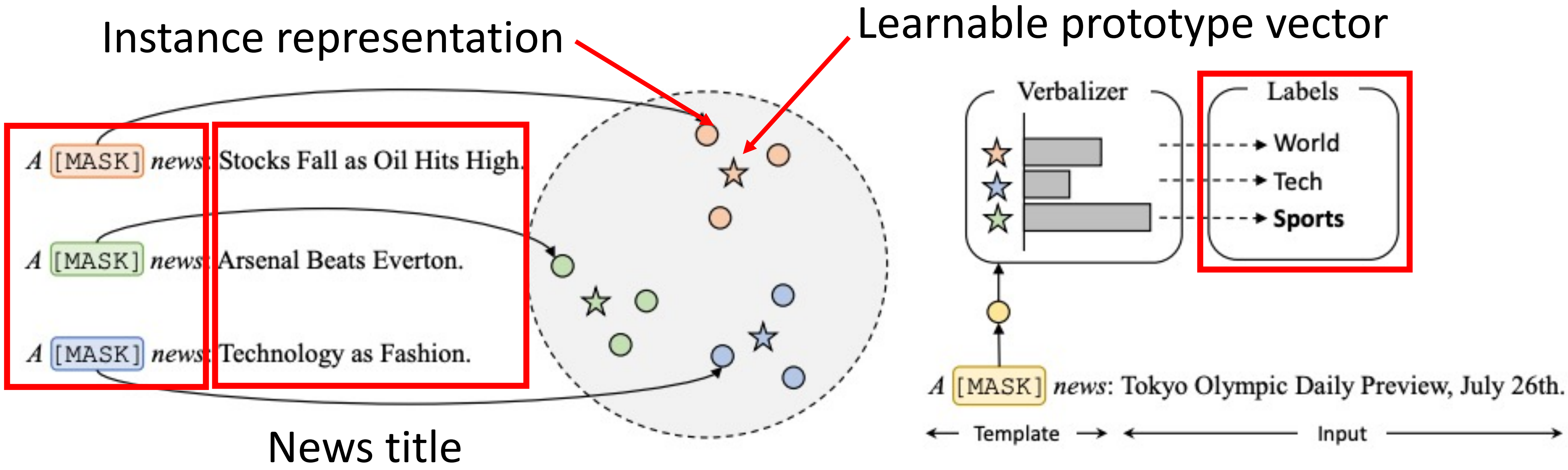
# Prompt tuning for few-shot learning

- How to select the verbalizer?
    - 1. Manual design: require task-specific knowledge



# Prompt tuning for few-shot learning

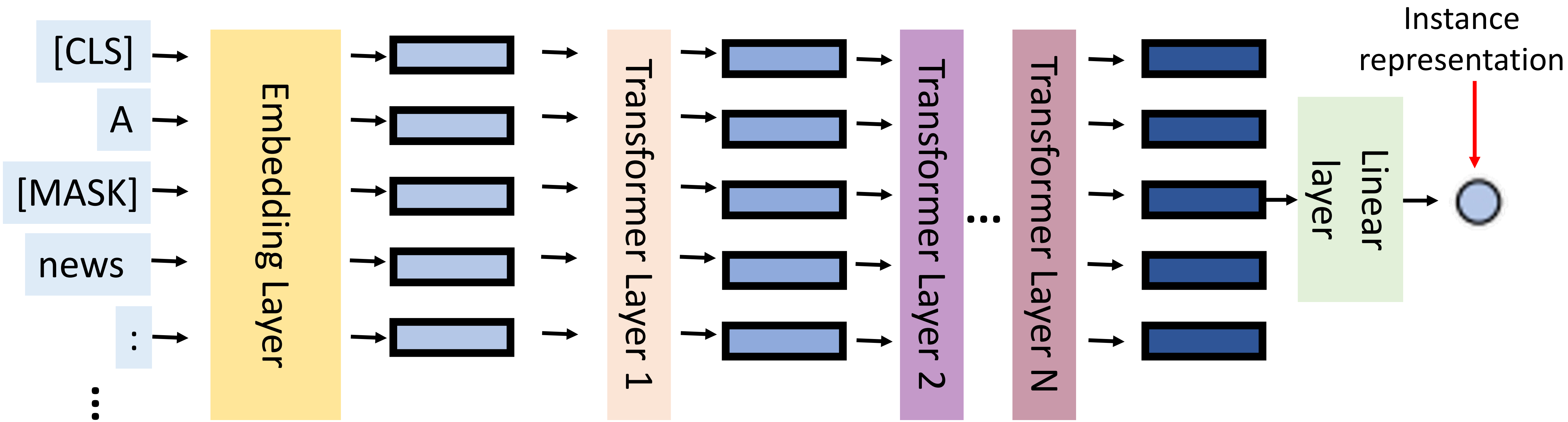
- How to select the verbalizer?
  - 2. Prototypical verbalizer: use learnable prototype vectors to represent a class, instead of using the words in the vocabulary




Cui, Ganqu, et al. "Prototypical Verbalizer for Prompt-based Few-shot Tuning." *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 2022.

# Prompt tuning for few-shot learning

- How to select the verbalizer?
  - 2. Prototypical verbalizer

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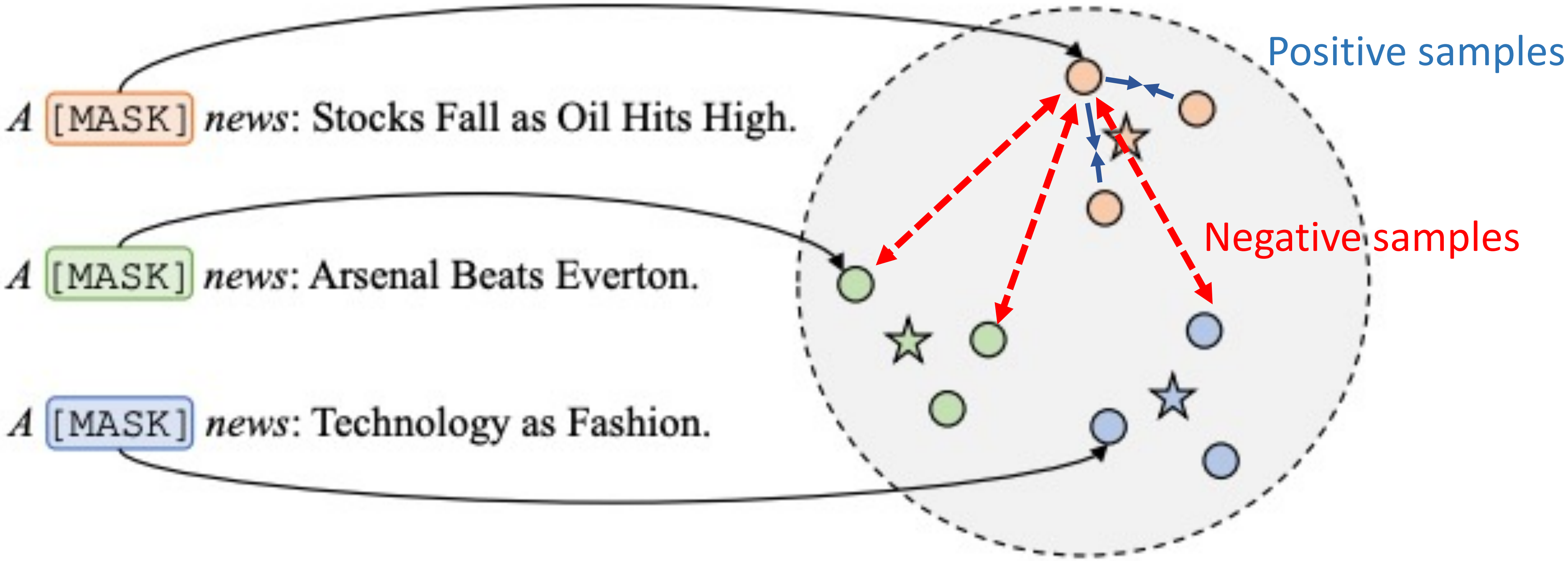
# Prompt tuning for few-shot learning

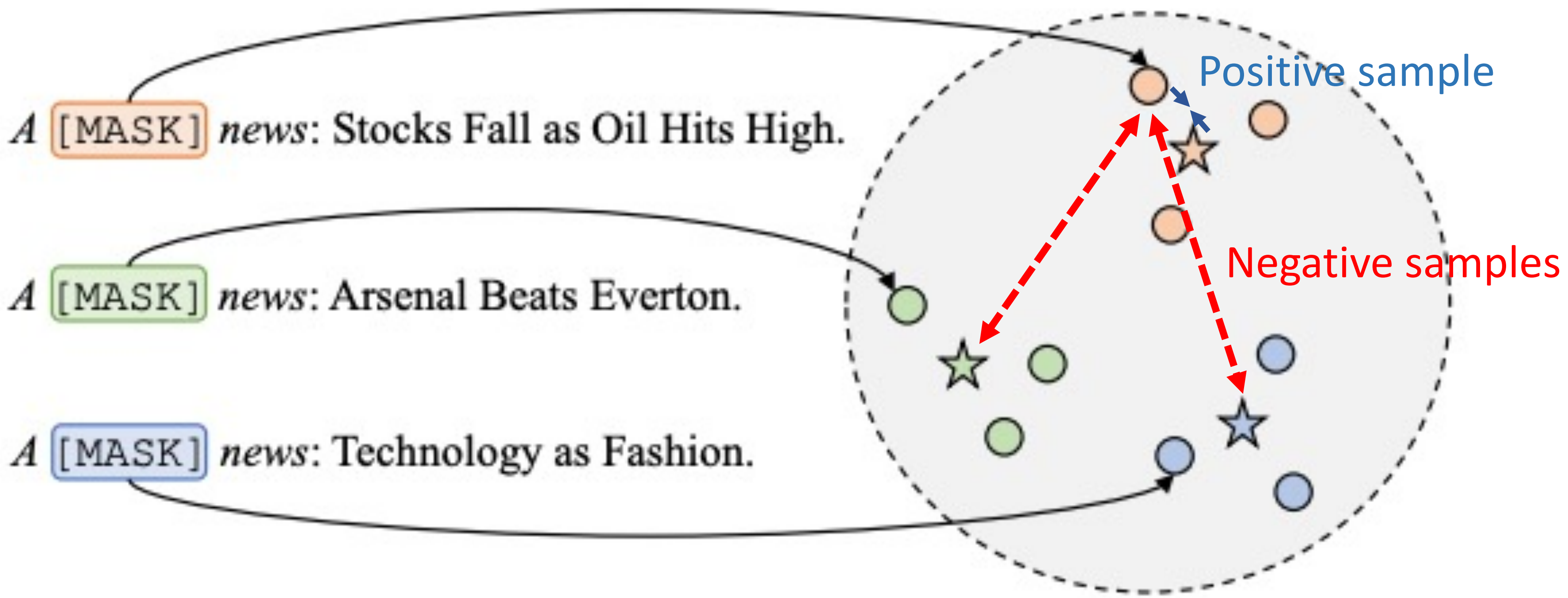
- How to select the verbalizer?
  - 2. Prototypical verbalizer
    - Trained by contrastive learning: (1) instance-instance contrastive




Cui, Ganqu, et al. "Prototypical Verbalizer for Prompt-based Few-shot Tuning." *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 2022.

# Prompt tuning for few-shot learning

- How to select the verbalizer?
  - 2. Prototypical verbalizer
    - Trained by contrastive learning: (2) instance-prototype contrastive

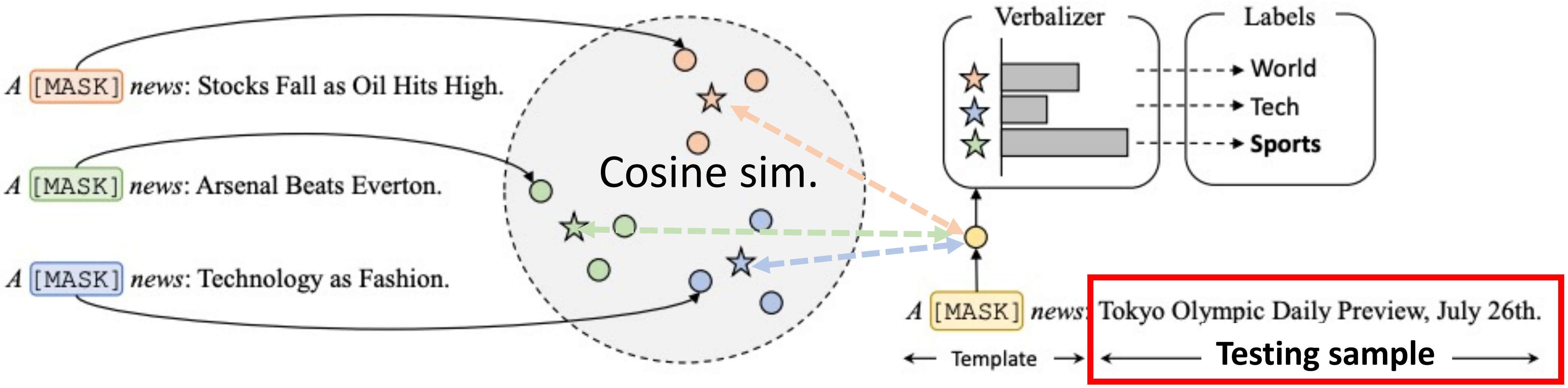




Cui, Ganqu, et al. "Prototypical Verbalizer for Prompt-based Few-shot Tuning." *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 2022.

# Prompt tuning for few-shot learning

- How to select the verbalizer?
  - 2. Prototypical verbalizer
    - Inference by finding the prototype that is most similar with the testing data's instance representation




Cui, Ganqu, et al. "Prototypical Verbalizer for Prompt-based Few-shot Tuning." *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 2022.

# Prompt tuning for few-shot learning

- How to select the verbalizer?

$K$: Number of training data for each class

| $K$ | Method | AG | DB | Yahoo | Few |
|---|---|---|---|---|---|
| 0 | ManualVerb | *75.13* | *67.06* | *43.11* | *20.00* |
| 1 | ManualVerb | *76.67* | *85.47* | *50.22* | *41.68* |
| | SearchVerb | 41.50 | 60.06 | 27.39 | 20.88 |
| | ProtoVerb | **64.19** | **72.85** | **36.12** | **25.00** |
| 2 | ManualVerb | *81.06* | *93.61* | *58.65* | *46.44* |
| | SearchVerb | 65.82 | 78.21 | 40.71 | 31.28 |
| | ProtoVerb | **77.34** | **85.49** | **46.30** | **35.72** |
| 4 | ManualVerb | *84.73* | *95.83* | *61.41* | *52.54* |
| | SearchVerb | 77.43 | 86.40 | 51.58 | 43.10 |
| | ProtoVerb | **81.65** | **90.91** | **55.08** | 48.28 |
| 8 | ManualVerb | *85.85* | *96.46* | *64.12* | *56.59* |
| | SearchVerb | 82.17 | 88.41 | 58.64 | 50.78 |
| | ProtoVerb | **84.03** | **95.75** | **61.40** | **56.06** |
| 16 | ManualVerb | *84.74* | *96.05* | *58.77* | *61.17* |
| | SearchVerb | 83.40 | 92.00 | 59.66 | 55.49 |
| | ProtoVerb | **84.48** | **96.30** | **64.35** | **61.29** |

Manual verbalizer is good most of the time, but it requires task-specific knowledge

Cui, Ganqu, et al. "Prototypical Verbalizer for Prompt-based Few-shot Tuning." *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 2022.

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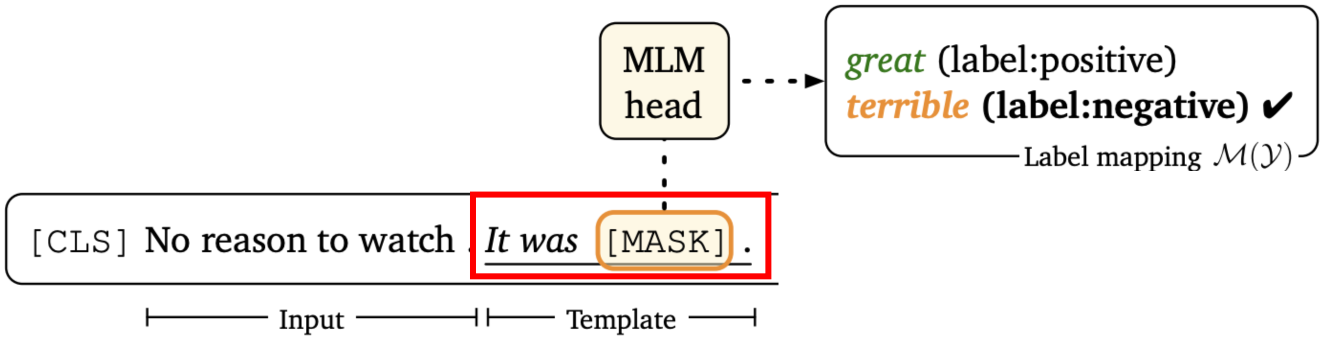
Prototypical verbalizer requires no task-specific knowledge and can work well even when there is only one label for each class

Cui, Ganqu, et al. "Prototypical Verbalizer for Prompt-based Few-shot Tuning." *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 2022.

# Prompt tuning for few-shot learning

- Can we further improve the few-shot performance of PLMs?
- LM-BFF: **b**etter **f**ew-shot **f**ine-tuning of **l**anguage **m**odels
  - Core concept: **prompt** + demonstration




Gao, Tianyu, Adam Fisch, and Danqi Chen. "Making Pre-trained Language Models Better Few-shot Learners." *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. 2021.

# Prompt tuning for few-shot learning

- LM-BFF
  - Demonstrations can improve the performance of prompt tuning and makes the variance smaller

| | | MNLI (acc) | MNLI-mm (acc) | SNLI (acc) | QNLI (acc) | RTE (acc) | MRPC (F1) | QQP (F1) | STS-B (Pear.) |
|---|---|---|---|---|---|---|---|---|---|
| $K=16$ | Standard fine-tuning | 45.8 (6.4) | 47.8 (6.8) | 48.4 (4.8) | 60.2 (6.5) | 54.4 (3.9) | 76.6 (2.5) | 60.7 (4.3) | 53.5 (8.5) |
| | Prompt tuning | 68.3 (2.3) | 70.5 (1.9) | 77.2 (3.7) | 64.5 (4.2) | 69.1 (3.6) | 74.5 (5.3) | 65.5 (5.3) | 71.0 (7.0) |
| | + demonstration (LM-BFF) | **70.7** (1.3) | **72.0** (1.2) | **79.7** (1.5) | **69.2** (1.9) | 68.7 (2.3) | 77.8 (2.0) | **69.8** (1.8) | 73.5 (5.1) |
| | Fine-tuning (full)† | *89.8* | *89.5* | *92.6* | *93.3* | *80.9* | *91.4* | *81.7* | *91.9* |

Gao, Tianyu, Adam Fisch, and Danqi Chen. "Making Pre-trained Language Models Better Few-shot Learners." *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. 2021.

# Prompt tuning for few-shot learning

- Question: What's the difference between prompting and probing
- Answer:
  - The concept of "prompting" is first used in recent NLP community for probing the factual knowledge of a PLM

Prompts →

| Query | Answer |
|---|---|
| Francesco Bartolomeo Conti was born in ____. | Florence |
| Adolphe Adam died in ____. | Paris |
| English bulldog is a subclass of ____. | dog |
| The official language of Mauritius is ____. | English |
| Patrick Oboya plays in ____ position. | midfielder |
| Hamburg Airport is named after ____. | Hamburg |

Petroni, Fabio, et al. "Language Models as Knowledge Bases?." *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*. 2019.

# Prompt tuning for few-shot learning

- Question: What’s the difference between prompting and probing
- Answer:
  - Probing is the process of exploring what knowledge is encoded in the PLM. PLMs are often fixed during probing.
  - Prompting means using natural language to query the PLM, perhaps for the downstream task. PLM can be fine-tuned during prompting.
  - The purpose of prompting and probing are different.

Petroni, Fabio, et al. "Language Models as Knowledge Bases?." *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*. 2019.

# Part 5:

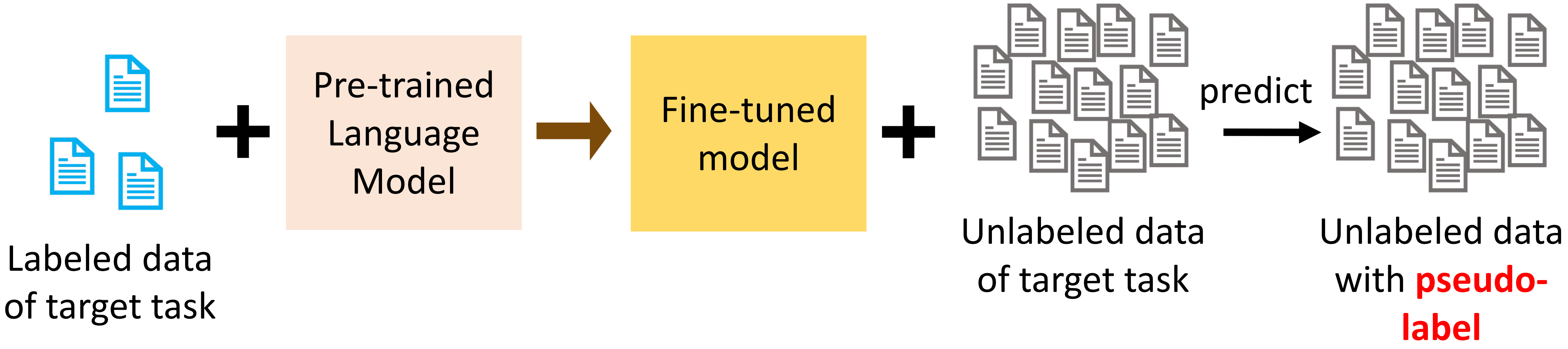
# How do PLMs work:

# Using PLMs with different amounts of data

## 5-3: Semi-supervised learning with PLMs

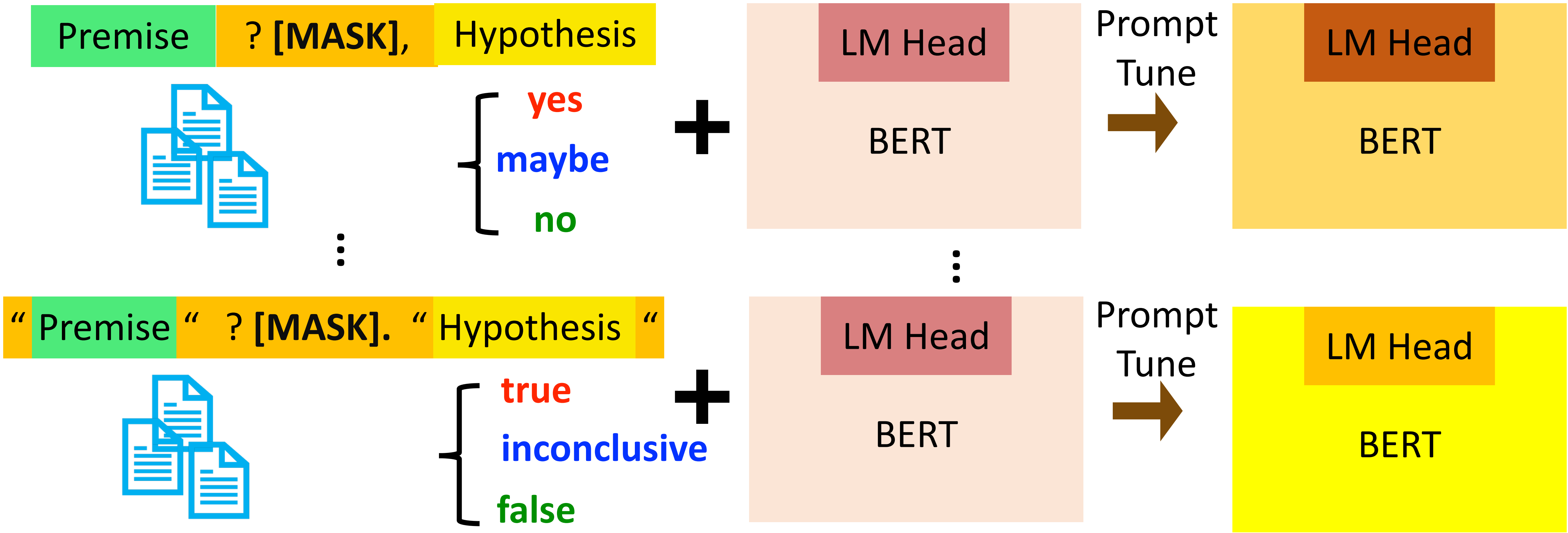
# Semi-supervised learning with PLMs

- Semi-Supervised learning: We have some labeled training data and a large amount of unlabeled data
- Core idea: use the labeled data to train a good model and use that model to label the unlabeled data



# Semi-supervised learning with PLMs: PET

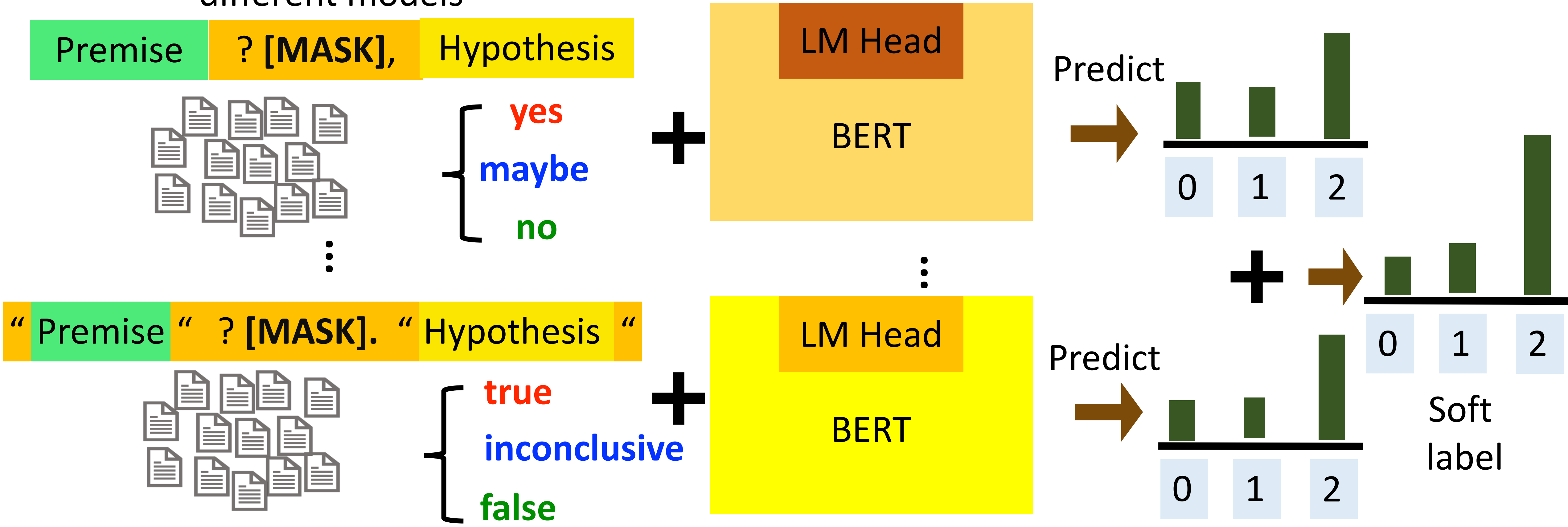
- Pattern-Exploiting Training (PET)
  - Step 1: Use different prompts and verbalizer to prompt-tune different PLMs on the labeled dataset




Schick, Timo, and Hinrich Schütze. "Exploiting Cloze-Questions for Few-Shot Text Classification and Natural Language Inference." *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*. 2021.

# Semi-supervised learning with PLMs: PET

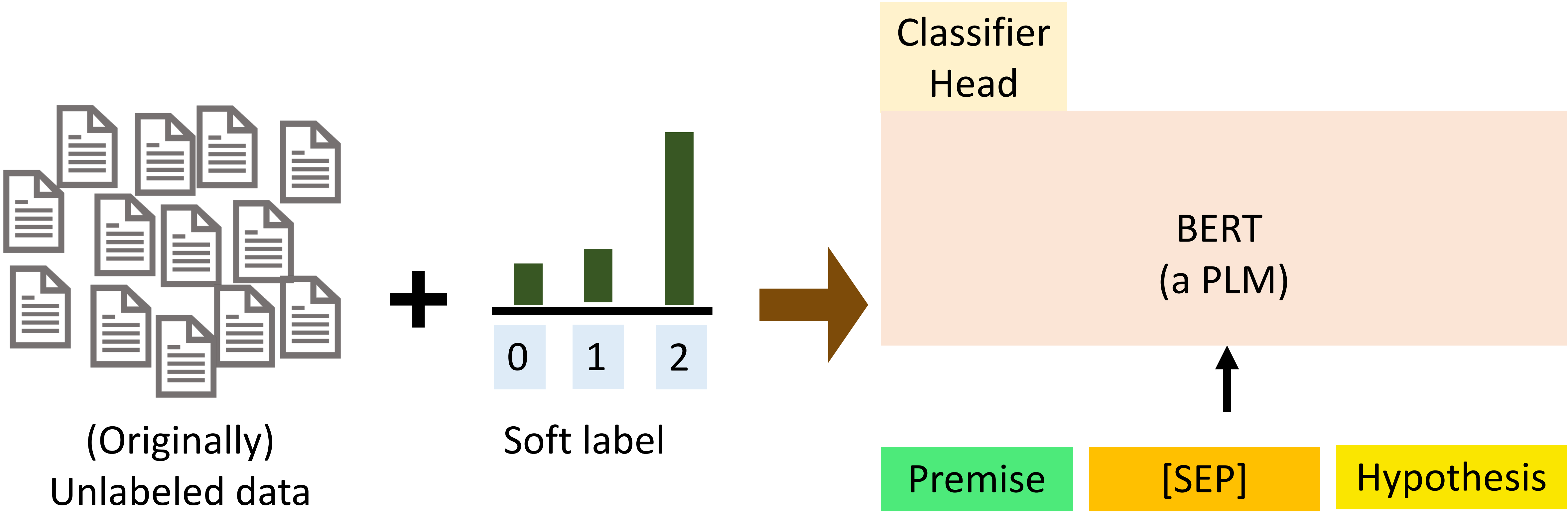
- Pattern-Exploiting Training (PET)
  - Step 2: Predict the unlabeled dataset and combine the predictions from different models




Schick, Timo, and Hinrich Schütze. "Exploiting Cloze-Questions for Few-Shot Text Classification and Natural Language Inference." *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*. 2021.

# Semi-supervised learning with PLMs: PET

- Pattern-Exploiting Training (PET)
  - Step 3: Use a PLM with classifier head to train on the soft-labeled data set




Schick, Timo, and Hinrich Schütze. "Exploiting Cloze-Questions for Few-Shot Text Classification and Natural Language Inference." *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*. 2021.

# Semi-supervised learning with PLMs: PET

- Pattern-Exploiting Training (PET)
  - Experiment results

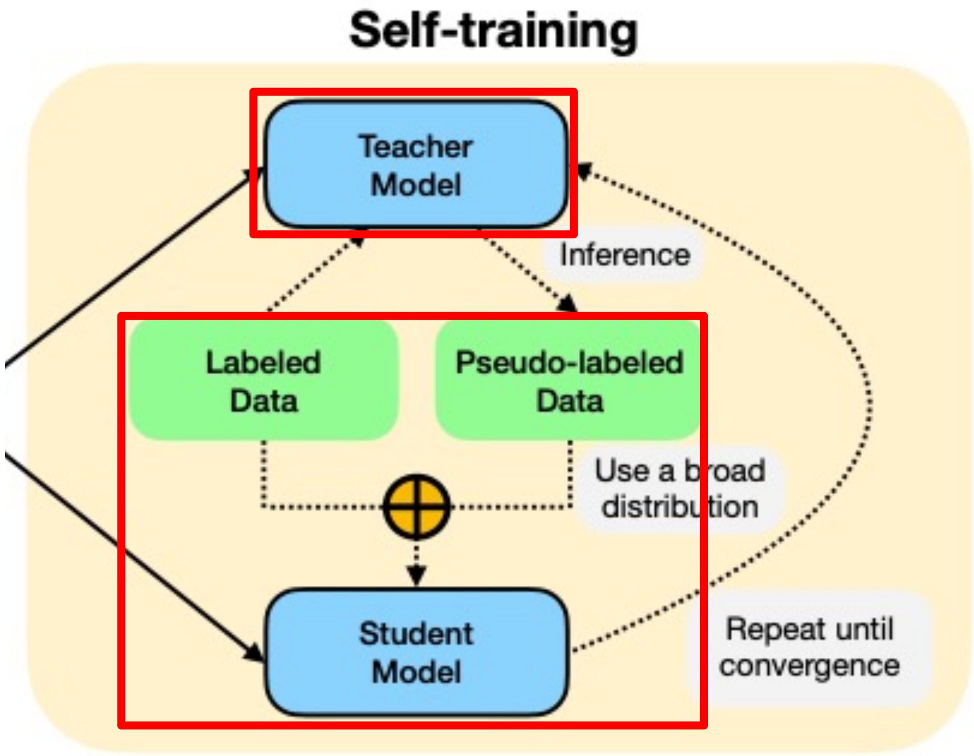
| Examples | Method | Yelp | AG's | Yahoo | MNLI (m/mm) |
|---|---|---|---|---|---|
| $\|\mathcal{T}\| = 10$ | $\boxed{\text{supervised}}$ | 21.1 ±1.6 | 25.0 ±0.1 | 10.1 ±0.1 | 34.2 ±2.1 / 34.1 ±2.0 |
| | $\boxed{\text{PET}}$ | 52.9 ±0.1 | 87.5 ±0.0 | 63.8 ±0.2 | 41.8 ±0.1 / 41.5 ±0.2 |
| $\|\mathcal{T}\| = 50$ | supervised | 44.8 ±2.7 | 82.1 ±2.5 | 52.5 ±3.1 | 45.6 ±1.8 / 47.6 ±2.4 |
| | PET | 60.0 ±0.1 | 86.3 ±0.0 | 66.2 ±0.1 | 63.9 ±0.0 / 64.2 ±0.0 |
| $\|\mathcal{T}\| = 100$ | supervised | 53.0 ±3.1 | 86.0 ±0.7 | 62.9 ±0.9 | 47.9 ±2.8 / 51.2 ±2.6 |
| | PET | 61.9 ±0.0 | 88.3 ±0.1 | 69.2 ±0.0 | 74.7 ±0.3 / 75.9 ±0.4 |
| $\|\mathcal{T}\| = 1000$ | supervised | 63.0 ±0.5 | **86.9** ±0.4 | 70.5 ±0.3 | 73.1 ±0.2 / 74.8 ±0.3 |
| | PET | **64.8** ±0.1 | **86.9** ±0.2 | **72.7** ±0.0 | **85.3** ±0.2 / **85.5** ±0.4 |

$|\mathcal{T}|$: # of labeled samples

Schick, Timo, and Hinrich Schütze. "Exploiting Cloze-Questions for Few-Shot Text Classification and Natural Language Inference." *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*. 2021.

# Semi-supervised learning with PLMs: STraTa

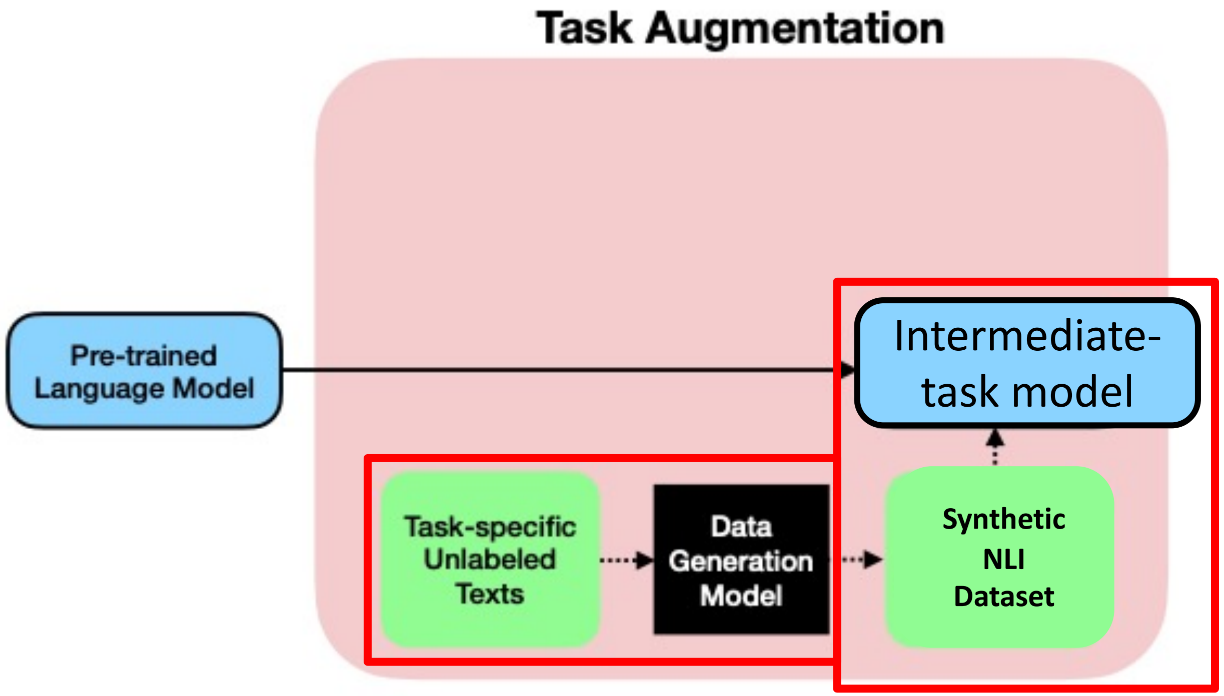
- **Self-Training** with **Task Augmentation (STraTA)**
  - Self-training: use the model's prediction on the unlabeled dataset as pseudo-label
  - How to initialize the models is critical to the performance




Vu, Tu, et al. "STraTA: Self-Training with Task Augmentation for Better Few-shot Learning." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

# Semi-supervised learning with PLMs: STraTa

- **S**elf-**Tra**ining with **T**ask **A**ugmentation (**STraTA**)
  - Task augmentation: use unlabeled data to generate an NLI dataset, and fine-tuned on the NLI dataset as the intermediate task to obtain the base model

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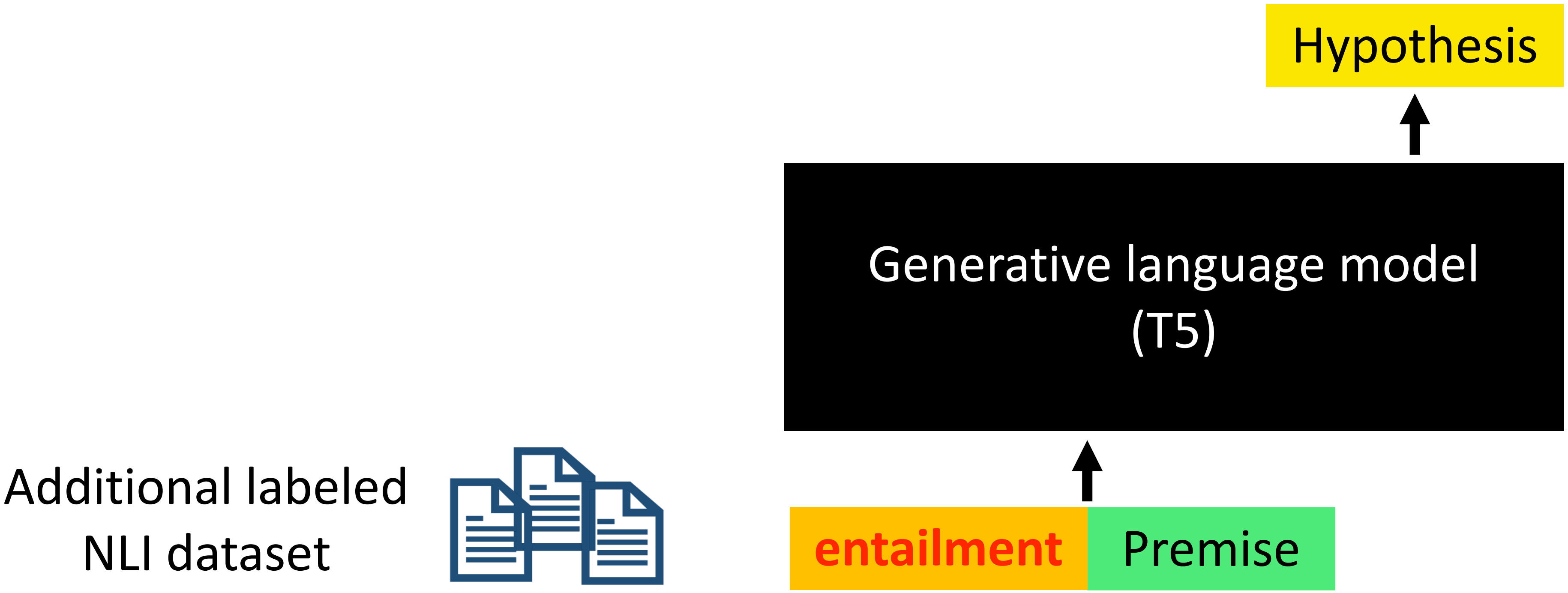
# Semi-supervised learning with PLMs: STraTa

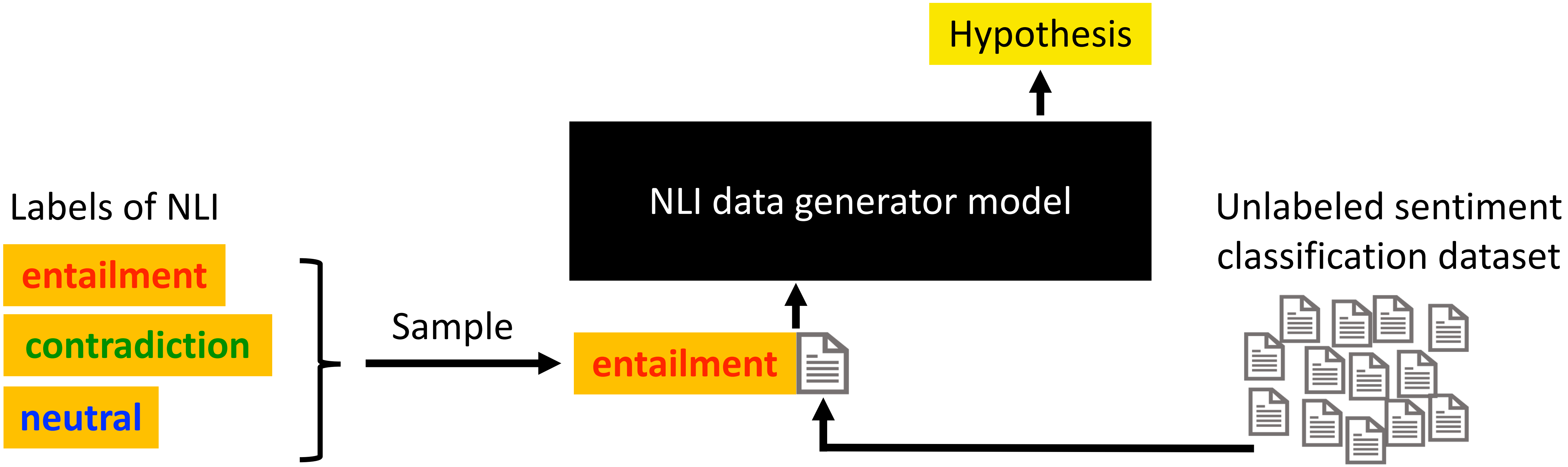
- **Self-Training with Task Augmentation (STraTA)**
  - Task augmentation: sentiment classification as the target task
    - Step 1: Train an NLI data generator using another labeled NLI dataset using a generative language model




Vu, Tu, et al. "STraTA: Self-Training with Task Augmentation for Better Few-shot Learning." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

# Semi-supervised learning with PLMs: STraTa

- **S**elf-**Tra**ining with **T**ask **A**ugmentation (**STraTA**)
  - Task augmentation: sentiment classification as the target task
    - Step 2: Use the trained data generator to generate NLI dataset using the in-domain unlabeled data

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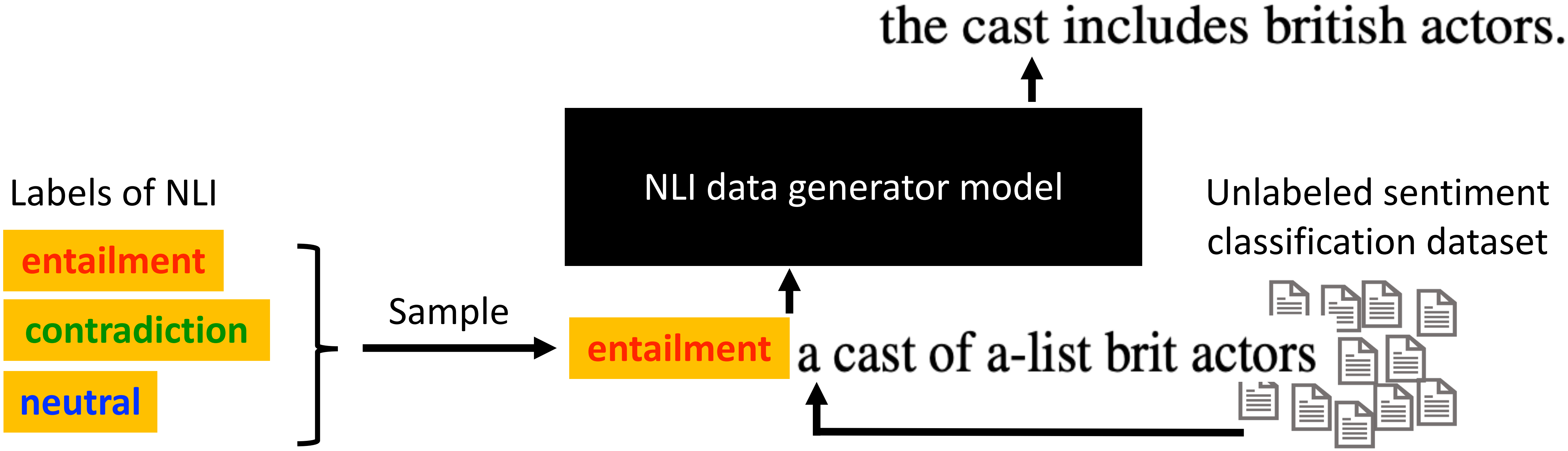
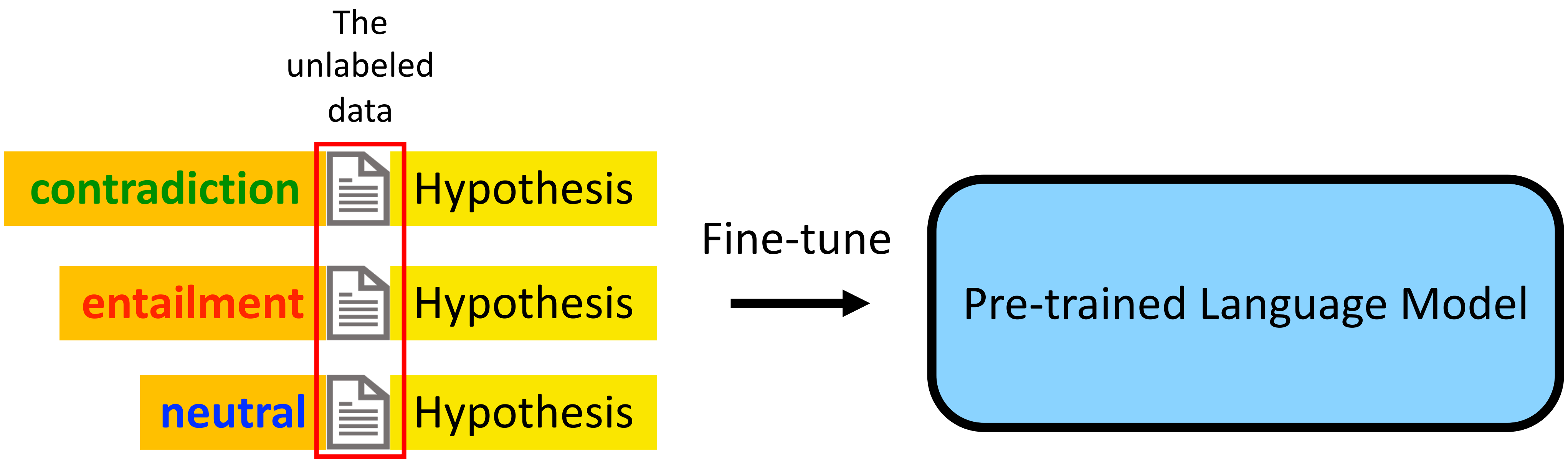



Vu, Tu, et al. "STraTA: Self-Training with Task Augmentation for Better Few-shot Learning." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

# Semi-supervised learning with PLMs: STraTa

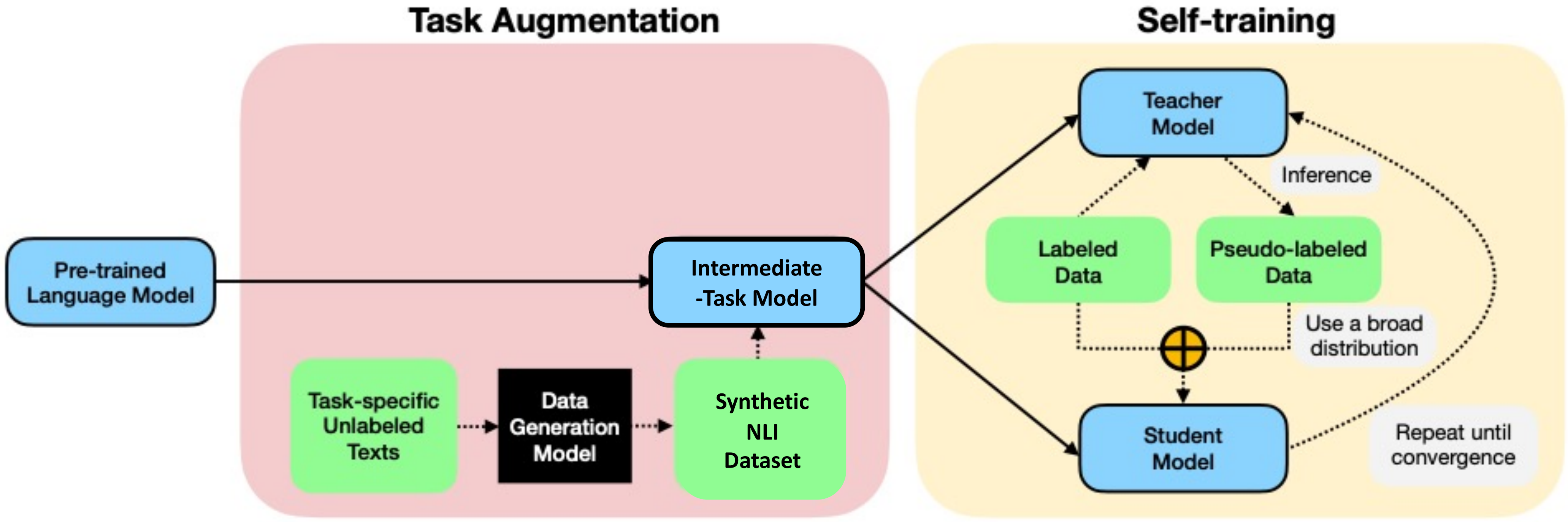
- **S**elf-**Tra**ining with **T**ask **A**ugmentation (**STraTA**)
  - Task augmentation: sentiment classification as the target task
    - Step 3: Use the generated in-domain NLI dataset to fine-tune an NLI model. The fine-tuned model is used to initialize the teacher model and student model in self-training




Vu, Tu, et al. "STraTA: Self-Training with Task Augmentation for Better Few-shot Learning." *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 2021.

# Semi-supervised learning with PLMs: STraTa

- **Self-Training** with **T**ask **A**ugmentation (**STraTA**)
  - Task augmentation: using sentiment classification as an example
    - Step 3: Use the generated in-domain NLI dataset to fine-tune an NLI model. The fine-tuned model is used to initialize the teacher model and student model in self-training

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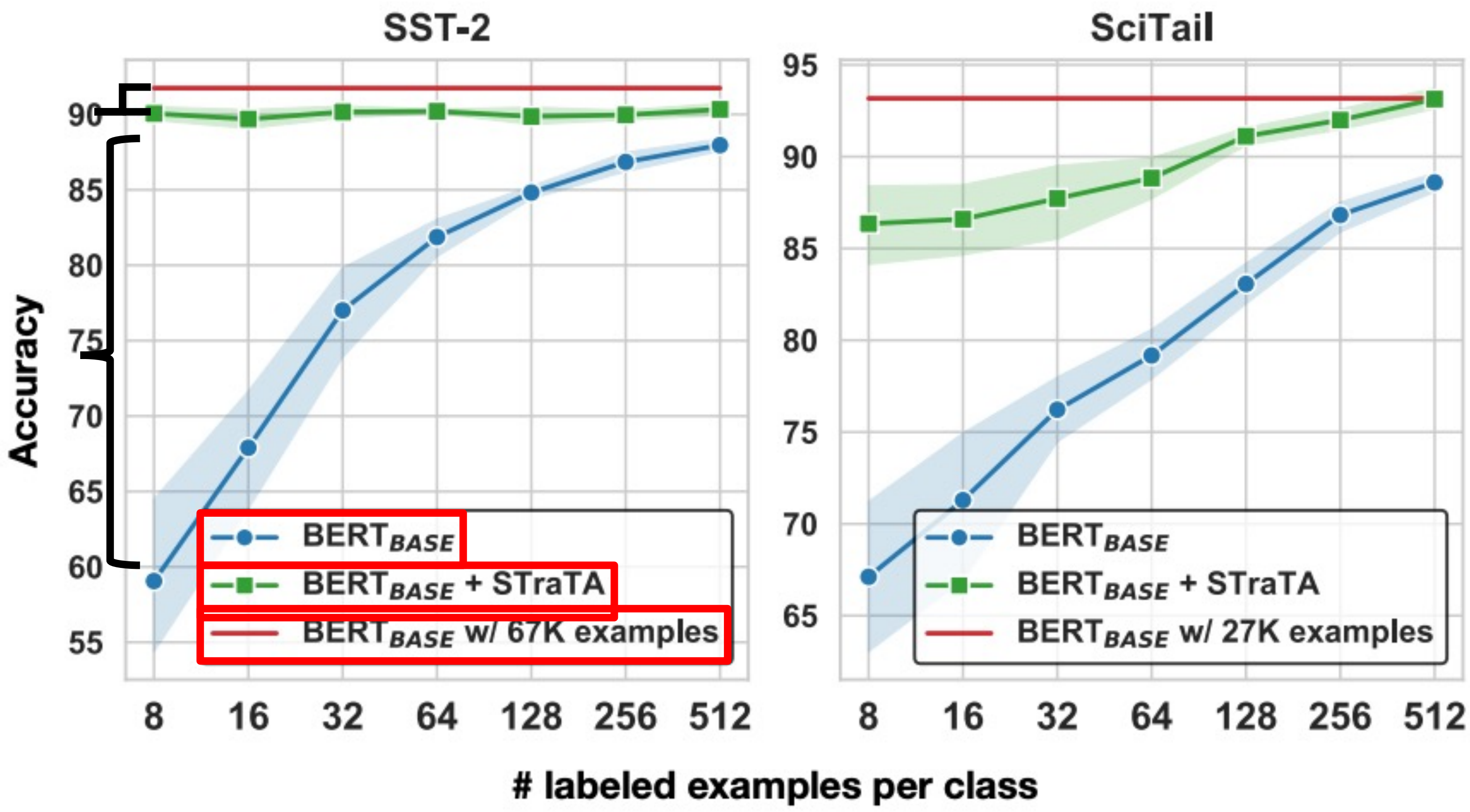
# Semi-supervised learning with PLMs: STraTa

- **Self-Training** with **Task Augmentation** (**STraTA**)





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2022 AACL-IJCNLP

# Part 5:

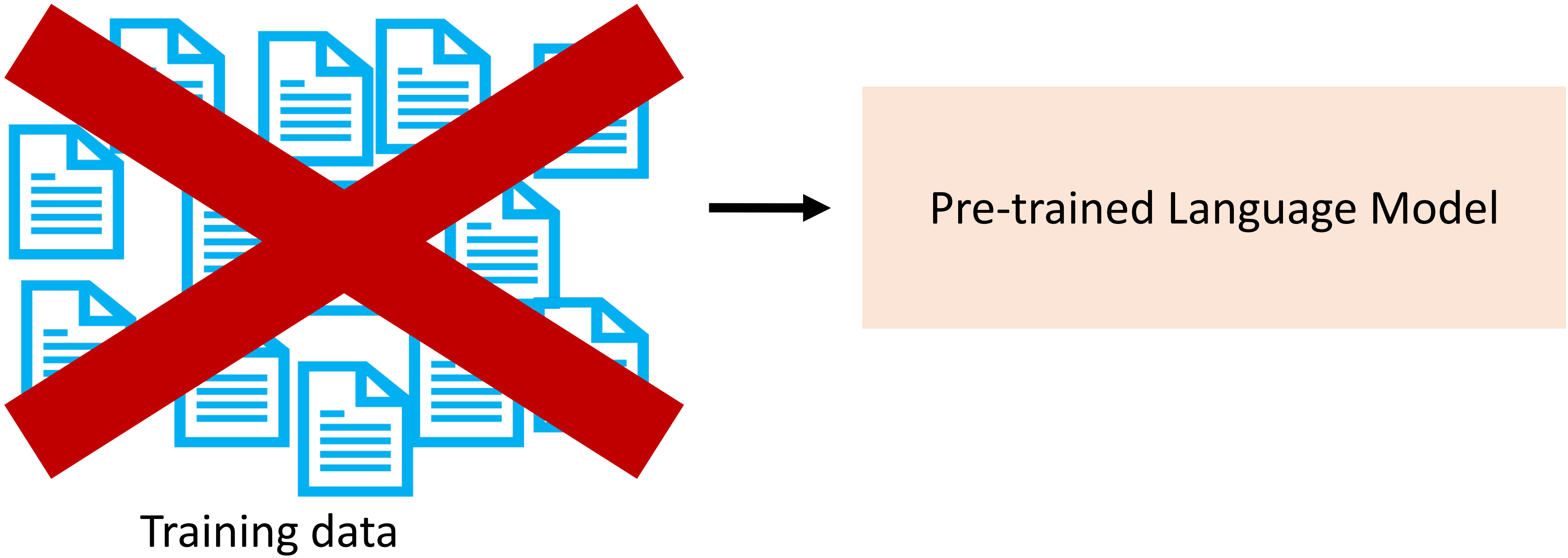
# How do PLMs work:

# Using PLMs with different amounts of data

## 5-4: Zero-shot learning

# Zero-shot learning

- Zero-shot inference: inference on the downstream task without any training data
- If you don't have training data, then we need a model that can zero-shot inference on downstream tasks



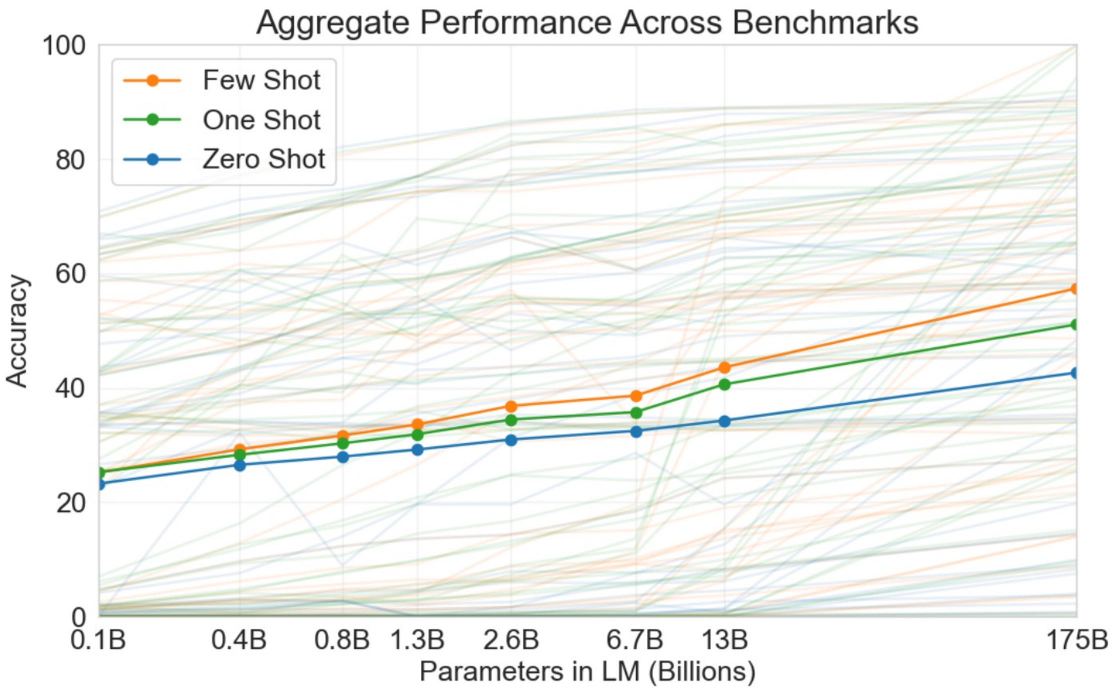
# Zero-shot learning

- GPT-3 shows that zero-shot (with task description) is possible

**Zero-shot**

The model predicts the answer given only a natural language description of the task. No gradient updates are performed.

```
Translate English to French:
cheese =>
```




Brown, Tom, et al. "Language models are few-shot learners." *Advances in neural information processing systems* 33 (2020): 1877-1901.

# Zero-shot learning

- Question: Where does this zero-shot ability spring from?
- Hypothesis: during pre-training, the training datasets implicitly contains a mixture of different tasks
    - QA

      **Q**: I got 4 papers. Should I expect this load in the future?

      **A**: The average monthly load for reviewers should be much closer to 2, but in certain periods (close to large conferences), it's possible that the load is higher.

    - Summarization

## Finetuned Language Models are Zero-Shot Learners

*Jason Wei, Maarten Bosma, Vincent Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M. Dai, Quoc V Le*

29 Sept 2021 (modified: 10 Feb 2022) ICLR 2022 Oral Readers: Everyone Show Bibtex Show Revisions

**Keywords:** natural language processing, zero-shot learning, language models

**Abstract:** This paper explores a simple method for improving the zero-shot learning abilities of language models. We show that instruction tuning—finetuning language models on a collection of datasets described via instructions—substantially improves zero-shot performance on unseen tasks. We take a 137B parameter pretrained language model and instruction tune it on over 60 NLP datasets verbalized via natural language instruction templates. We evaluate this instruction-tuned model, which we call FLAN, on unseen task types. FLAN substantially improves the performance of its unmodified counterpart and surpasses zero-shot 175B GPT-3 on 20 of 25 datasets that we evaluate. FLAN even outperforms few-shot GPT-3 by a large margin on ANLI, RTE, BoolQ, AI2-ARC, OpenbookQA, and StoryCloze. Ablation studies reveal that number of finetuning datasets, model scale, and natural language instructions are key to the success of instruction tuning.

**One-sentence Summary:** "Instruction tuning", which finetunes language models on a collection of tasks described via instructions, substantially boosts zero-shot performance on unseen tasks.

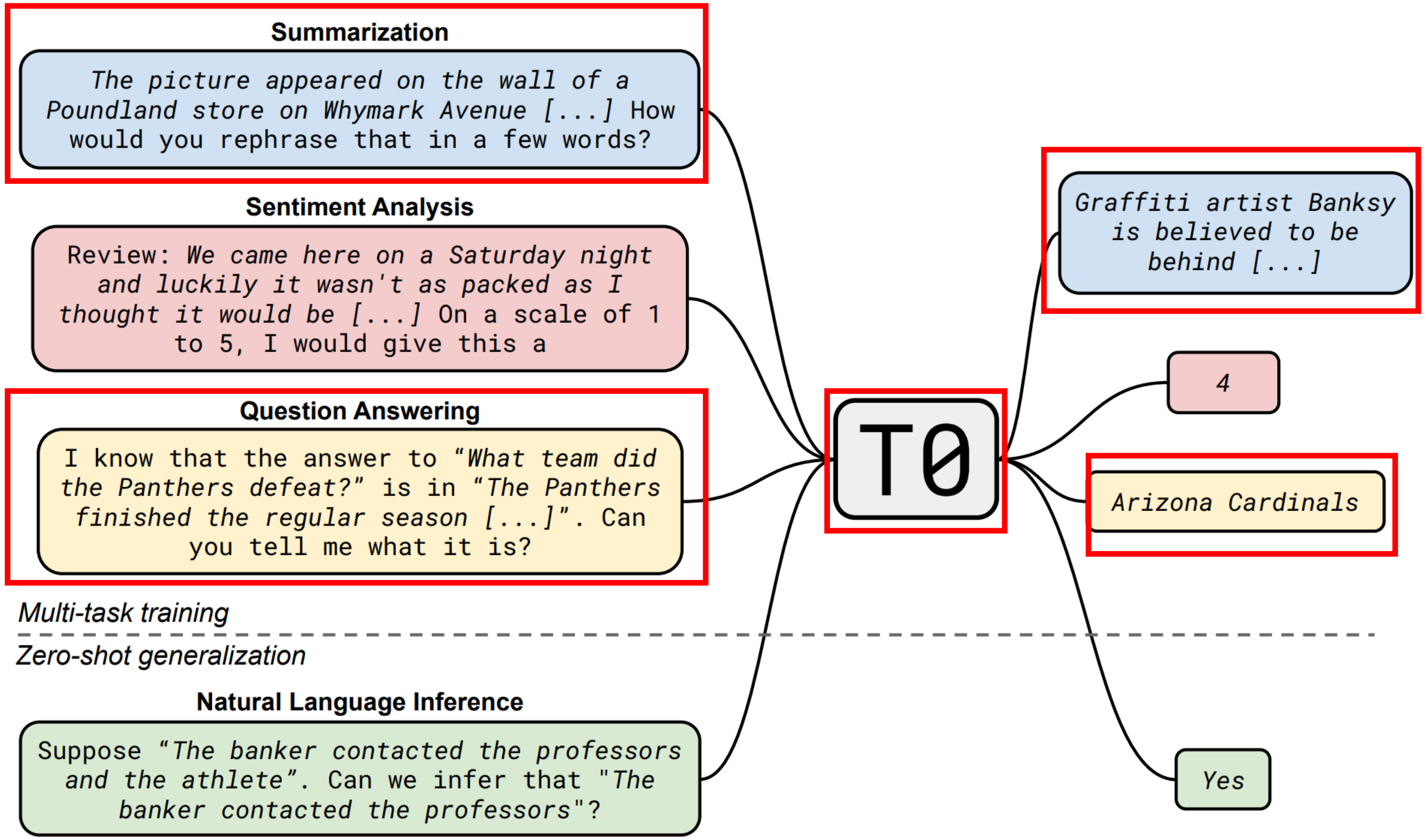
Wei, Jason, et al. "Finetuned Language Models are Zero-Shot Learners." *International Conference on Learning Representations*. 2022.

# Zero-shot learning

- Hypothesis: multi-task training enables zero-shot generalization
  - Why not train a model with multi-task learning on a bunch of dataset?

Multi-task intermediate-task fine-tuning

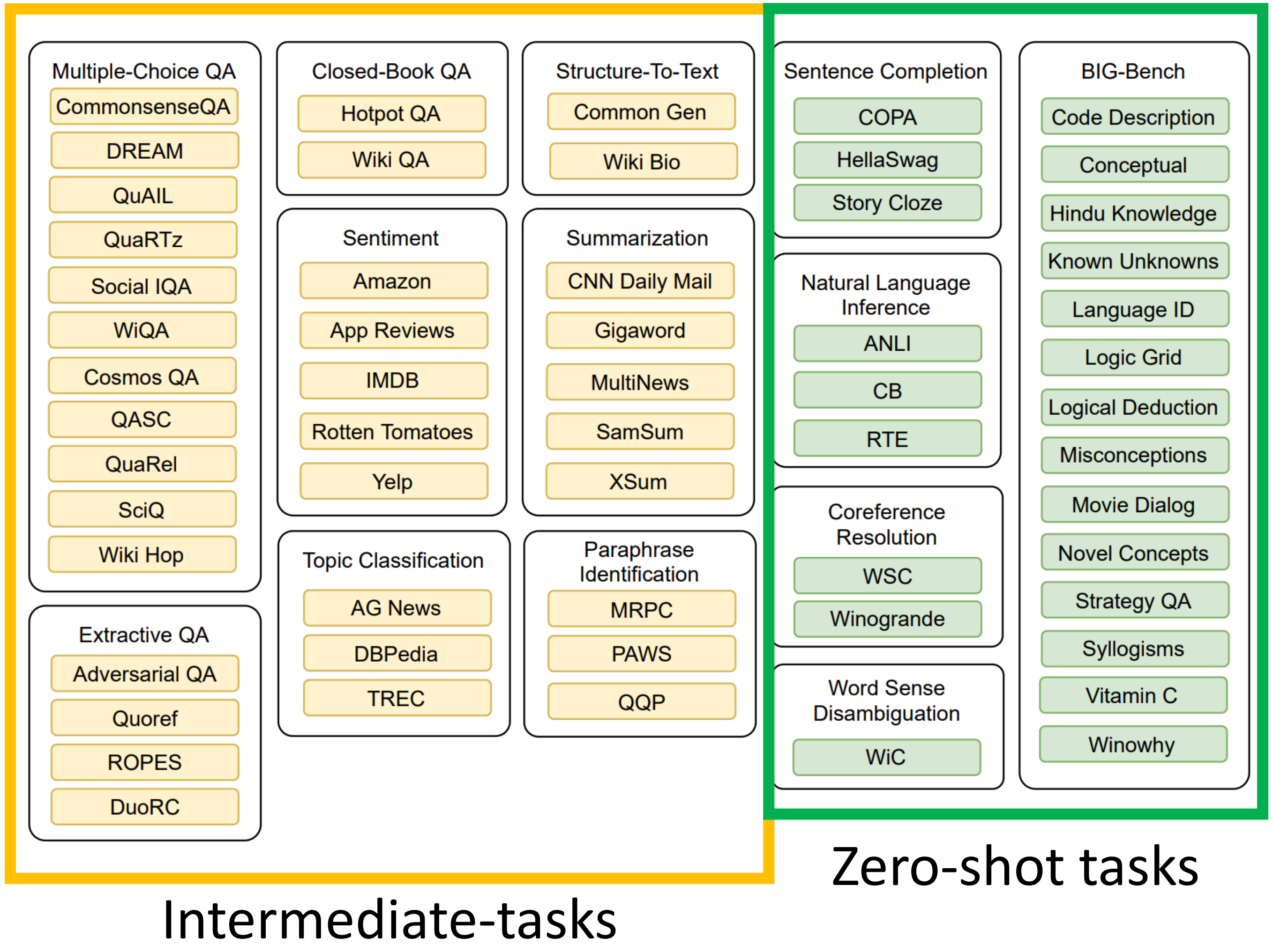
Zero-shot Generalization




Sanh, Victor, et al. "Multitask Prompted Training Enables Zero-Shot Task Generalization." *The Tenth International Conference on Learning Representations*. 2022.

# Zero-shot learning

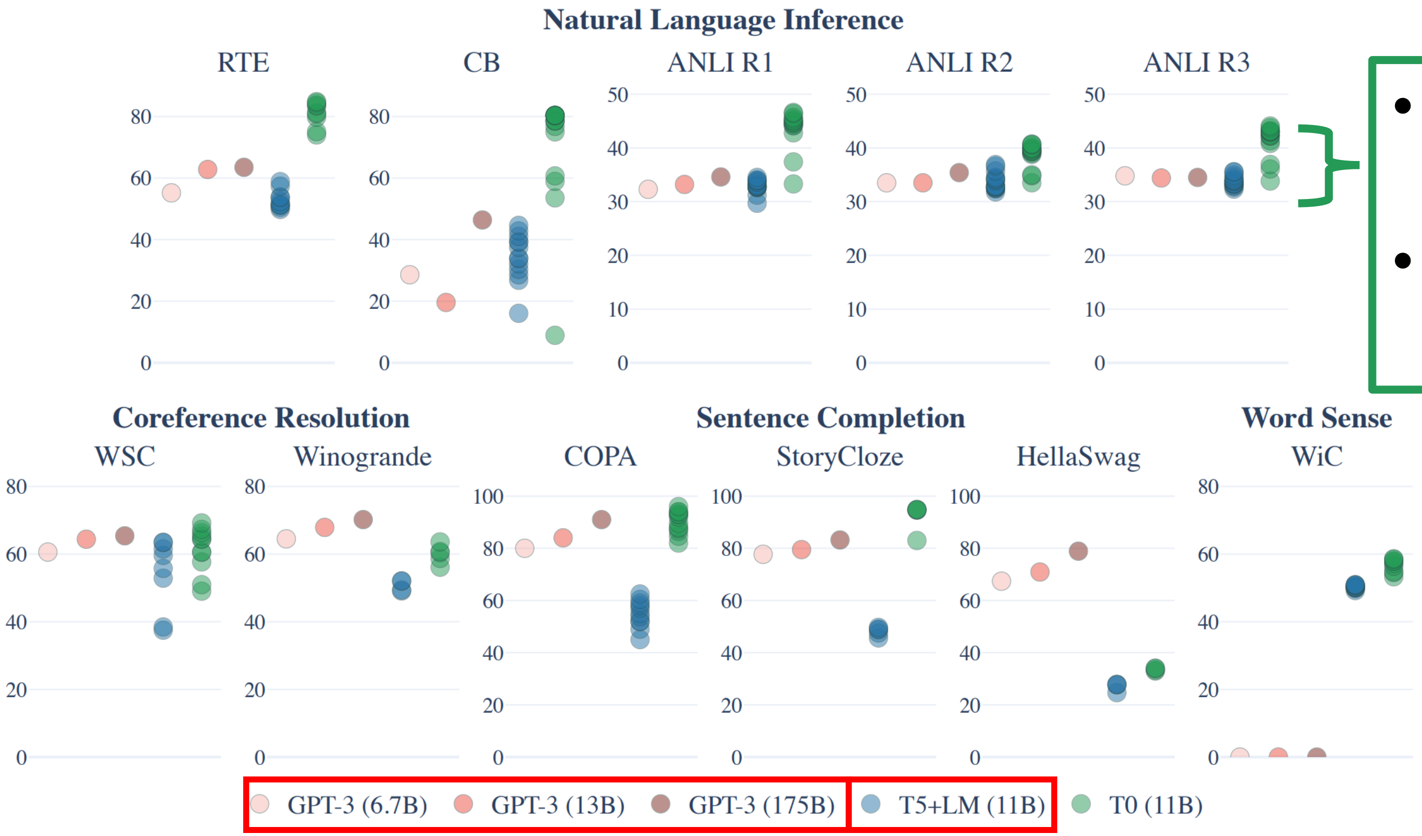
- Intermediate-task fine-tuning with some types of tasks
- Zero-shot inference on other types of tasks




Sanh, Victor, et al. "Multitask Prompted Training Enables Zero-Shot Task Generalization." *The Tenth International Conference on Learning Representations*. 2022.

# Zero-shot learning

- Sometimes achieves performance better than GPT-3 (175B parameters) with ***only 11B*** parameters

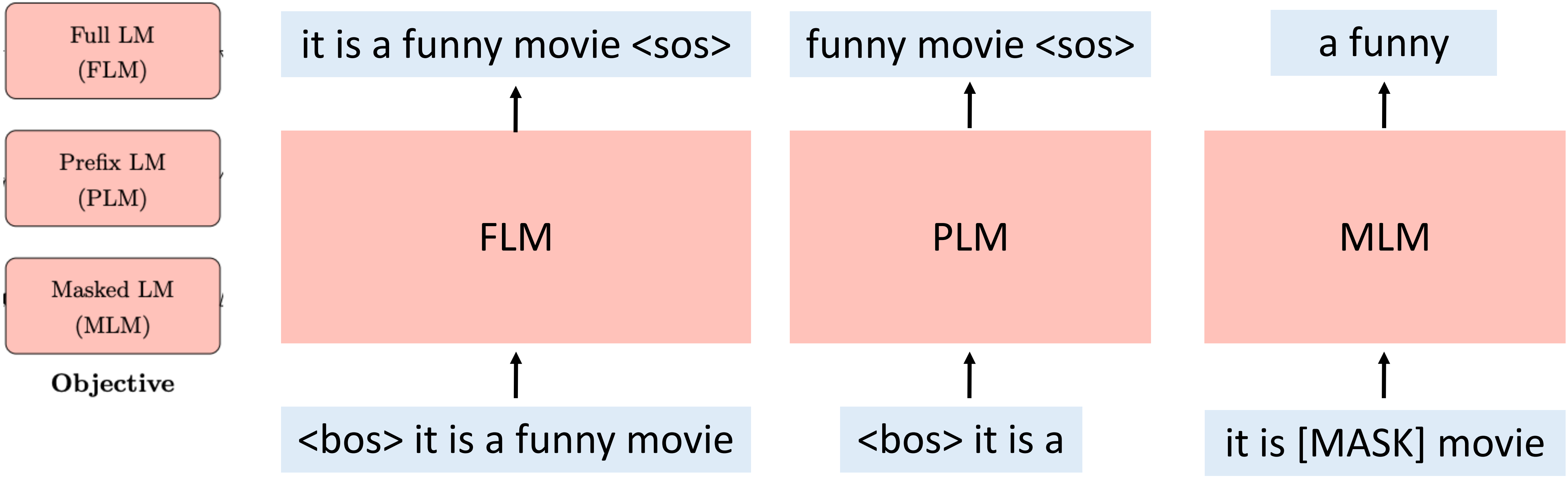



- Different points represents different prompts
- Variance due to prompts can be large

Sanh, Victor, et al. "Multitask Prompted Training Enables Zero-Shot Task Generalization." *The Tenth International Conference on Learning Representations*. 2022.

# Zero-shot learning

- What language model architecture and pre-training objective work best for zero-shot generalization?




Wang, Thomas, et al. "What Language Model Architecture and Pretraining Objective Work Best for Zero-Shot Generalization?." *arXiv preprint arXiv:2204.05832* (2022).

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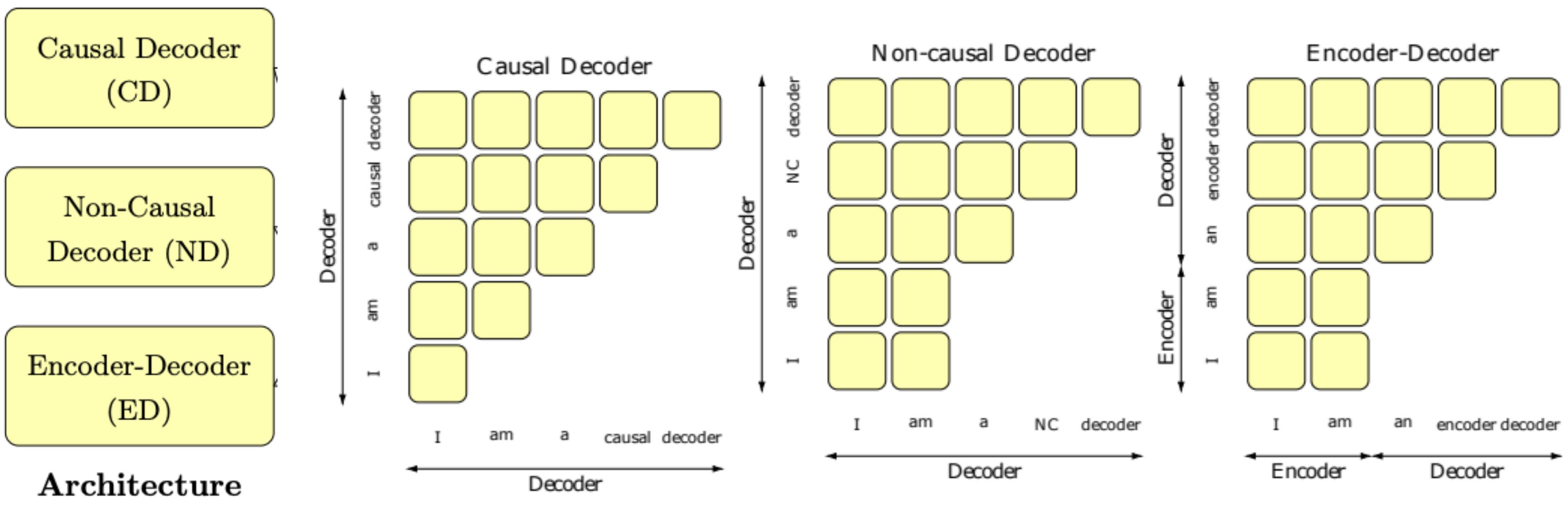


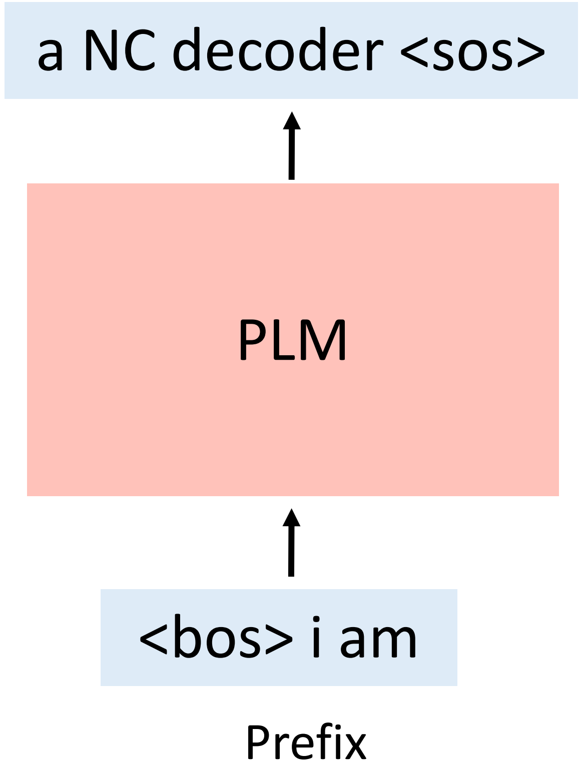


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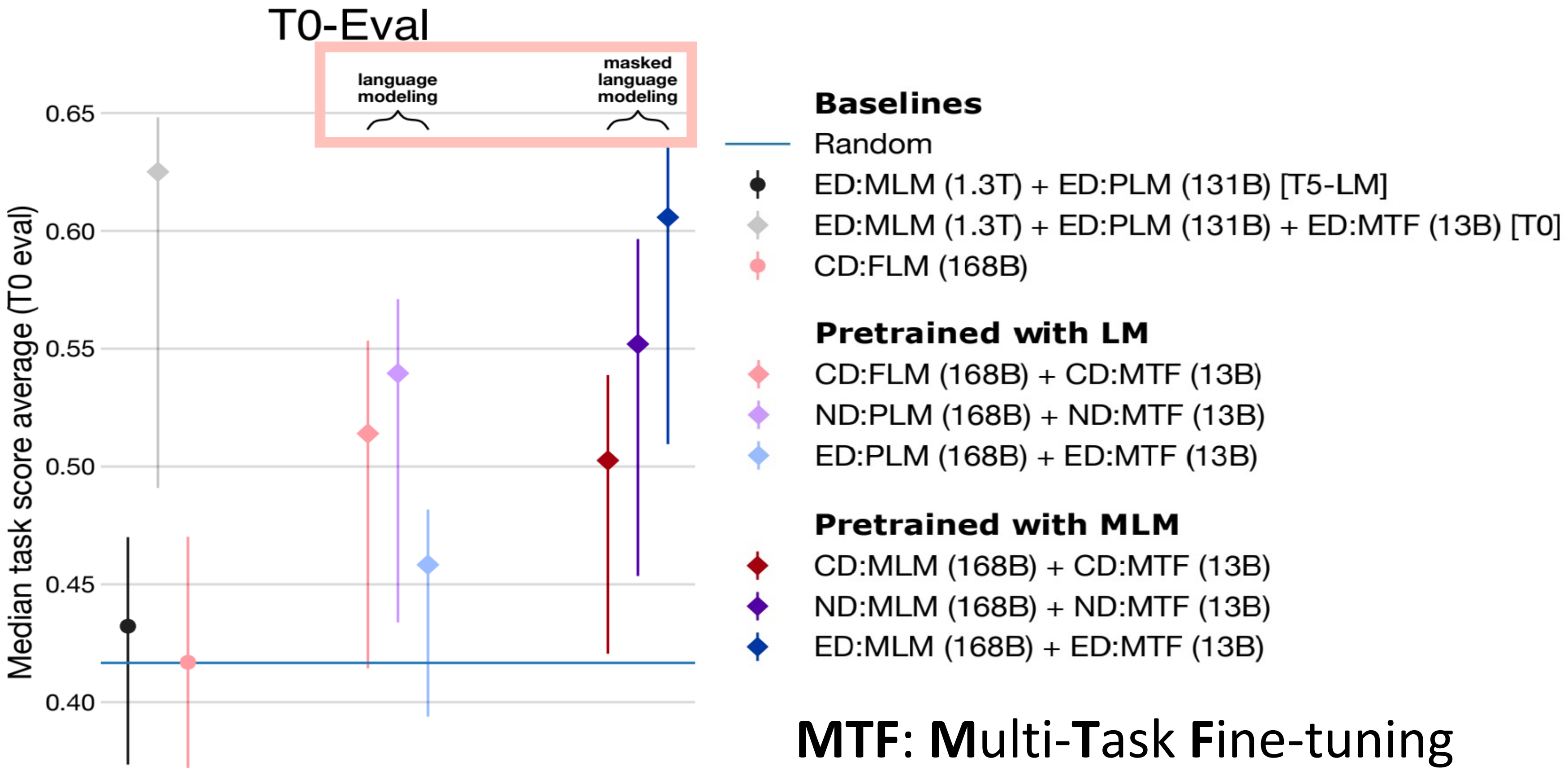


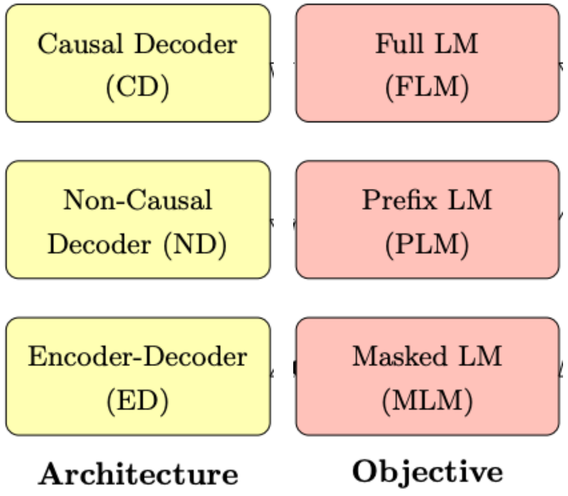


**MTF**: **M**ulti-**T**ask **F**ine-tuning

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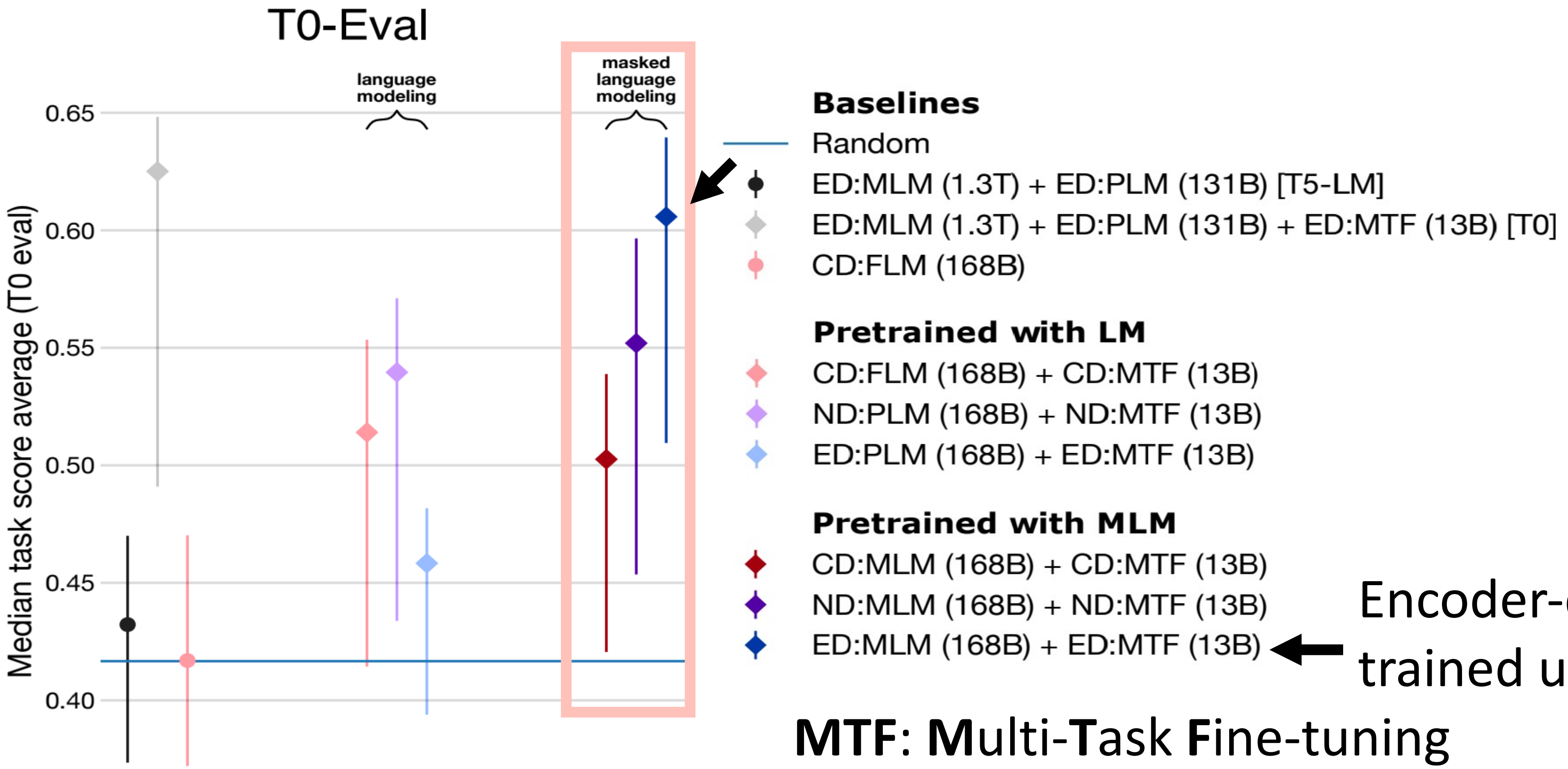


Encoder-decoder model pre-trained using MLM is the best

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# Part 5:

# How do PLMs work:

# Using PLMs with different amounts of data

## 5-5: Short summary

# Using PLMs with different amount of data

- PLMs can be used with different amount of labeled and unlabeled data
- Special designs need to be made under different scenarios

Target task dataset (labeled)

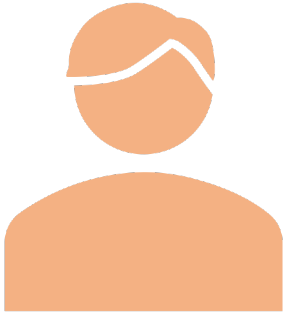
Datasets of other tasks (labeled)

Data related to target task (Unlabeled)

# Using PLMs with different amount of data

- Use natural language prompts and add scenario-specific designs

  - [CLS] The spring break is coming soon. Is it true that the spring break was over? >>> no
  - [CLS] I am going to have dinner. Is it true that I am going to eat something? >>> yes
  - [CLS] Mary likes pie. Is it true that Mary hates pie. [SEP] >>> ?



yes

# Schedule

| | |
|---|---|
| 17:00 – 17:10 | **Part 1** Introduction [Hung-yi] |
| 17:10 – 17:40 | **Part 2** Why do PLMs work [Hung-yi] |
| 17:40 – 18:20 | **Part 3** How to use PLMs: Contrastive Learning for PLMs [Yung-Sung] |
| 18:20 – 18:30 | Q&A for Part 1+2+3 |
| 18:30 – 18:40 | Break |
| 18:40 – 19:05 | **Part 4** How to use PLMs: Parameter-efficient fine-tuning [Cheng-Han] |
| 19:05 – 19:50 | **Part 5** How to use PLMs: Using PLMs with different amounts of data [Cheng-Han] |
| 19:50 – 20:00 | Conclusion and Future work + Q&A |

# Conclusion and Future Work + Q&A

# Conclusion

- Researchers have studied why PLMs are useful from many aspects
- Contrastive learning is a powerful method to obtain high quality sentence embedding in an unsupervised way
- Parameter-efficient fine-tuning can achieve comparable performance to full-model fine-tuning
- PLMs can be used in with different amount of labeled and unlabeled datasets, and incorporating human knowledge is very critical the performance

# Future work

- Why PLMs work is not completely answered yet, including the mathematical theory / learning theory behind the PLMs
- How can we create better negative and positive samples for contrastive learning in an unsupervised way?
- How can we combine parameter-efficient fine-tuning methods with other methods (pruning, compression, quantization) to further reduce the parameters?
- How does those few-shot learning methods perform domain-specific datasets?
- How trust-worthy are the prediction of PLMs, especially in few-shot and zero-shot?

# Future work

- Why is the variance between different prompts very large for certain tasks? Does this imply the PLM fail to understand human language?
- How do we continuously adapt PLMs to different domain and datasets from different time?

Still a long way to go!

2022 AACL-IJCNLP

# Recent Advances in PLMs: Why Do They Work and How to Use Them

**Part 1** Introduction
**Part 2** Why do PLMs work
**Part 3** How to Use PLMs: Contrastive learning
**Part 4** Parameter-efficient finetuning
**Part 5** Using PLMs with different amounts of data

# Any questions?