PennState

Parameter Efficiency: *Democratizing AI at Scale*

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Agenda

- Motivation
- Pruning
- BERT Model
- Recent Work

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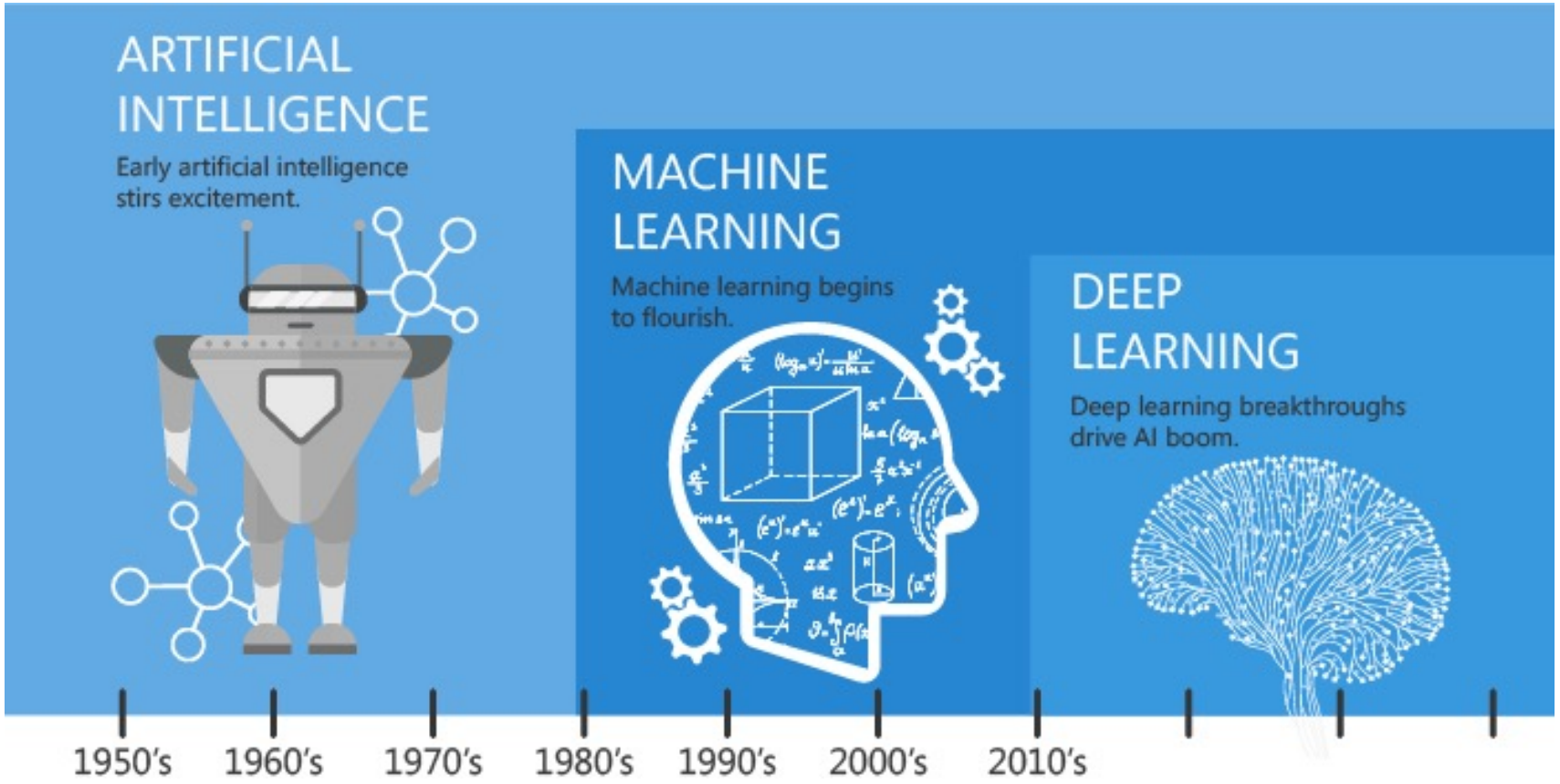
- **Motivation**
- Pruning
- BERT Model
- Recent Work

Evolution of Artificial Intelligence (AI)

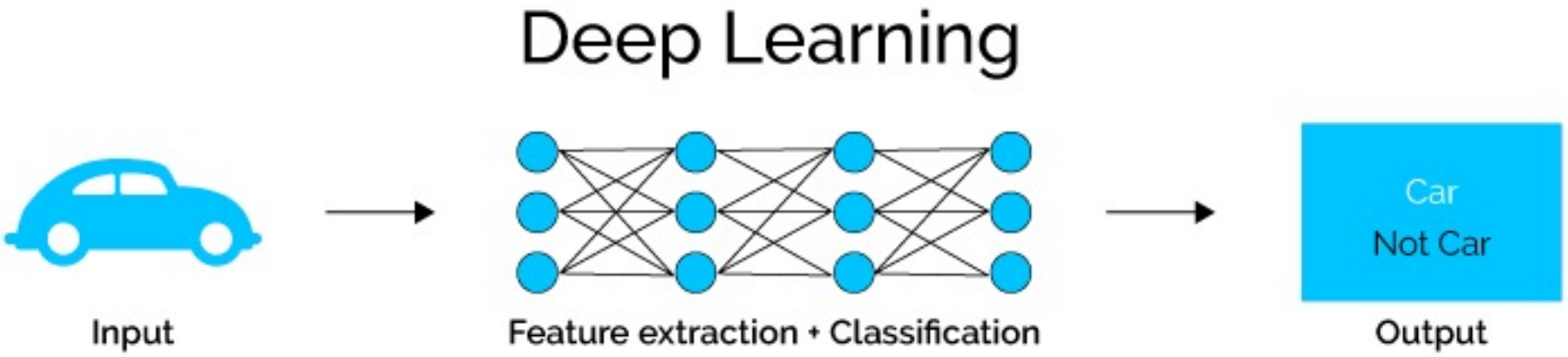
- AI vs Machine Learning vs Deep Learning [1]



[1] https://towardsdatascience.com/artificial-intelligence-vs-machine-learning-vs-deep-learning-2210ba8cc4ac

Deep Learning Spreads

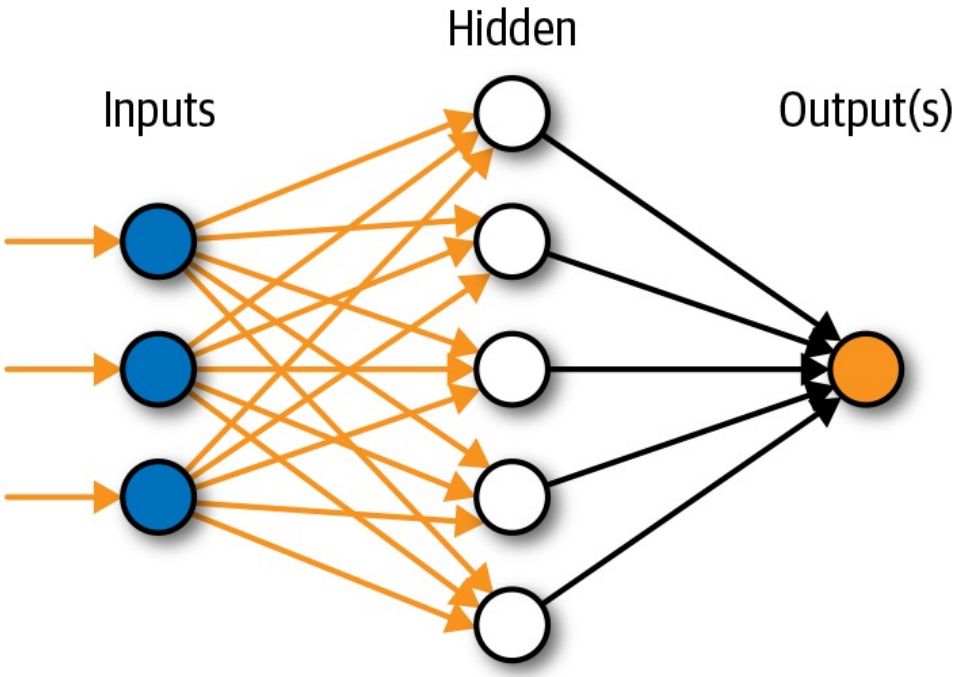
- Deep Learning: Deep Neural Networks
- Classification Task [1]



[1] https://semiengineering.com/deep-learning-spreads/

Deep Neural Networks

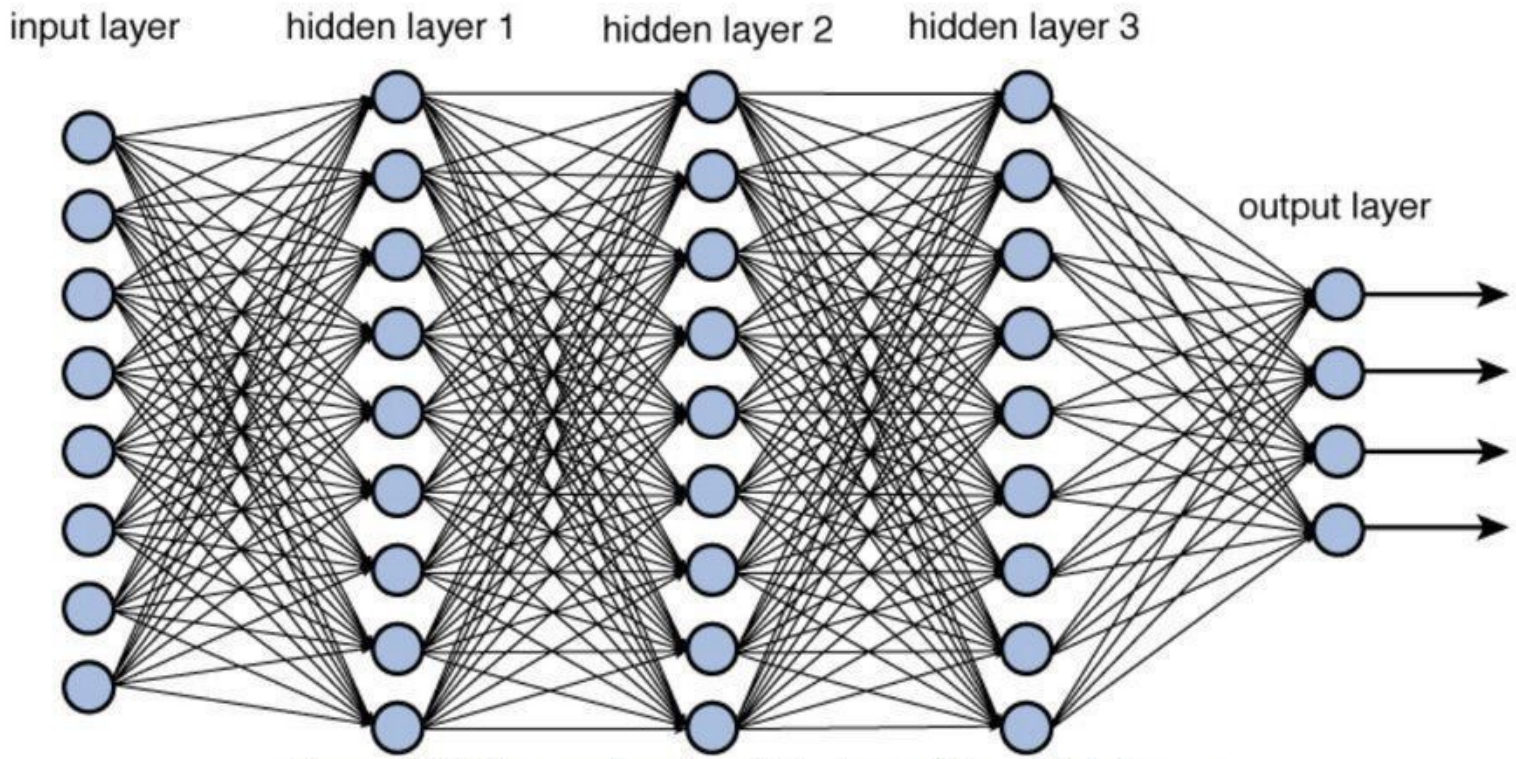
- What you think usually looks like [1]



[1] https://www.innoarchitech.com/blog/artificial-intelligence-deep-learning-neural-networks-explained

Deep Neural Networks

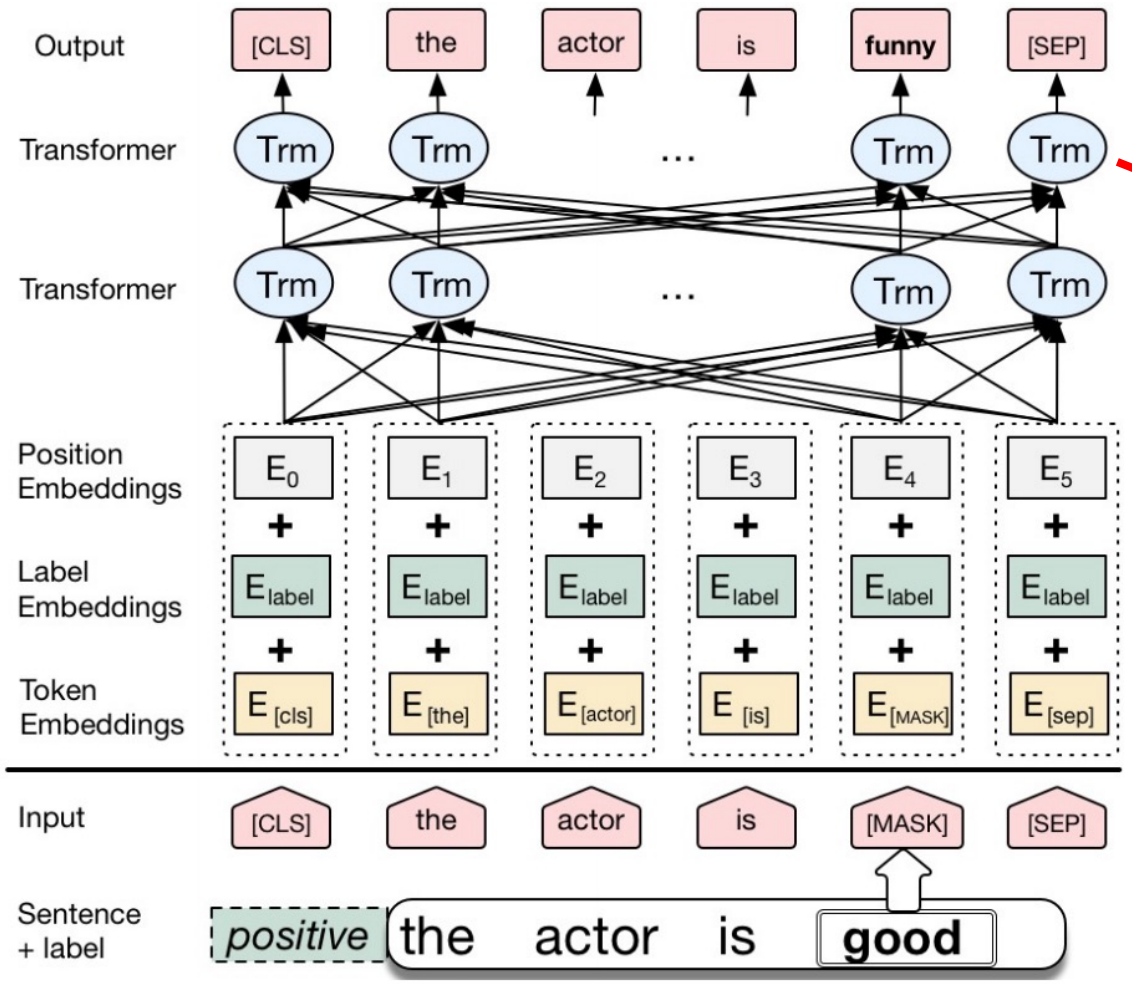
- But it could be multiple layers [1]

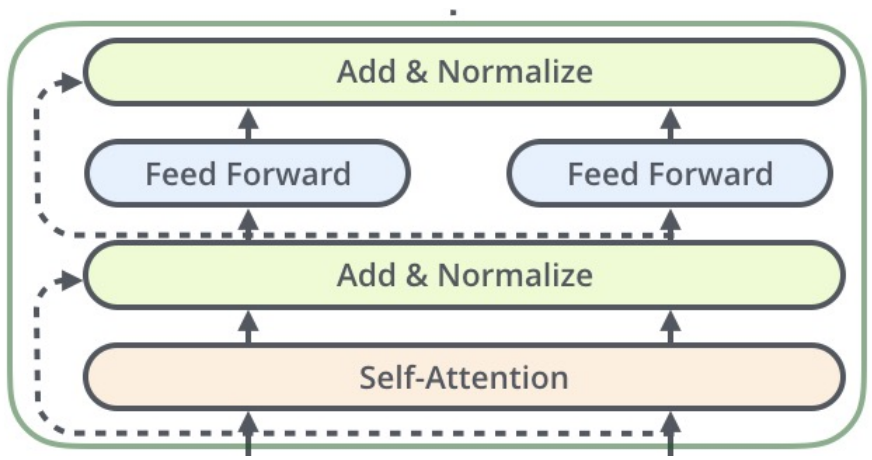


[1] https://towardsdatascience.com/training-deep-neural-networks-9fdb1964b964

Deep Neural Networks

- Even more complex [1]



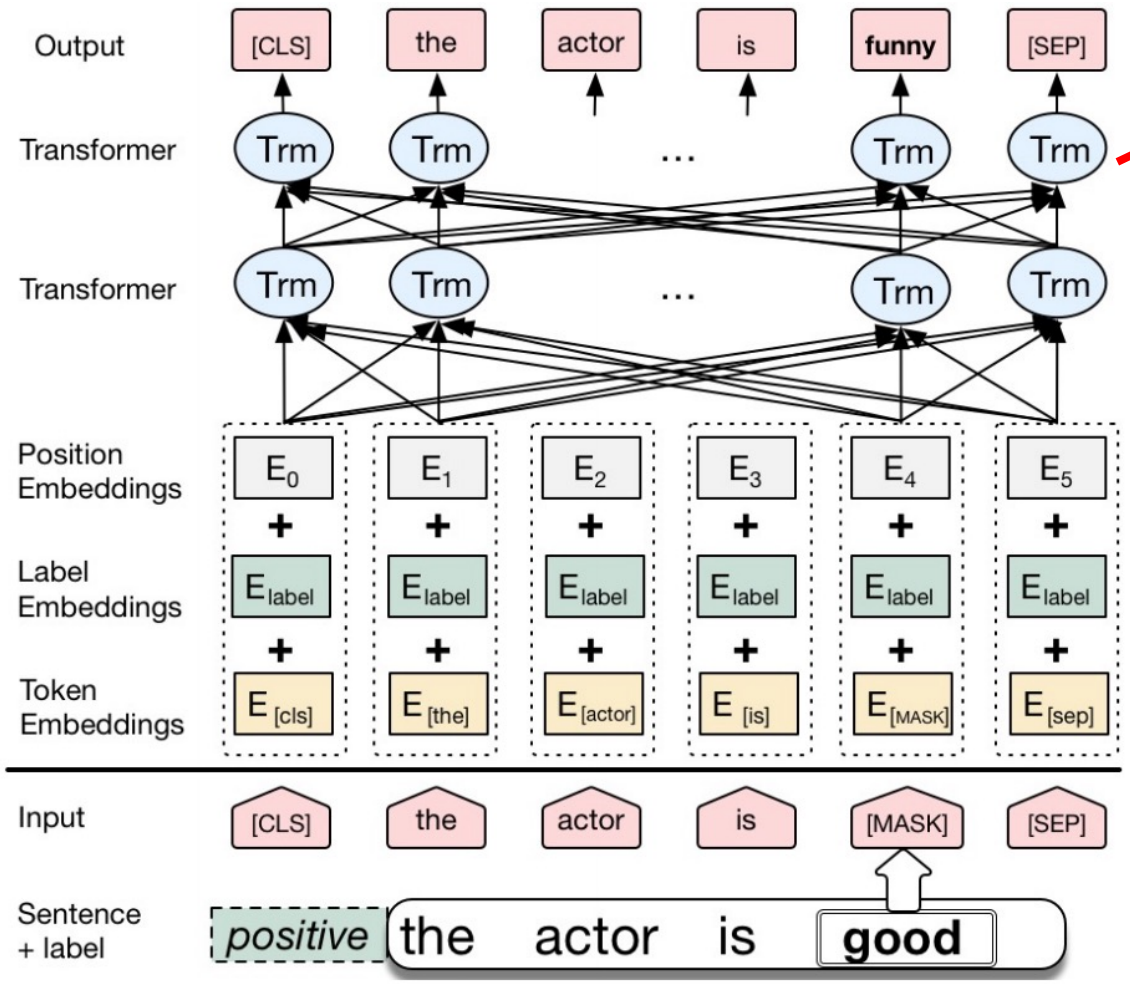


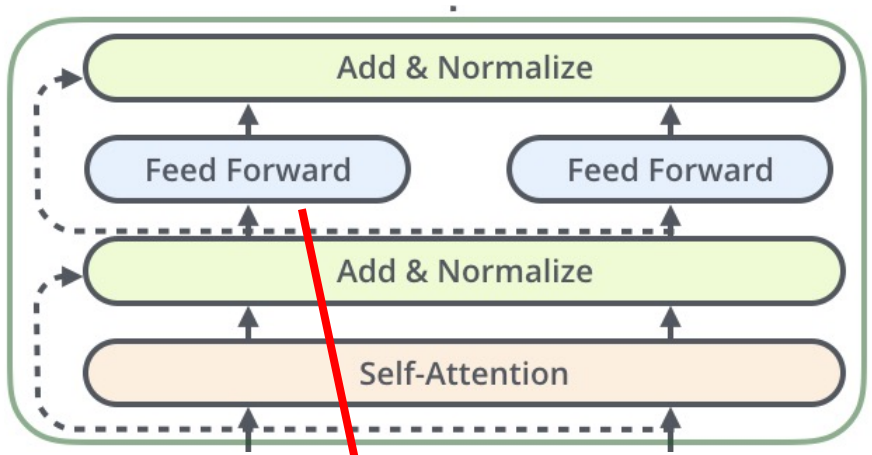
Architecture of Transformer Encoder

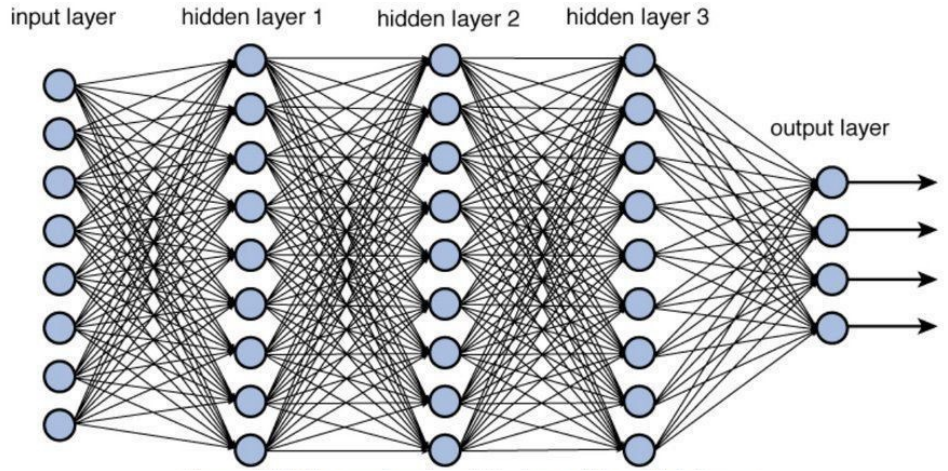
[1] Wu, X., Lv, S., Zang, L., Han, J., & Hu, S. (2019, June). Conditional bert contextual augmentation. In ICCS.

Deep Neural Networks

- Even more complex [1]







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Neural Networks at Scale

- Evolution of deep learning models over time

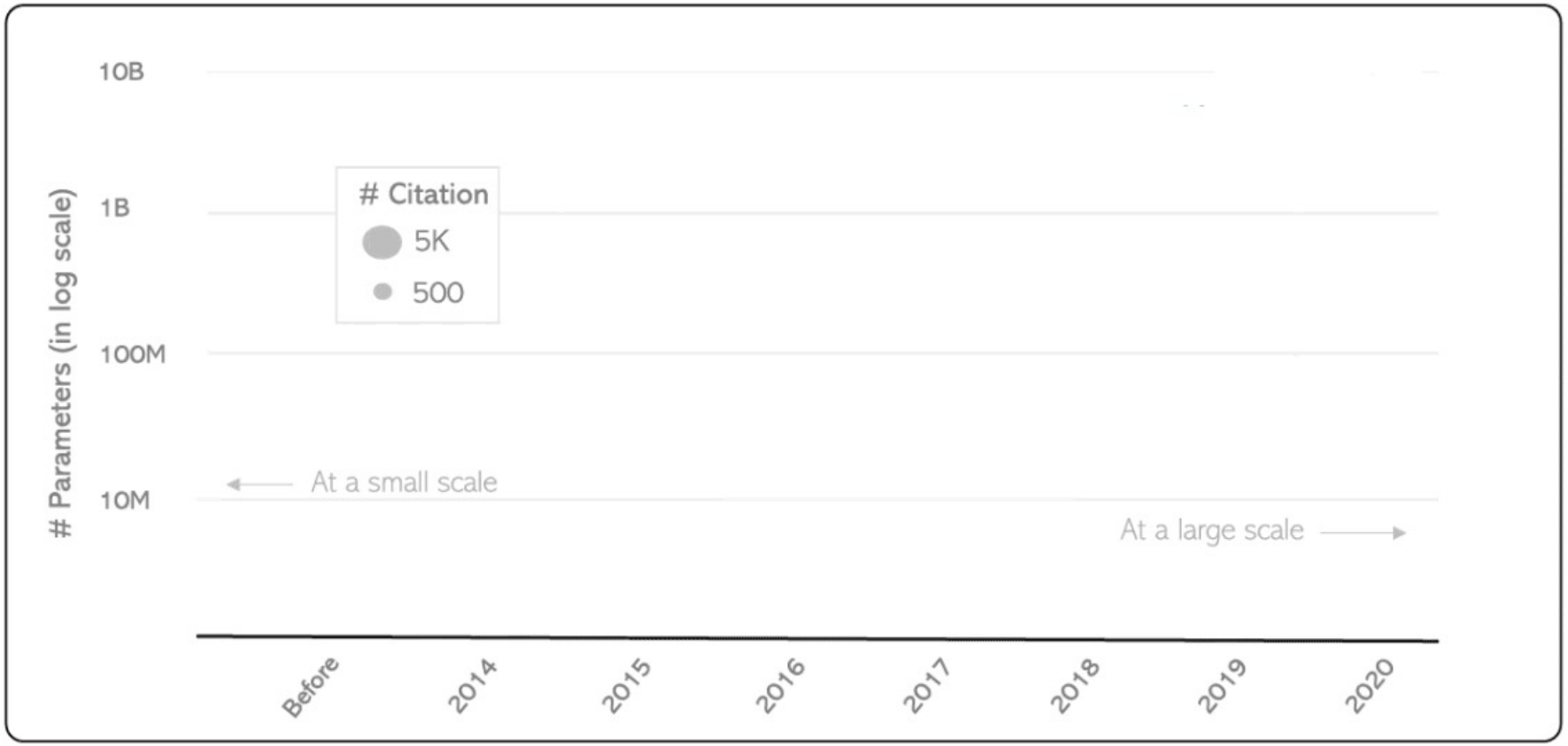


Figure: A brief evolution of deep learning models over time, measured by **model size (number of parameters)** and scientific impact (**number of citations to date**) [1]

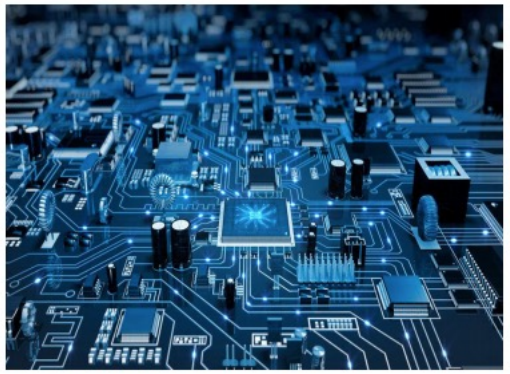
[1] https://www.microsoft.com/en-us/research/blog/a-deep-generative-model-trifecta-three-advances-that-work-towards-harnessing-large-scale-power/

Resources Are Limited

- Large neural networks require huge memory, computations, power
- Resource constrained environments[1]

Memory & Computations

Power Consumption



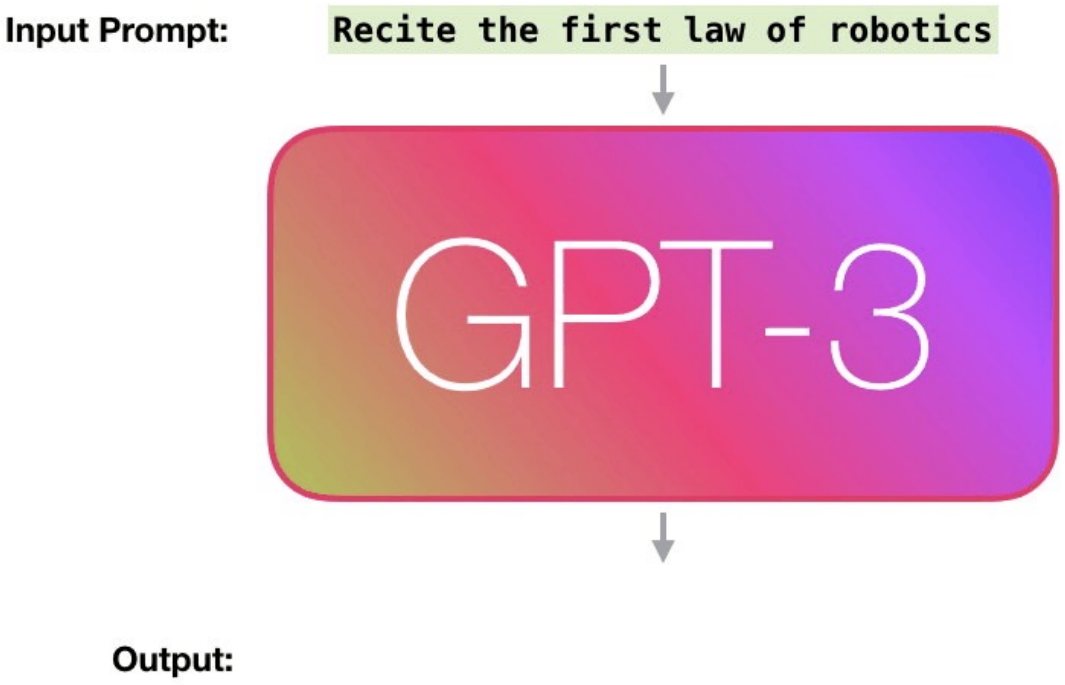
Embedded Systems e.g., Mobile Devices

Real-Time Tasks e.g., Autonomous Car

[1] https://www.robots.ox.ac.uk/~namhoon/doc/slides-snip-msr.pdf

Powerful AI Model

- GPT-3, the most powerful AI language model [1]
- Can generate human-like news articles



[1] https://en.wikipedia.org/wiki/GPT-3.

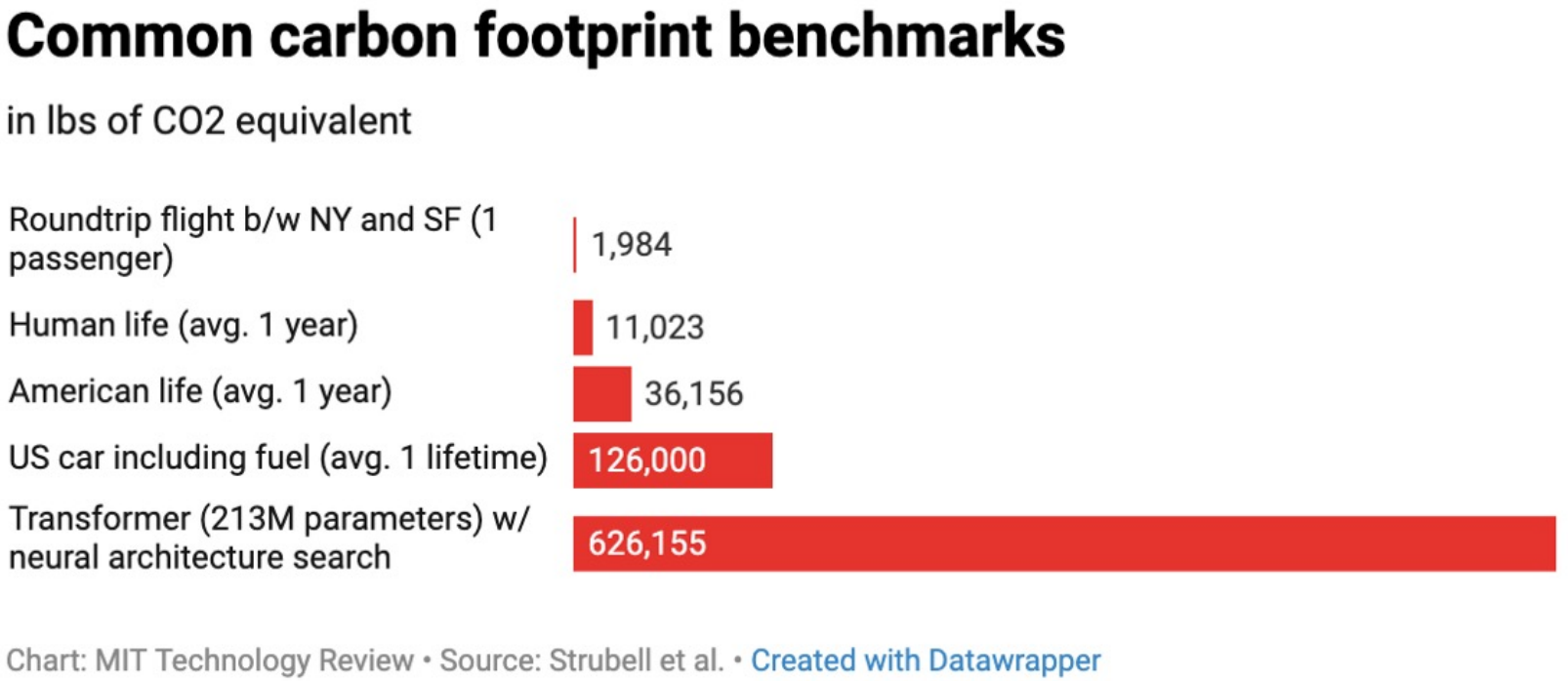
Democratization Issues

- GPT-3 is a resource hungry beast
  - 350GB of memory to load the model
  - 355 years of training on via a single GPU
  - 570GB of training text
- Free AI: Big Companies vs Individuals [1-2]

[1] https://get.agorize.com/8-things-your-company-should-do-like-startups/
[2] https://freedomhouse.org/sites/default/files/2021-09/FOTN_2021_Complete_Booklet_09162021_FINAL_UPDATED.pdf

Environmental Issues

- Training a certain neural network involves the carbon dioxide emissions which is equivalent to five times the lifetime emissions of the average U.S. car[1]



[1] Emma Strubell, Ananya Ganesh, and Andrew McCallum. Energy and policy considerations for deep learning in NLP. In ACL, pages 3645–3650, July 2019.

Model Compression is Desirable

- The goal
  - Reduce the size of network without compromising accuracy
- Pruning is a popular compression approach

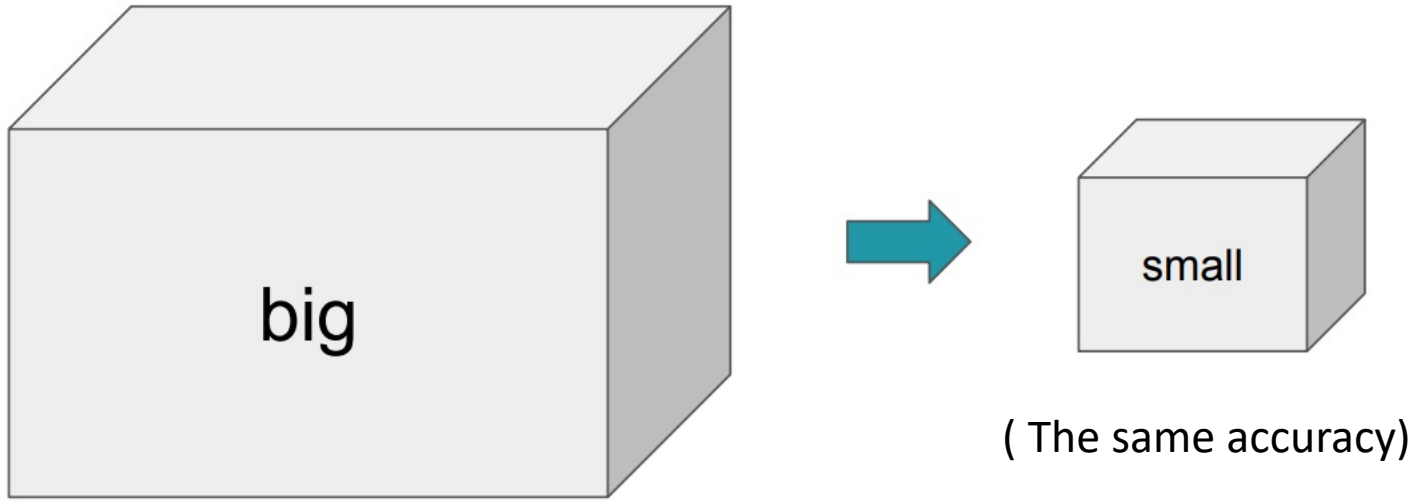


Illustration of model compression [1]

[1] https://www.robots.ox.ac.uk/~namhoon/doc/slides-snip-msr.pdf

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- **Pruning**
- BERT Model
- Recent Work

Neural Network Pruning

- Systematically removing parameters/connections from a network

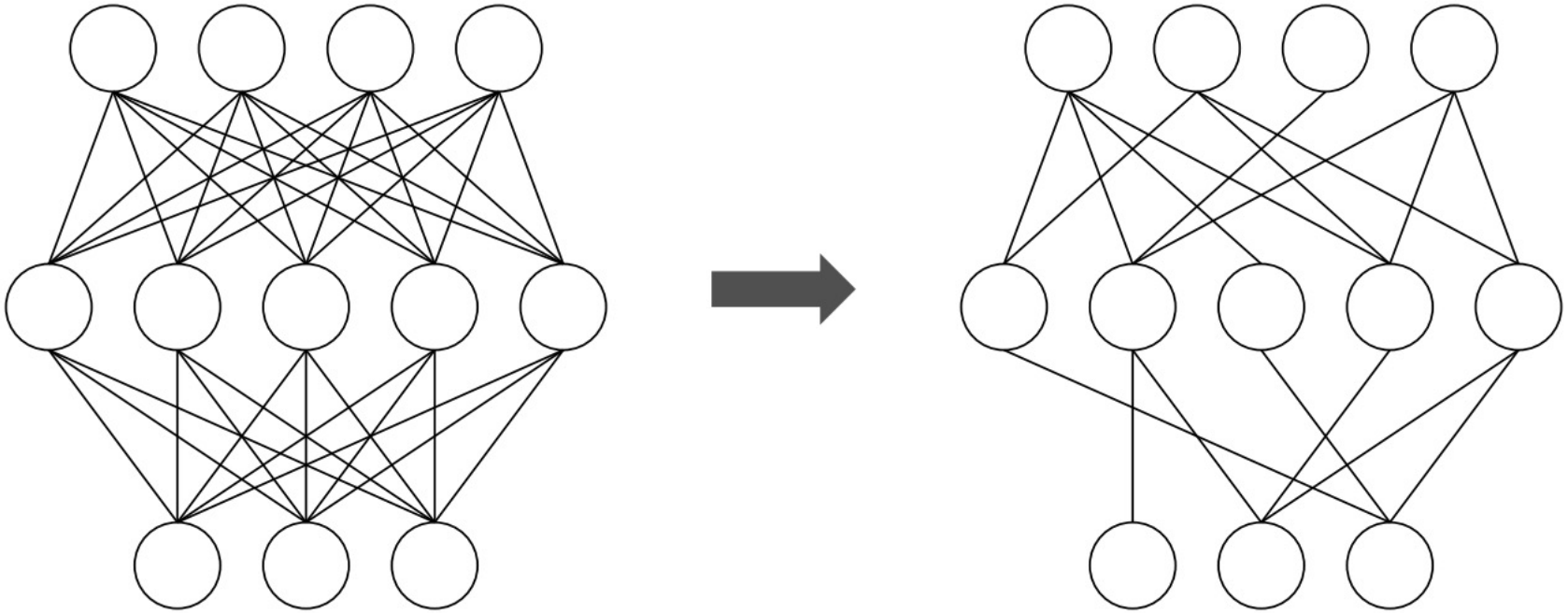

Illustration of neural network pruning [1]

[1] https://mlsys.org/media/Slides/mlsys/2020/balla(02-14-30)-02-14-30-1413-what_is_the.pdf

Typical Pruning Pipeline

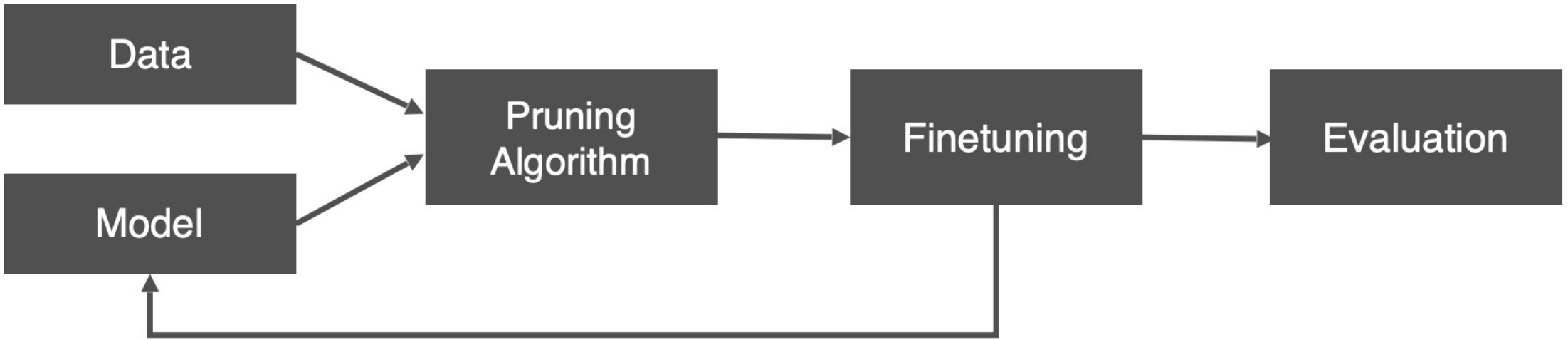

Illustration of pruning pipeline [1]

[1] https://mlsys.org/media/Slides/mlsys/2020/balla(02-14-30)-02-14-30-1413-what_is_the.pdf

Typical Pruning Pipeline: Cyclic Compression

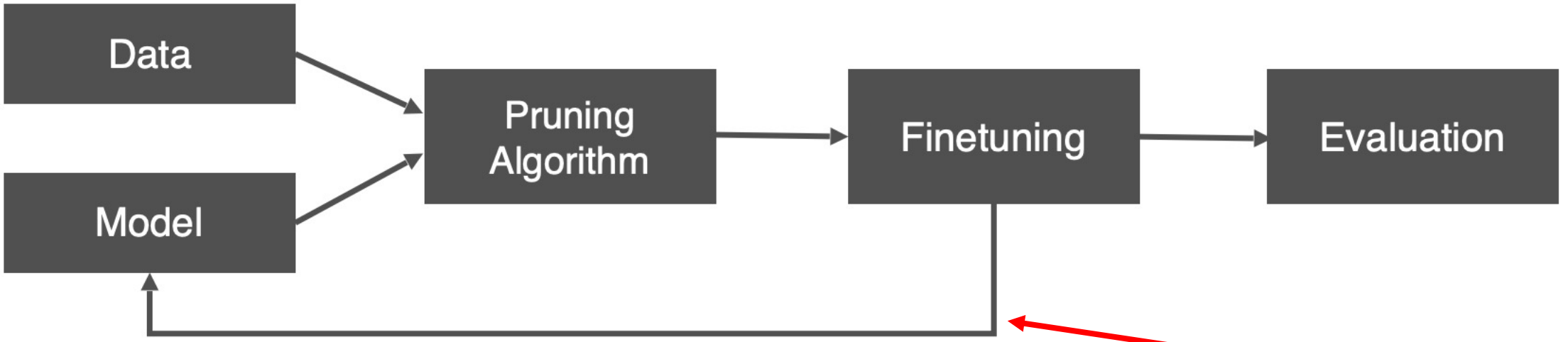

Illustration of pruning pipeline [1]

Usually, we do not compress to the compression ratio we want at once

[1] https://mlsys.org/media/Slides/mlsys/2020/balla(02-14-30)-02-14-30-1413-what_is_the.pdf

Typical Pruning Pipeline

- Many design choices
  - Scoring importance of parameters
  - Structure of induced sparsity
  - Schedule of pruning, training / finetuning

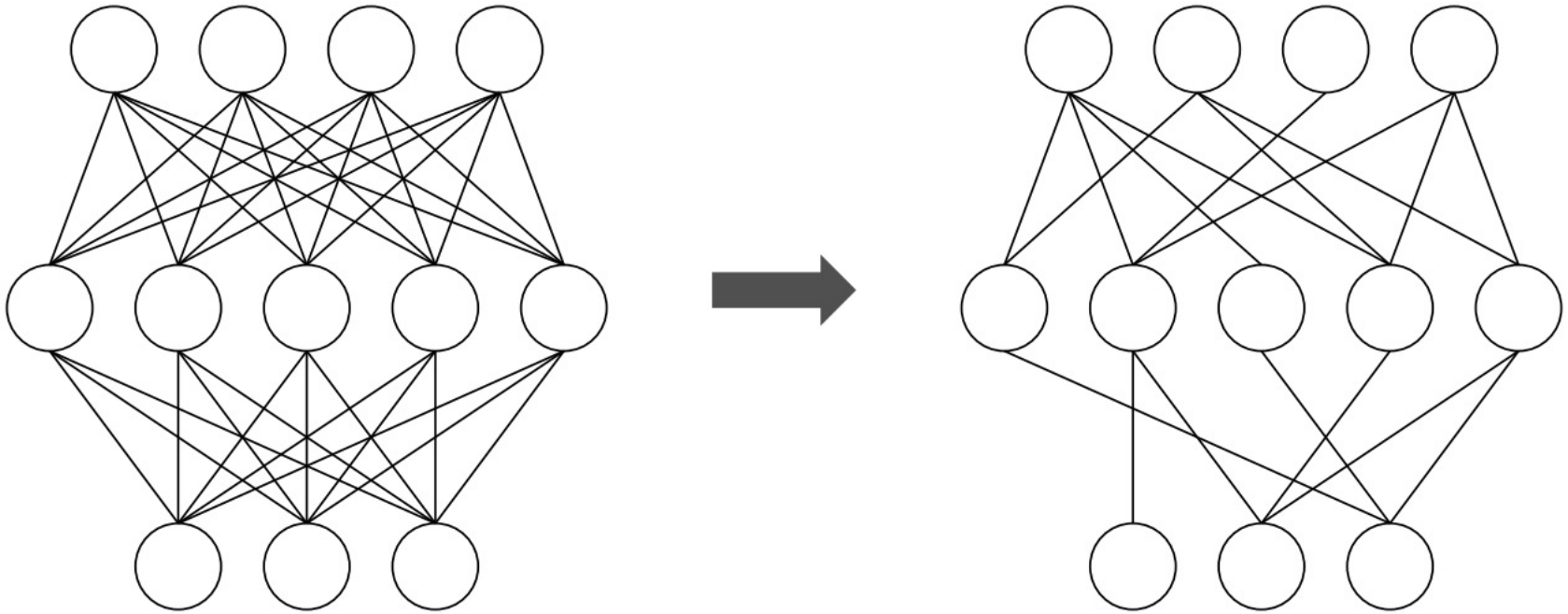

Illustration of neural network pruning

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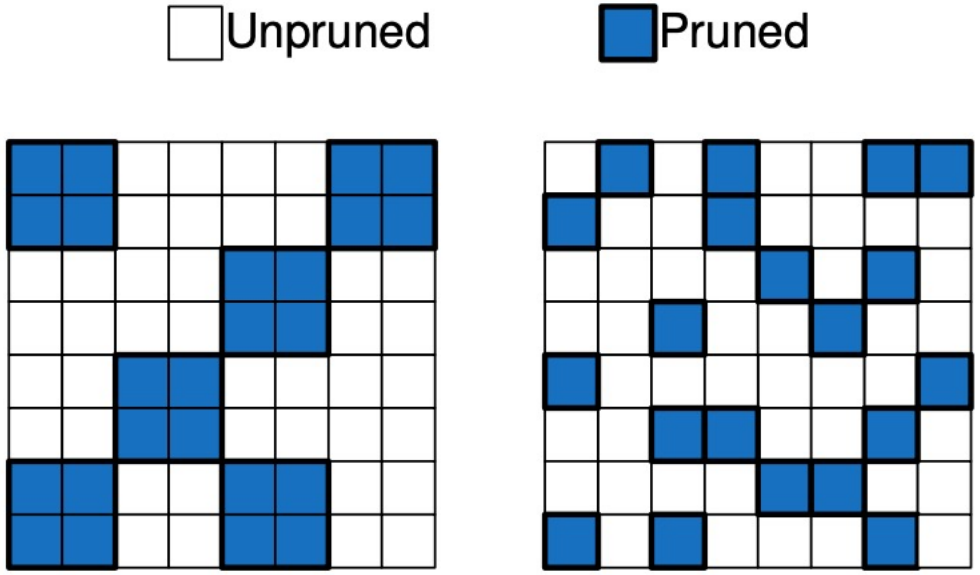
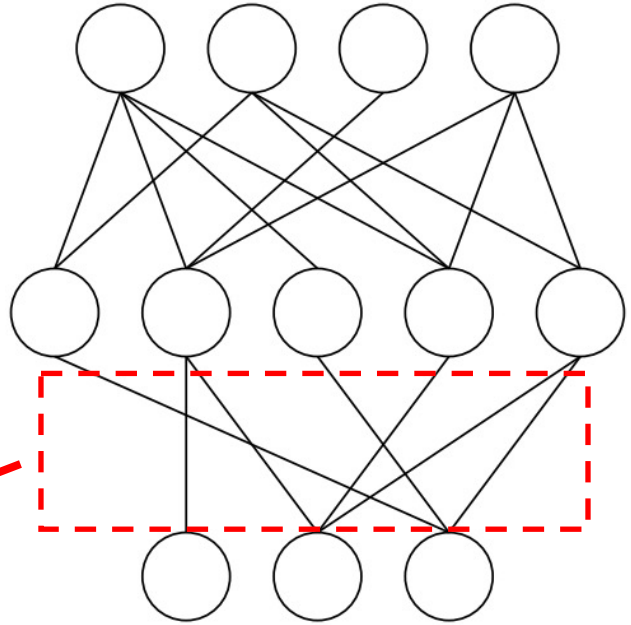


Different structures of sparsity [1]

Connections are represented by a transformation matrix



Pruned neural network

[1] Kwon, S. J., Lee, D., Kim, B., Kapoor, P., Park, B., & Wei, G. Y. (2020). Structured compression by weight encryption for unstructured pruning and quantization. In CVPR.

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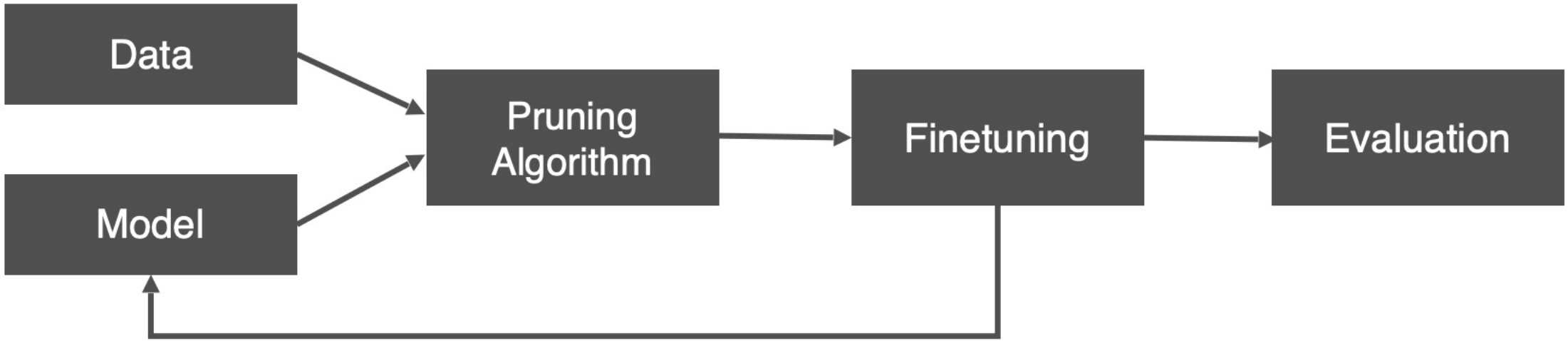


Illustration of pruning pipeline [1]

[1] https://mlsys.org/media/Slides/mlsys/2020/balla(02-14-30)-02-14-30-1413-what_is_the.pdf

Evaluating Neural Network Pruning [1]

- Goal
  - Increase efficiency of network as much as possible with **minimal drop** in quality
- Metrics
  - Quality = Accuracy
  - Efficiency = FLOPs (floating point operations per second), compression, latency
- Trade-off
  - Between **accuracy** and **compression**

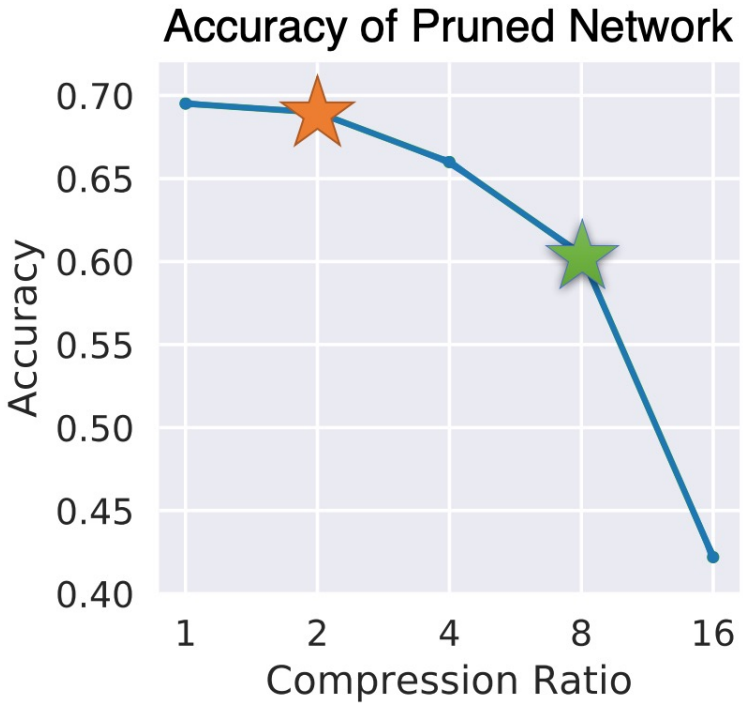
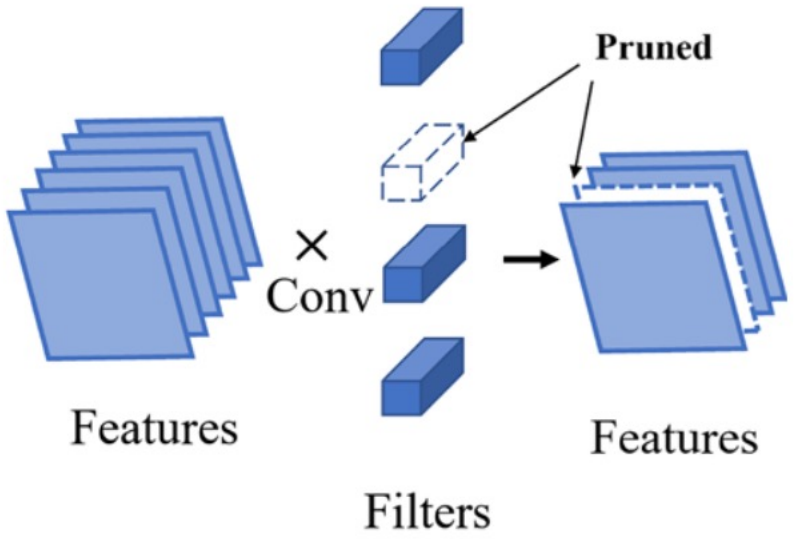


Illustration of trade-off [1]

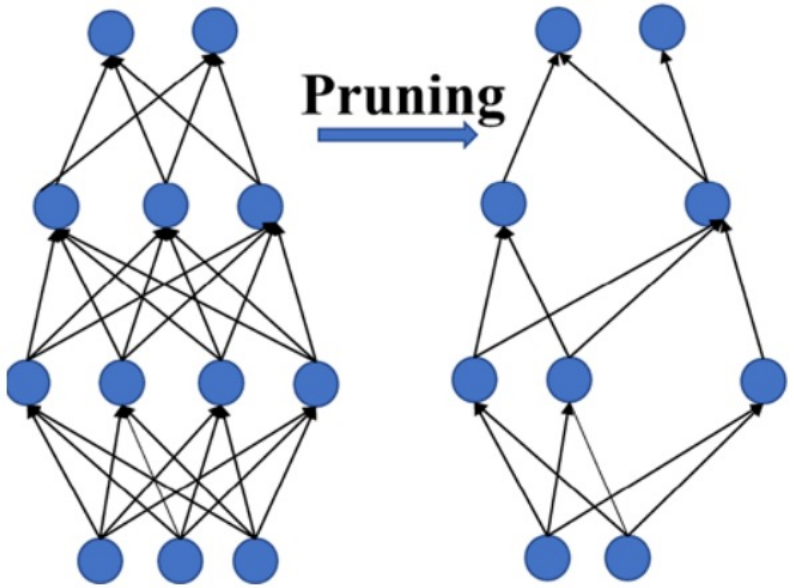
[1] https://mlsys.org/media/Slides/mlsys/2020/balla(02-14-30)-02-14-30-1413-what_is_the.pdf

Structural Pruning vs. Sparse Pruning [1]

- Structural pruning: **a channel, a layer**
- Sparse pruning: **a neuron**



Structural pruning for CNN



Sparse pruning for fully connected networks

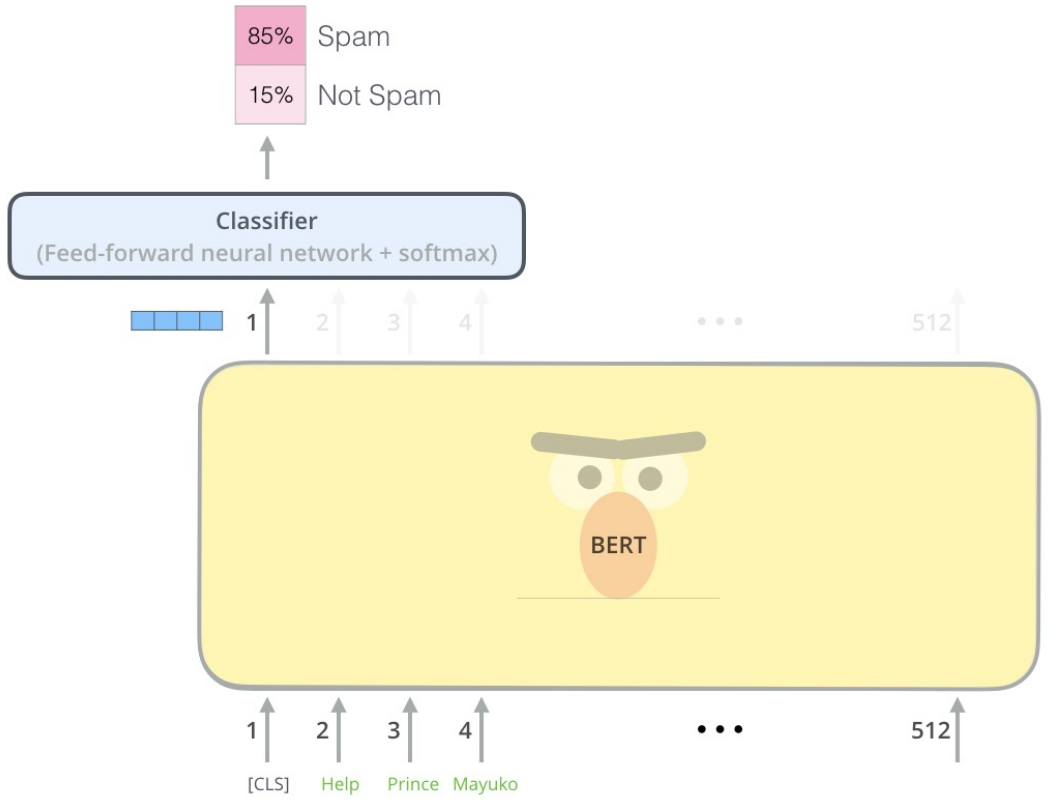
[1] Chen, L., Chen, Y., Xi, J., & Le, X. (2021). Knowledge from the original network: restore a better pruned network with knowledge distillation. Complex & Intelligent Systems, 1-10.

Agenda

- Motivation
- Pruning
- **BERT Model**
- Recent Work

BERT (Bidirectional Encoder Representations from Transformers)

- Published by Google AI Language [1]
- Achieved state-of-the-art results in various NLP/CV tasks [2]

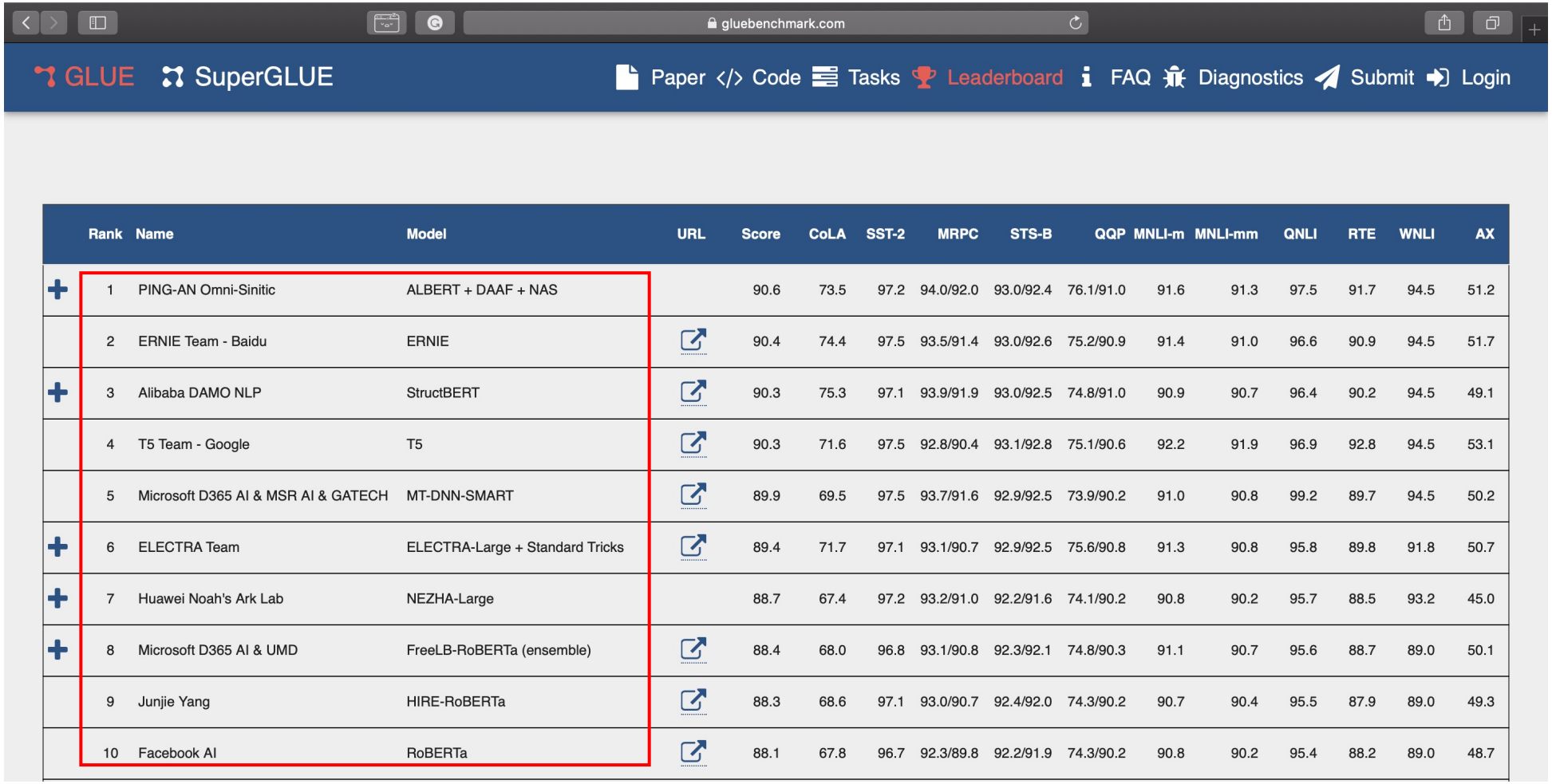


[1] Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*
[2] https://www.garysnotebook.com/20210117_1

Background

- Performance on **GLUE** (General Language Understanding Evaluation) Benchmark
  - The most popular collection for training, evaluating and analyzing NLP systems [1]
  - Constructed by NYU, UW and DeepMind

Support BERT
-> Support All

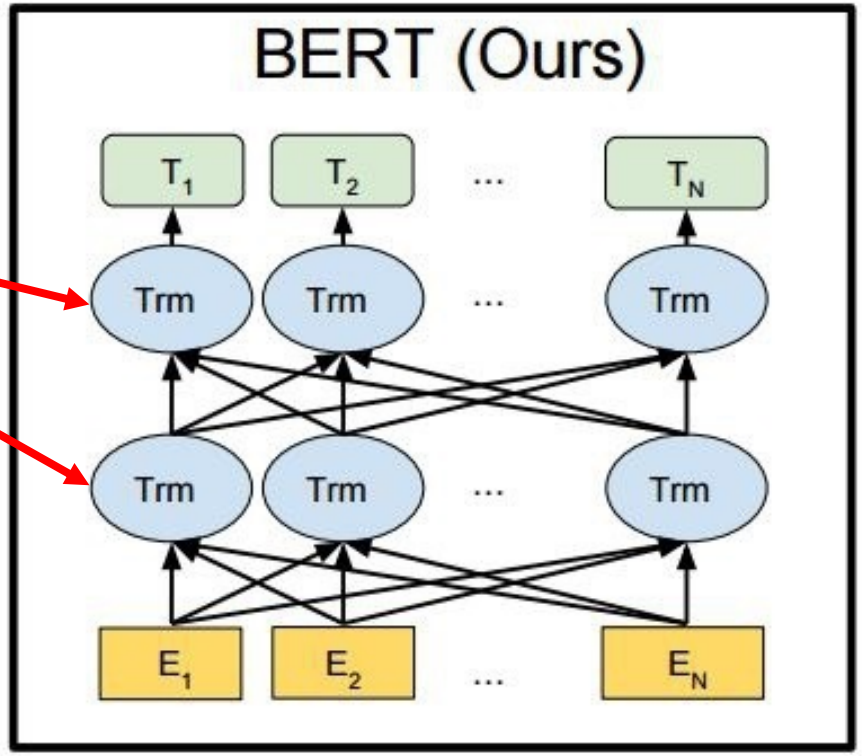


Rank	Name	Model	URL	Score	CoLA	SST-2	MRPC	STS-B	QQP	MNLI-m	MNLI-mm	QNLI	RTE	WNLI	AX
1	PING-AN Omni-Sinitic	ALBERT + DAAF + NAS		90.6	73.5	97.2	94.0/92.0	93.0/92.4	76.1/91.0	91.6	91.3	97.5	91.7	94.5	51.2
2	ERNIE Team - Baidu	ERNIE		90.4	74.4	97.5	93.5/91.4	93.0/92.6	75.2/90.9	91.4	91.0	96.6	90.9	94.5	51.7
3	Alibaba DAMO NLP	StructBERT		90.3	75.3	97.1	93.9/91.9	93.0/92.5	74.8/91.0	90.9	90.7	96.4	90.2	94.5	49.1
4	T5 Team - Google	T5		90.3	71.6	97.5	92.8/90.4	93.1/92.8	75.1/90.6	92.2	91.9	96.9	92.8	94.5	53.1
5	Microsoft D365 AI & MSR AI & GATECH	MT-DNN-SMART		89.9	69.5	97.5	93.7/91.6	92.9/92.5	73.9/90.2	91.0	90.8	99.2	89.7	94.5	50.2
6	ELECTRA Team	ELECTRA-Large + Standard Tricks		89.4	71.7	97.1	93.1/90.7	92.9/92.5	75.6/90.8	91.3	90.8	95.8	89.8	91.8	50.7
7	Huawei Noah's Ark Lab	NEZHA-Large		88.7	67.4	97.2	93.2/91.0	92.2/91.6	74.1/90.2	90.8	90.2	95.7	88.5	93.2	45.0
8	Microsoft D365 AI & UMD	FreeLB-RoBERTa (ensemble)		88.4	68.0	96.8	93.1/90.8	92.3/92.1	74.8/90.3	91.1	90.7	95.6	88.7	89.0	50.1
9	Junjie Yang	HIRE-RoBERTa		88.3	68.6	97.1	93.0/90.7	92.4/92.0	74.3/90.2	90.7	90.4	95.5	87.9	89.0	49.3
10	Facebook AI	RoBERTa		88.1	67.8	96.7	92.3/89.8	92.2/91.9	74.3/90.2	90.8	90.2	95.4	88.2	89.0	48.7

[1] *https://gluebenchmark.com*

Overall

- General architecture
  - Multiple Transformer encoders
  - Input: Embeddings of words
  - Output: Hidden representations of words



Architecture of BERT

- Downstream task
  - e.g., sentence classification

- How BERT works
  - Pre-training
    - The model is trained on unlabeled data over different pre-training tasks.
  - Fine-tuning
    - The model is first initialized with the pre-trained parameters, and all the parameters are fine-tuned using labeled data from the downstream tasks.

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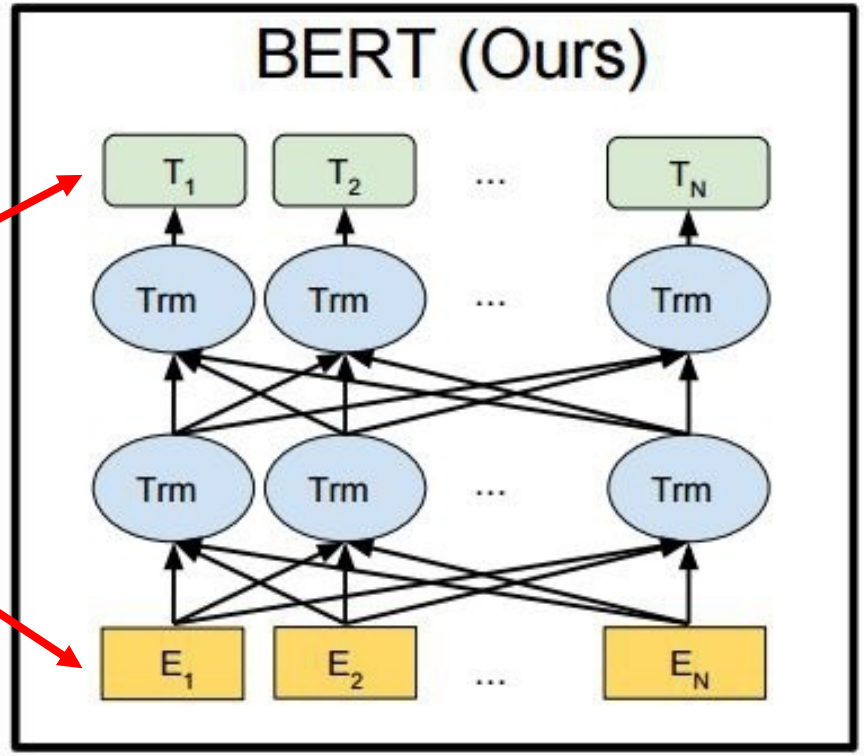

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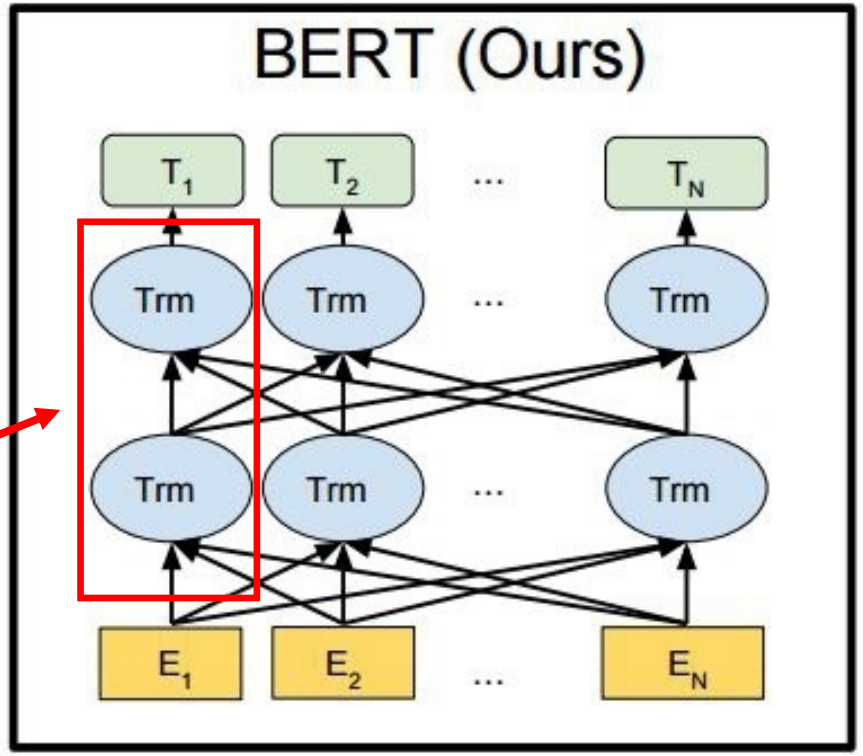
1. Only one series of encoders
2. Shared by all word embeddings



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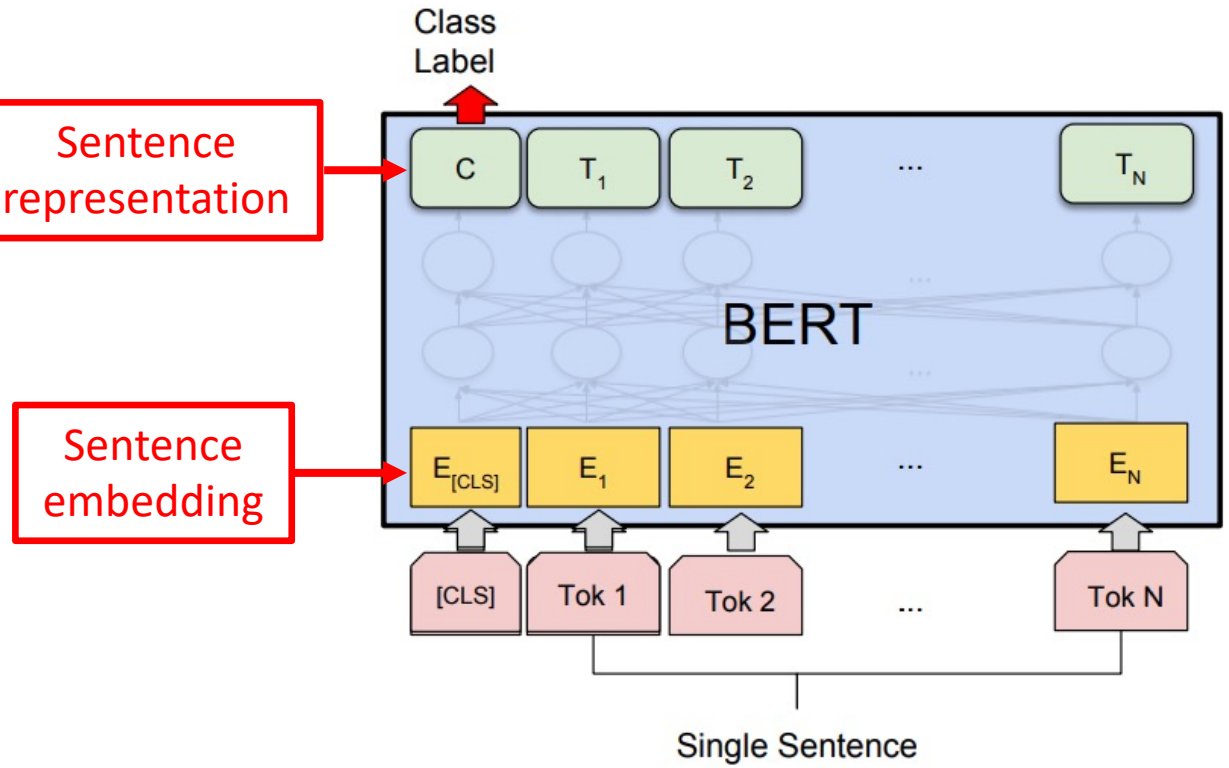

Illustration of BERT on classification

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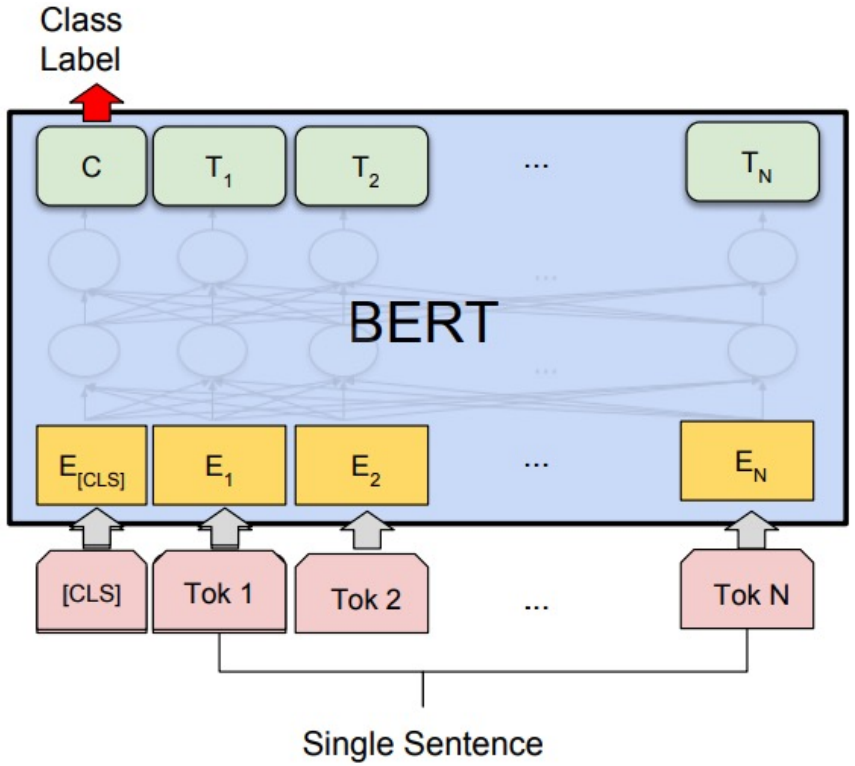

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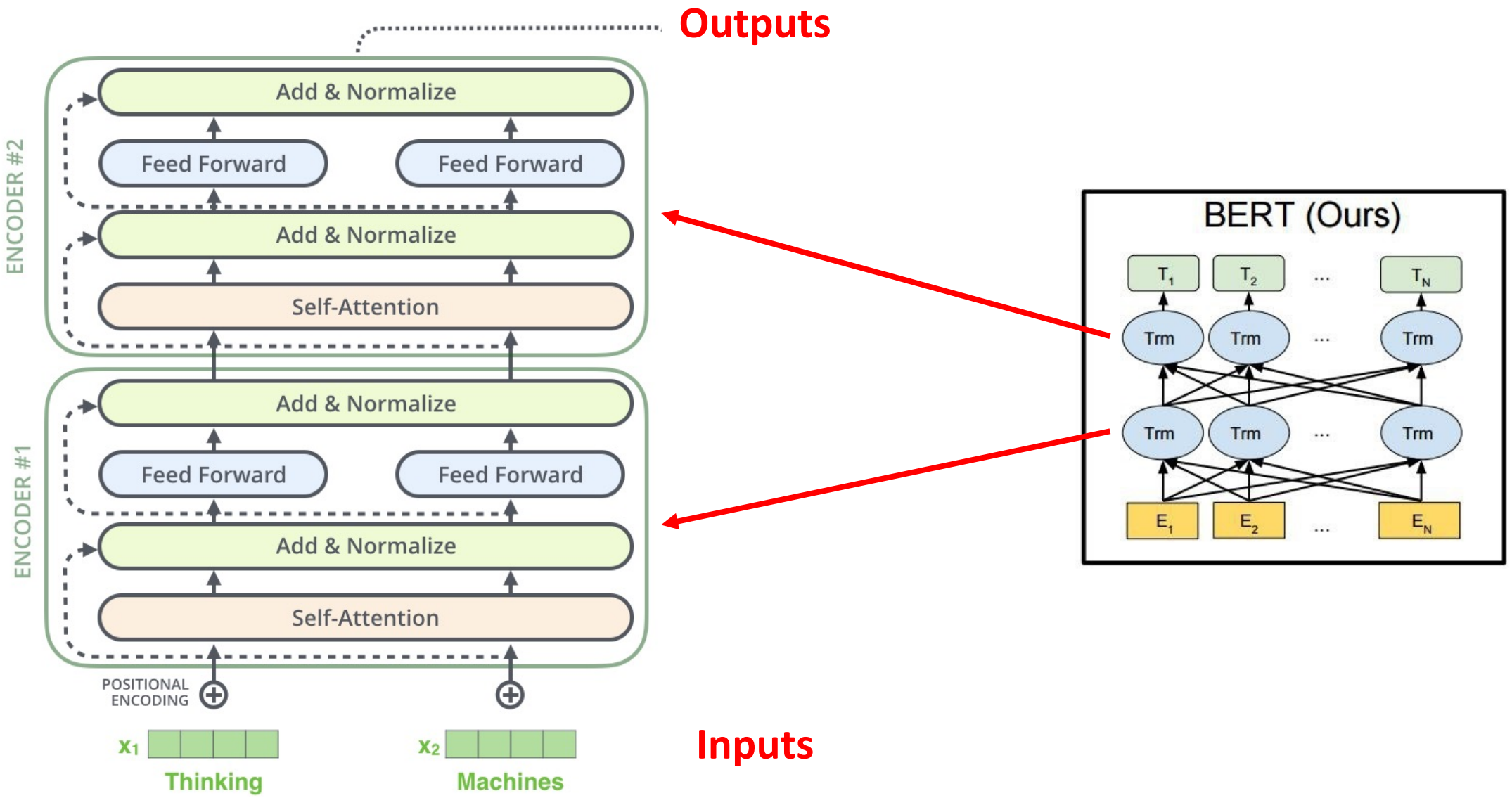
    - The model is first initialized with the pre-trained parameters, and all the parameters are fine-tuned using labeled data from the downstream tasks.

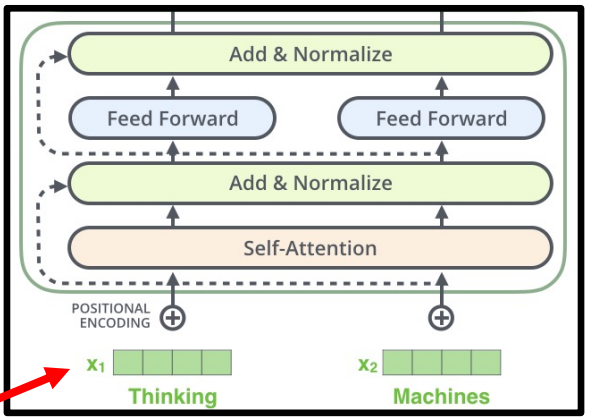
Transformer Encoder



Architecture of Encoder (Two Encoders Here)

Embedding Layer

- Embedding is the element-wise sum of three embeddings
- Goal
  - To give the model a sense of the order of the words



Architecture of Transformer Encoder

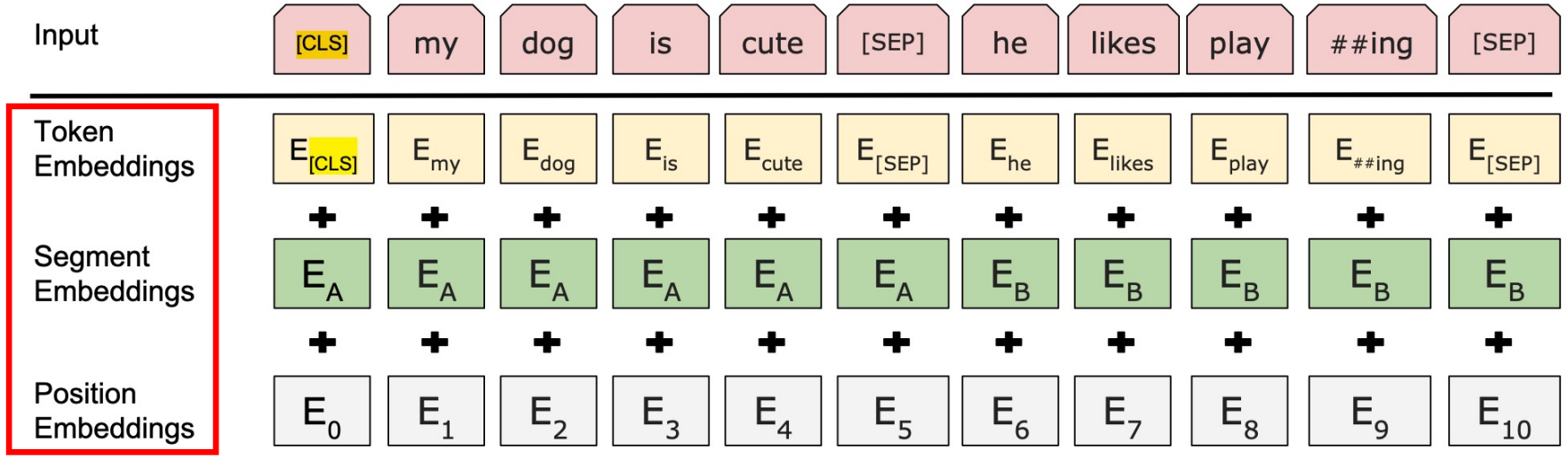


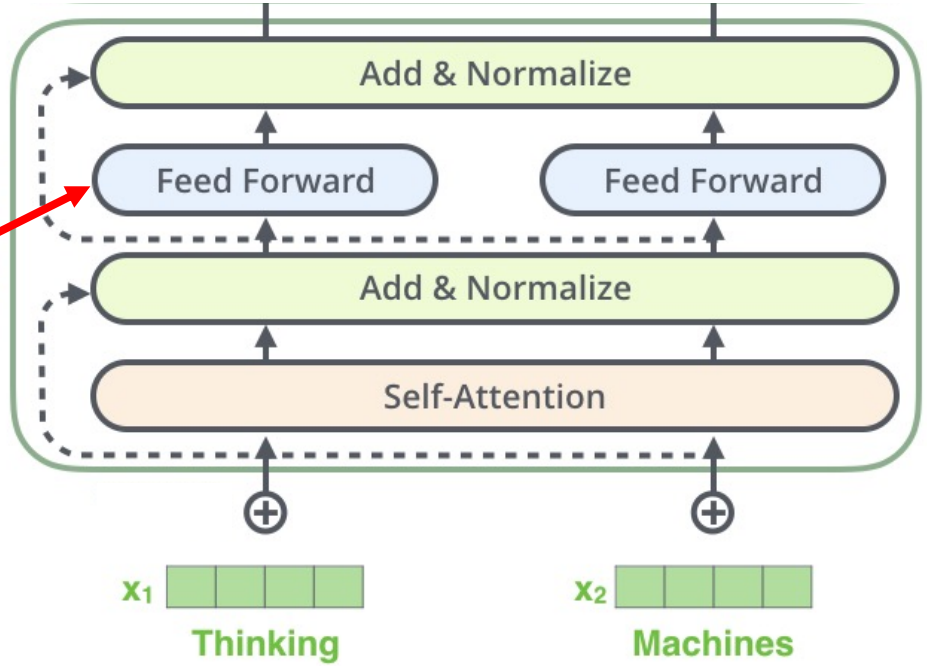
Illustration of BERT Input Representation

Feed-Forward Networks

- Architecture
  - Two linear transformations with a ReLU in between
  - Dimension of input and output =512
  - Dimension of inner-layer = 512*4

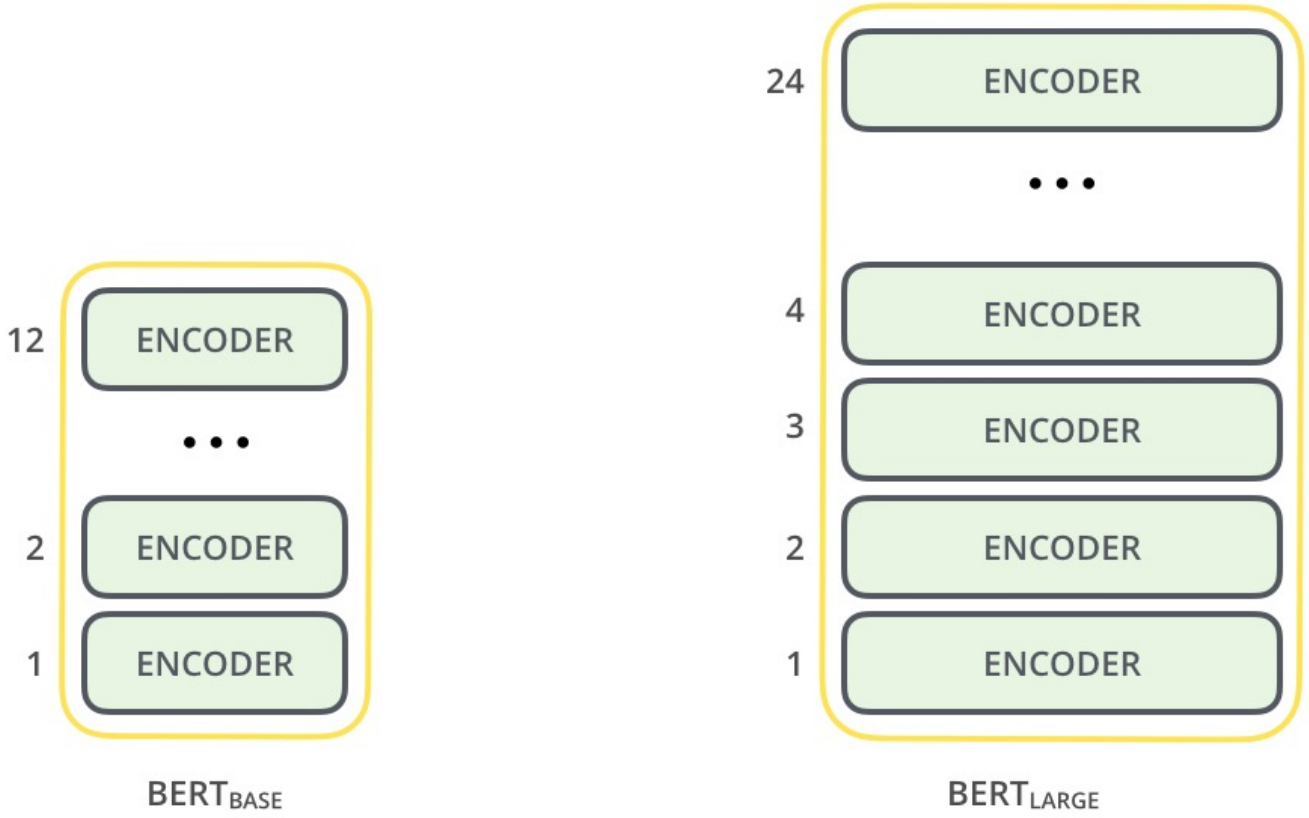
- Formula

$$\mathrm{FFN}(x) = \max(0, xW_1 + b_1)W_2 + b_2$$



$\text{BERT}_{\text{Base}}$ *vs.* $\text{BERT}_{\text{Large}}$

- $\text{BERT}_{\text{Base}}$
  - #parameters = **110M**, #encoders = **12**, #dimension = **768**, #head = **12**
  - #FLOPs = 123M * sentence_length * #Batch



Comparison between $\text{BERT}_{\text{Base}}$ and $\text{BERT}_{\text{Large}}$

Other Transformer/BERT NLP Models

- **XLNet (CMU + Google AI)**
  - Yang, Z., Dai, Z., Yang, Y., Carbonell, J., Salakhutdinov, R. R., & Le, Q. V. (2019). Xlnet: Generalized autoregressive pretraining for language understanding. In *Advances in neural information processing systems* (pp. 5754-5764).
- **ALBERT (Google Language)**
  - Lan, Z., Chen, M., Goodman, S., Gimpel, K., Sharma, P., & Soricut, R. (2019). Albert: A lite bert for self-supervised learning of language representations. arXiv preprint arXiv:1909.11942.
- **RoBERTa (Facebook AI)**
  - Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., ... & Stoyanov, V. (2019). Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.
- **Transformer-XL (CMU + Google Brain)**
  - Dai, Z., Yang, Z., Yang, Y., Carbonell, J., Le, Q. V., & Salakhutdinov, R. (2019). Transformer-xl: Attentive language models beyond a fixed-length context. arXiv preprint arXiv:1901.02860.
- **ERNIE (Baidu)**
  - Sun, Y., Wang, S., Li, Y., Feng, S., Chen, X., Zhang, H., ... & Wu, H. (2019). Ernie: Enhanced representation through knowledge integration. *arXiv preprint arXiv:1904.09223*.
- **GPT-2 (OpenAI)**
  - Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2019). Language models are unsupervised multitask learners. OpenAI Blog, 1(8), 9.

Novel CV Applications using Transformers/BERT [1]

- Transformer for Image Synthesis - 🔗 Esser et al. (2020)
- Transformer for Multi-Object Tracking - 🔗 Sun et al. (2020)
- Transformer for Music Generation - 🔗 Hsiao et al. (2021)
- Transformer for Dance Generation with Music - 🔗 Huang et al. (2021)
- Transformer for 3D Object Detection - 🔗 Bhattacharyya et al. (2021)
- Transformer for Point-Cloud Processing - 🔗 Guo et al. (2020)
- Transformer for Time-Series Forecasting - 🔗 Lim et al. (2020)
- Transformer for Vision-Language Modeling - 🔗 Zhang et al. (2021)
- Transformer for Lane Shape Prediction - 🔗 Liu et al. (2020)
- Transformer for End-to-End Object Detection - 🔗 Zhu et al. (2021)

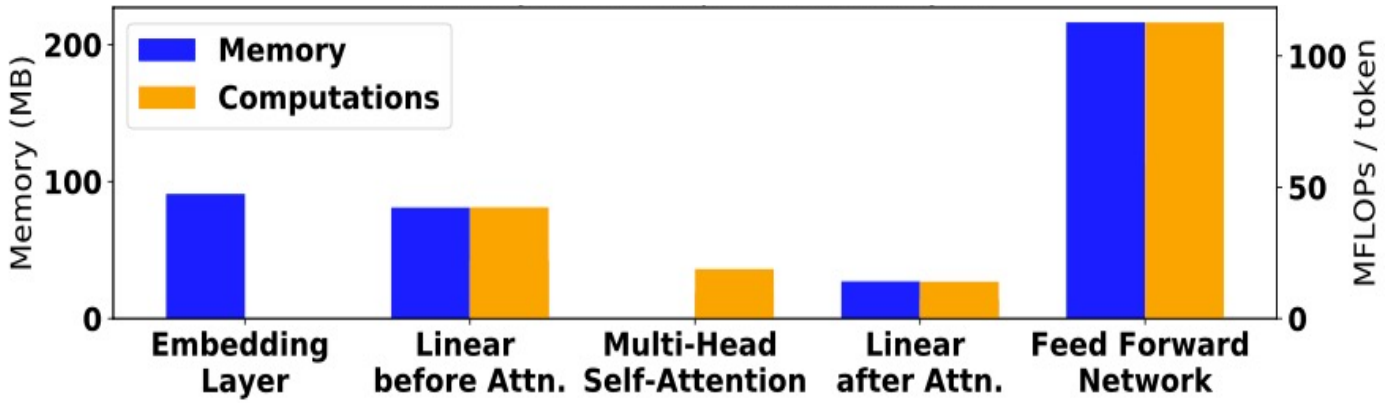
[1] https://paperswithcode.com/newsletter/3

Agenda

- Motivation
- Pruning
- BERT Model
- **Recent Work**

Parameter / FLOPs Distributions

- Memory (#parameters) is dominated by **embedding** and **linear layers**
- FLOPs is dominated by **linear layers**



Memory and computation analysis [1]

[1] BGanesh, P., etc. (2020). Compressing large-scale transformer-based models: A case study on bert. arXiv preprint arXiv:2002.11985.

Preliminary: Knowledge Distillation

- Inputs: teacher model, student model, data
- Output: student with similar behaviors of teacher
- How? Minimize the difference between the outputs of teacher and student

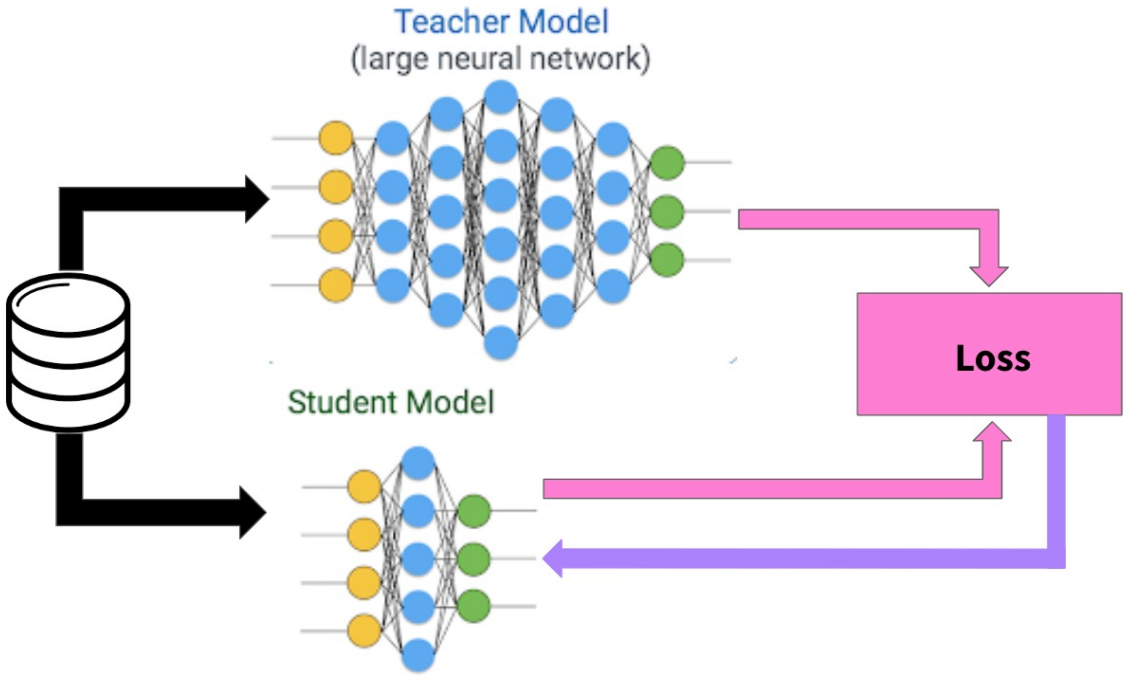
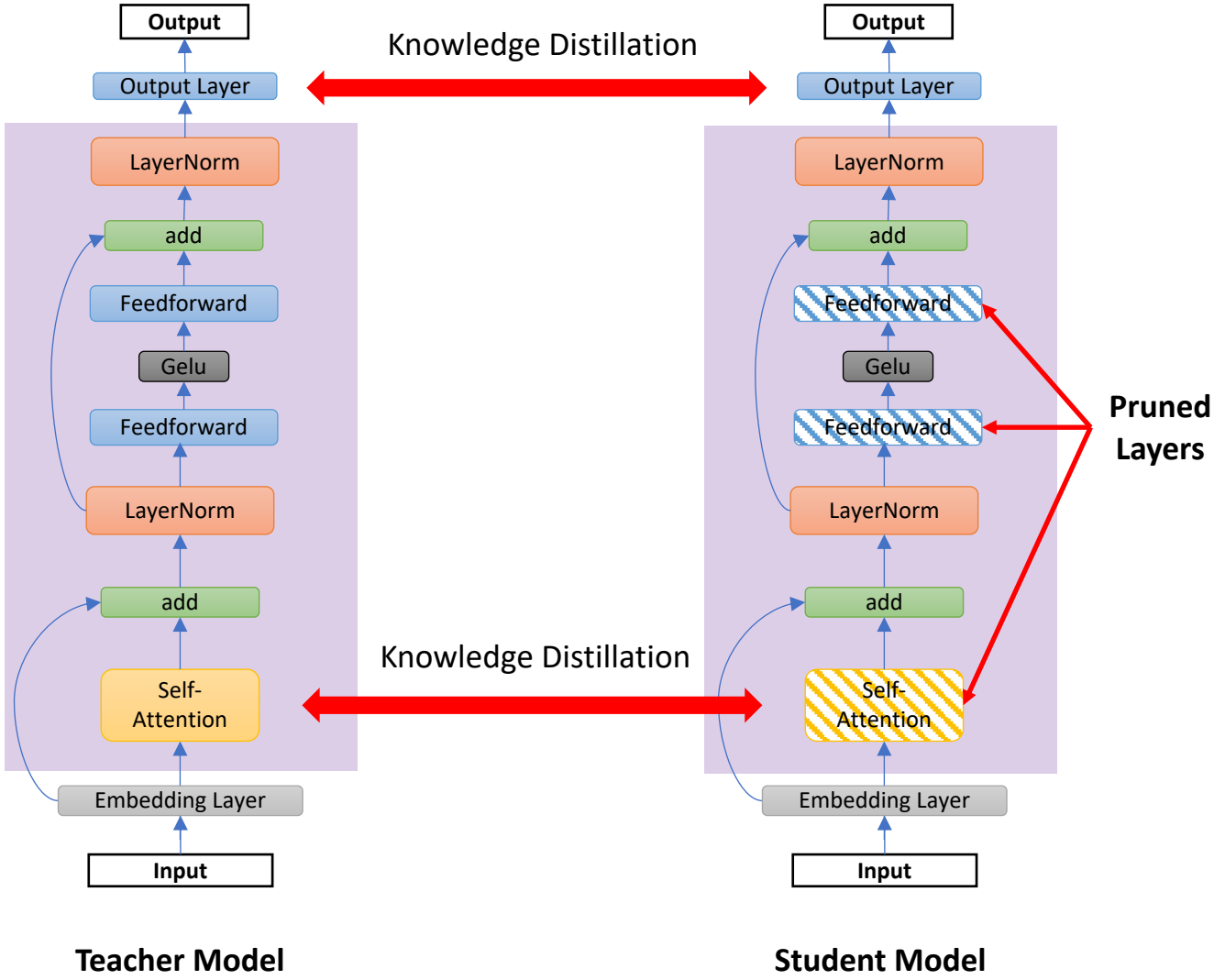


Illustration of knowledge distillation [1]

[1] https://towardsdatascience.com/knowledge-distillation-simplified-dd4973dbc764

SparseBERT: Knowledge-Aware Sparse Pruning [1]

- Motivation: gap of pruning
- Core idea: Pruning while distillation



[1] Dongkuan Xu, Ian En-Hsu Yen, Jinxi Zhao, Zhibin Xiao. Rethinking Network Pruning -- under the Pre-train and Fine-tune Paradigm. *NAACL 2021.*

SparseBERT: Knowledge-Aware Sparse Pruning [1]

- Achieved SOTA
  - Compression ratio = **x20**
  - But only **1.4% performance drop**

Method	Remain. Weights	QNLI (Acc)	MRPC (F1)	RTE (Acc)	CoLA (Mcc)	Avg.
		Without Pruning				
BERT-base	-	91.8	88.6	69.3	56.3	76.5
ELMo	-	71.1	76.6	53.4	44.1	61.3
		Structural Pruning				
$BERT_6$-PKD	50%	89.0	85.0	65.5	45.5	71.3
BERT-of-Theseus	50%	89.5	89.0	68.2	51.1	74.5
DistilBERT	50%	89.2	87.5	59.9	51.3	72.0
$MiniLM_6$	50%	91.0	88.4	71.5	49.2	75.0
$TinyBERT_6$	50%	90.4	87.3	66.0	54.0	74.4
$TinyBERT_4$	18%	88.7	86.8	66.5	49.7	72.9
		Sparse Pruning				
BERT-Tickets	30-50%	88.9	84.9	66.0	53.8	73.2
CompressBERT	10%	76.8	-	-	-	-
RPP	11.6%	88.0	81.9	67.5	-	-
SparseBERT	5%	90.6	88.5	69.1	52.1	75.1

Table 1: Comparison on the dev sets of GLUE.

[1] Dongkuan Xu, Ian En-Hsu Yen, Jinxi Zhao, Zhibin Xiao. Rethinking Network Pruning -- under the Pre-train and Fine-tune Paradigm. *NAACL 2021.*

SparseBERT: Knowledge-Aware Sparse Pruning [1]

- Sparse pruning: ***Trending and with promising future***
- *Hardware performance*

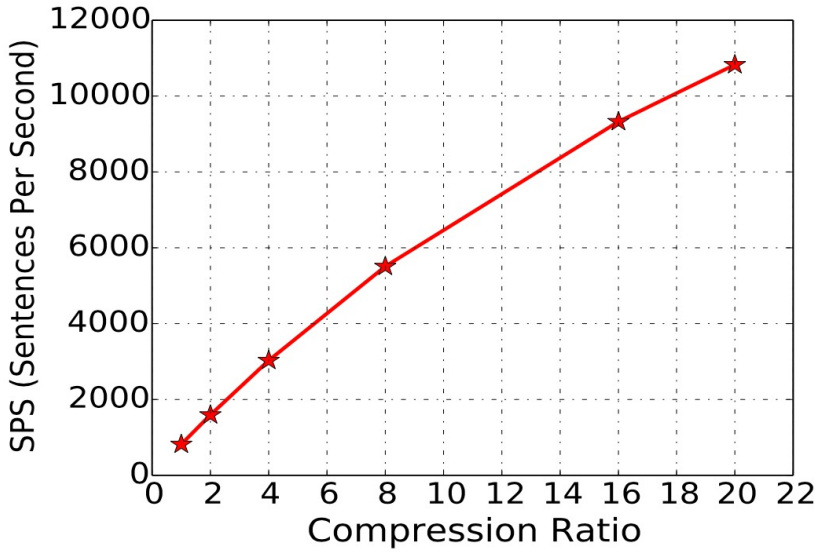
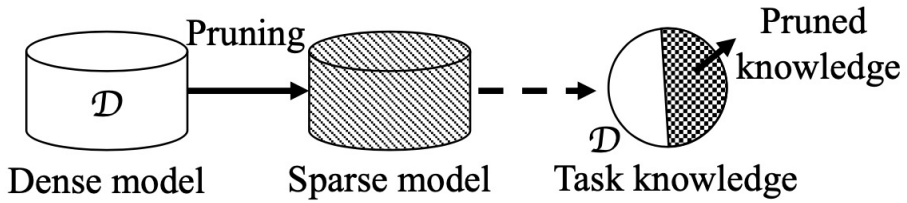


Figure 6: Hardware performance under different compression ratios on the MRPC dataset, with 818, 1594, 3029, 5508, 9326, and 10826 SPS (sentences per second) respectively.

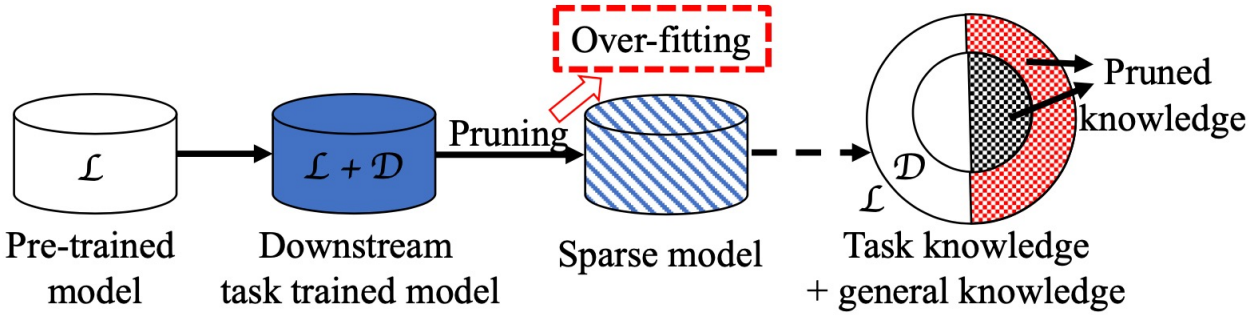
[1] Dongkuan Xu, Ian En-Hsu Yen, Jinxi Zhao, Zhibin Xiao. Rethinking Network Pruning -- under the Pre-train and Fine-tune Paradigm. *NAACL 2021.*

Sparse Progressive Distillation: Resolving Overfitting under Pretrain-and-Finetune Paradigm [1]

- Motivation



(a) Pruning under non pretrain-and-finetune paradigm (e.g., CNN, LSTM, GNN)



(b) Pruning under pretrain-and-finetune paradigm

[1] Huang, Shaoyi, Dongkuan Xu, Ian EH Yen, etc. "Sparse Progressive Distillation: Resolving Overfitting under Pretrain-and-Finetune Paradigm." arXiv preprint arXiv:2110.08190 (2021).

Sparse Progressive Distillation[1]

- Motivation

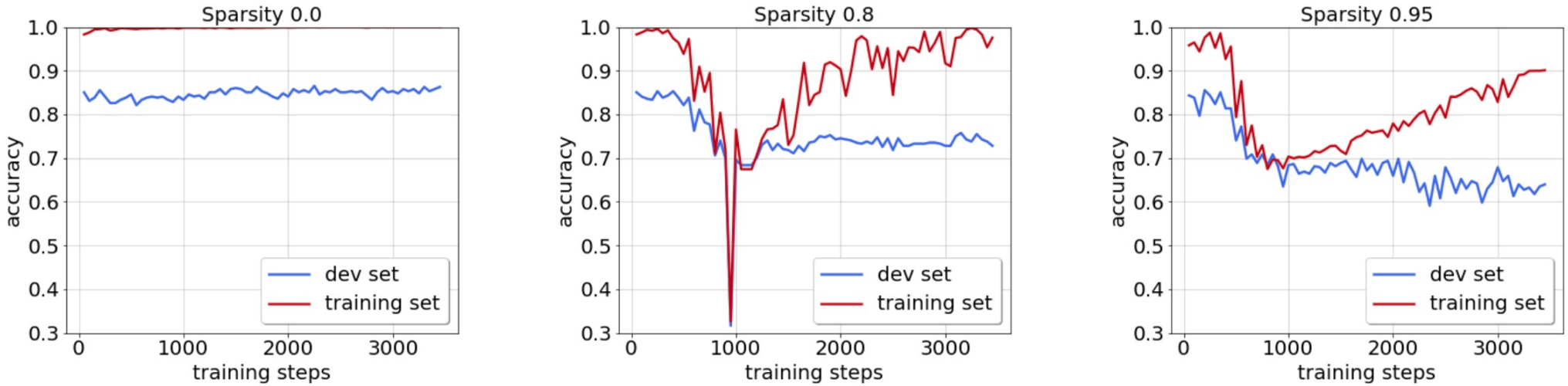


Figure 2: Visualization of the overfitting issue when pruning weight matrices of $\text{BERT}_{\text{BASE}}$ on MRPC at the fine-tuning phase. Overfitting issue becomes more severe with the increasing of pruning rate.

[1] Huang, Shaoyi, Dongkuan Xu, Ian EH Yen, etc. "Sparse Progressive Distillation: Resolving Overfitting under Pretrain-and-Finetune Paradigm." arXiv preprint arXiv:2110.08190 (2021).

Sparse Progressive Distillation [1]

- Methodology (main idea)

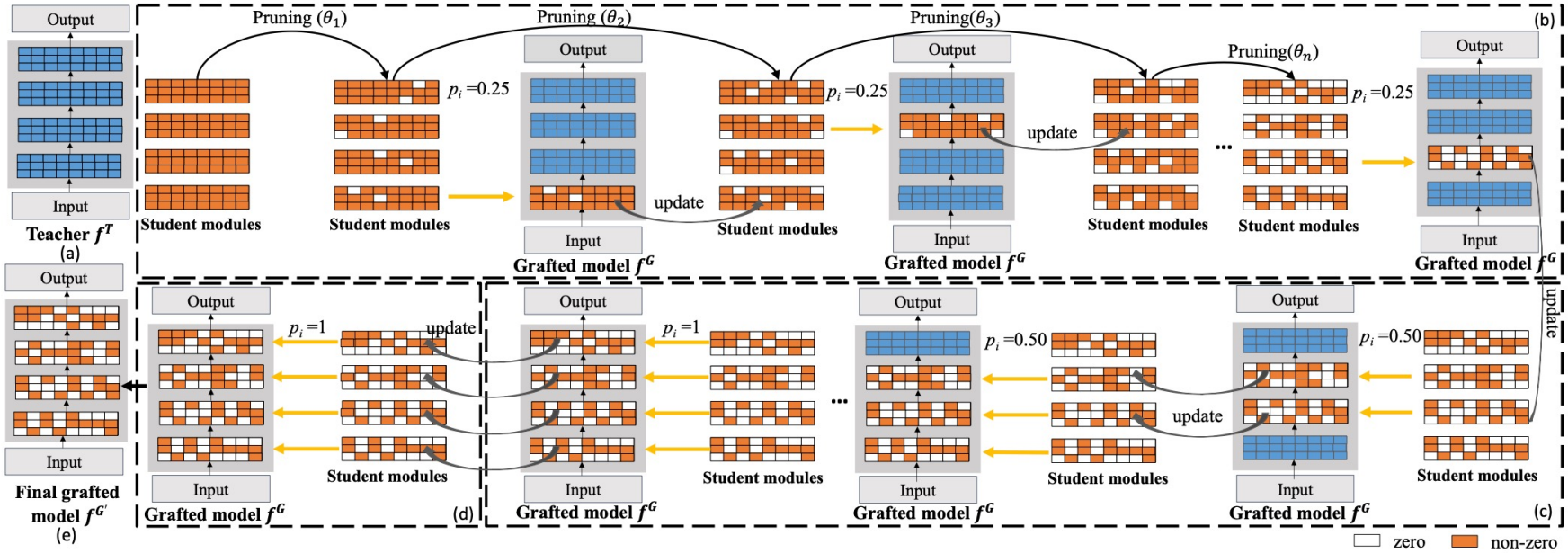


Figure 3: An overview of our sparse progressive distillation method. (a) Teacher model. (b) Pruning to target sparsity. (c) Module grafting with increasing probability. (d) Fine-tuning. (e) Final grafted model.

[1] Huang, Shaoyi, Dongkuan Xu, Ian EH Yen, etc. "Sparse Progressive Distillation: Resolving Overfitting under Pretrain-and-Finetune Paradigm." arXiv preprint arXiv:2110.08190 (2021).

Sparse Progressive Distillation [1]

- Experimental Results

Model	#Param	MNLI (393k) Acc	QQP (364k) F1	QNLI (105k) Acc	SST-2 (67k) Acc	CoLA (8.5k) Mcc	STS-B (5.7k) Spea	MRPC (3.7k) F1	RTE (2.5k) Acc	#Avg.
$\text{BERT}_{\text{BASE}}$ (Devlin et al., 2018)	109M	84.6	91.2	90.5	93.5	52.1	85.8	88.9	66.4	81.6
$\text{BERT}_{\text{BASE}}$ (ours)	109M	83.9	91.4	91.1	92.7	53.4	85.8	89.8	66.4	81.8
Fine-tuned $\text{BERT}_{\text{BASE}}$ (teacher)	109M	84.0	91.4	91.6	92.9	57.9	89.1	90.2	72.2	83.7
non-progressive										
BERT_6-PKD (Sun et al., 2019)	67M	81.5	88.9	88.4	91.0	45.5	86.2	85.7	66.5	79.2
DistilBERT (Sanh et al., 2019)	67M	82.2	88.5	89.2	92.7	51.3	86.9	87.5	59.9	79.8
MiniLM_6 (Wang et al., 2020)	67M	84.0	91.0	91.0	92.0	49.2	-	88.4	71.5	-
TinyBERT_6 (Jiao et al., 2020)	67M	84.5	91.1	91.1	93.0	54.0	90.1	90.6	**73.4**	83.5
SparseBERT (Xu et al., 2021)	67M	84.2	91.1	91.5	92.1	57.1	89.4	89.5	70.0	83.1
E.T. (Chen et al., 2021)	67M	83.7	86.5	88.9	90.8	55.6	87.6	88.7	69.5	81.4
progressive										
Theseus (Xu et al., 2020)	67M	82.3	89.6	89.5	91.5	51.1	88.7	89.0	68.2	81.2
SPD (ours)	67M	**85.0**	**91.4**	**92.0**	**93.0**	**61.4**	**90.1**	**90.7**	72.2	**84.5**

Table 1: Results on the dev set of the GLUE benchmark. The results of DistilBERT and TinyBERT_6 are taken from (Jiao et al., 2020). Mcc refers to Matthews correlation, and Spea refers to Spearman.

[1] Huang, Shaoyi, Dongkuan Xu, Ian EH Yen, etc. "Sparse Progressive Distillation: Resolving Overfitting under Pretrain-and-Finetune Paradigm." arXiv preprint arXiv:2110.08190 (2021).

All The Ways You Can Compress BERT [1]

- Literatures

Paper	Prune	Factor	Distill	W. Sharing	Quant.	Pre-train	Downstream
Compressing BERT: Studying the Effects of Weight Pruning on Transfer Learning	☑					☑	☑
Are Sixteen Heads Really Better than One?	☑						☑
Pruning a BERT-based Question Answering Model	☑						☑

- Experimental Results

Paper	Reduction	Of	Speed-up	Accuracy?	Comments
Compressing BERT: Studying the Effects of Weight Pruning on Transfer Learning	30%	params	?	Same	Some interesting ablation experiments and fine-tuning analysis
Are Sixteen Heads Really Better than One?	50-60%	attn heads	1.2x	Same	
Pruning a BERT-based Question Answering Model	50%	attn Heads + FF	2x	-1.5 F1	

[1] http://mitchgordon.me/machine/learning/2019/11/18/all-the-ways-to-compress-BERT.html

Thank You!

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