Natural Language Processing

Efficiency

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April 24, 2023

(many slides credits to EMNLP 2020 High Performance NLP tutorial)

Efficiency

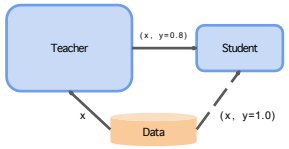
Today

- Knowledge Distillation
- Quantization
- Pruning
- Efficient Attention
- Efficient Architectures

Knowledge Distillation

Hinton et al., 2015

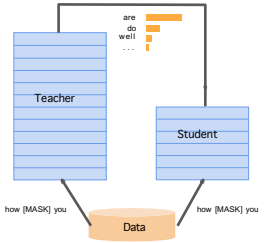
Distilling the Knowledge in a Neural Network



Knowledge Distillation for Pre-training

Sanh et al., 2019

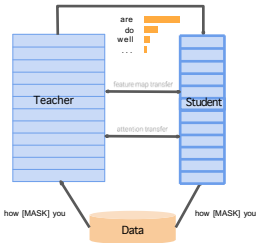
DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter



Knowledge Distillation for Pretraining

Sun et al., 2019

MobileBERT: a Compact Task-Agnostic BERT for Resource-Limited Devices



Knowledge Distillation for Fine-Tuning

1 Regular Pre-training

Student

how [MASK] you

Data

Turc et al., 2019

Well-Read Students Learn Better: On the Importance of Pre-training Compact Models

2 Fine-tuning via distillation

Teacher

(x , y=0.8)

Student

x

Data

3 (Optional) regular fine-tuning

Student

(x , y=1.0)

Data

Knowledge Distillation for Fine-Tuning

1 Pre-training via distillation

Jiao et al., 2019

TinyBERT: Distilling BERT for Natural Language Understanding

Teacher

per-layer transfer

Student

embeddings transfer

(x , y=0.8)

how [MASK] you

Data

2 Fine-training via distillation

Teacher

per-layer transfer

Student

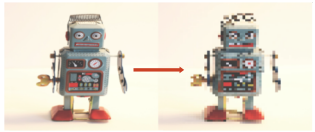
embeddings transfer

(x , y=1)

Data

84

Quantization



Quantization

Definition

$Q(z) = q_j \qquad z \in (t_j, t_{j+1}] \qquad j=0, \ldots, 2^k-1$

q_j: real-valued tensor (activation or weight)

Q: quantization operator

k: quantization precision

Linear Quantization

$z = S\,(q_j - Z)$

Z: zero point

S: scaling factor

Quantization

Jacob et al., 2017

Quantization and Training of Neural Networks for Efficient Integer-Arithmetic-Only Inference

Quantization-Aware Training

Forward pass in

Backward pass in

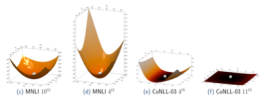
$w^{t+1} = \text{UpdateParameter}(w^t, \frac{\partial L}{\partial \hat{w}^t}, \eta^t)$

Quantization

Shen et al., 2019

Q-BERT: Hessian Based Ultra Low Precision Quantization of BERT

- **Q-BERT**: uniform quantization to $\{0, \ldots, 2^k-1\}$ with:
  - mixed precision (higher Hessian spectrum => higher precision for layer)
  - group precision (each matrix W_q W_k W_v W_o is its own group)



Quantization with Distillation

Zhang et al., 2020
TernaryBERT: Distillation-aware Ultra-low Bit BERT

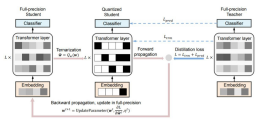


Figure 2: Depiction of the proposed distillation-aware ternarization of BERT model.

Pruning

Definition

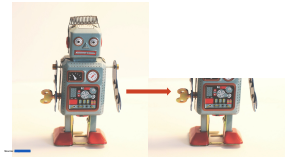
Pruning removes "unimportant" weights from a network:

$$a = (W \odot M)\, x$$

input, pruning mask, model weight, activation

Main Questions (Hoefler et al. and Gale)

- Which weights should be eliminated?
- How should the remaining weights be adjusted?
- How can such network pruning be done in an efficient way?



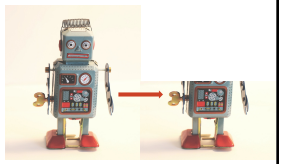
Pruning

LeCun et al., 1990
OBD: Optimal Brain Damage

Hassibi and Stork, 1993
OBS: Second order derivatives for network pruning: Optimal Brain Surgeon

Main Idea

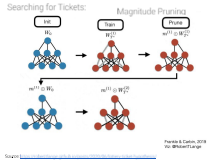
- Start with a "reasonably large" network
- Train it to convergence
- Prune in multiple iterations, based on second-order derivatives:
  - OBD: prune and train
  - OBS: prune and update weights based on second-order statistics



Lottery Ticket Hypothesis

Frankle and Carbin, 2018
The Lottery Ticket Hypothesis: Finding Sparse, Trainable Neural Networks

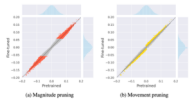
The Lottery Ticket Hypothesis. *A randomly-initialized, dense neural network contains a subnetwork that is initialized such that—when trained in isolation—it can match the test accuracy of the original network after training for at most the same number of iterations.*



Movement Pruning

Sanh et al., 2020
Movement Pruning: Adaptive Sparsity by Fine-Tuning

- **First-order** strategy: "instead of selecting weights that are far from zero, we retain connections that are moving away from zero during the training process"
- The pruning mask $\mathbf{M}$ is learnt together with the model parameters.
  - **hard** version: $\mathbf{M} = \text{Top}_\nu(\mathbf{S})$, where score $\mathbf{S}$ is learnt and ν is a hyperparameter
  - **soft** version: $\mathbf{M} = (\mathbf{S} > \tau)$, where score $\mathbf{S}$ is learnt and threshold τ is a hyperparameter.



(a) Magnitude pruning (b) Movement pruning

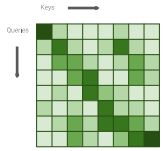
Movement Pruning

	Unstructured Pruning	Structured Pruning
Storage	✓	✓
Inference	✗	✓
Reliability	✓	✗

Efficient Attention

Goal:

Approximate the computation of attention via more efficient operations



Efficient Attention

- Data-Independent
- Data-Dependent
- Kernels
- Recurrence
- I/O Aware-Attention

Data-Independent Patterns

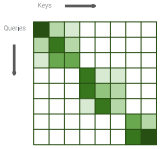
Blockwise Patterns

Divide sequence into local blocks and restrict attention within them

Examples:

Blockwise Transformer (Qiu et al., 2019)

Local Attention (Parmar et al., 2018)



Data-Independent Patterns

Strided Patterns

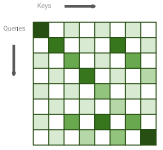
Skip some query/key pairs.

Quadratic in sequence length / stride

Examples:

Sparse Transformer (Child et al., 2019)

Longformer (Beltagy et al., 2020)



Data-Independent Patterns

Diagonal Patterns

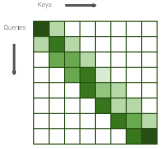
Compute attention over the diagonal.

Linear in sequence length and window size.

Examples:

Longformer (Beltagy et al., 2020)

Big Bird (Zaheer et al., 2020)



Data-Independent Patterns

Global Attention

Applied to one or a few special tokens, often prepended to the sequence.

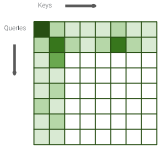
Usually combined with other patterns

Examples:

Big Bird (Zaheer et al., 2020)

Longformer (Beltagy et al., 2020)

ETC (Ainslie et al., 2020)



Data-Dependent Patterns

Buckets

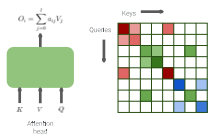
Create buckets/clusters and compute attention within.

Ideally, buckets should contain the highests attention weights in the matrix

Examples:

Reformer (Kitaev et al., 2020)

Routing Transformer (Roy et al., 2020)



Data-Dependent Patterns

Buckets: Hashing

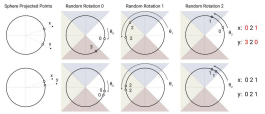
Locality-Sensitive Hashing (LSH)

Key idea: take a random projection matrix R, compute hash for a vector x through:

$$h(x) = \arg\max([xR; -xR])$$

Examples:

Reformer (Kitaev et al., 2020)



Data-Dependent Patterns

Compression

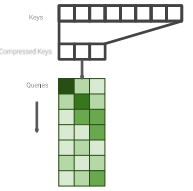
E.g. pooling, strided convolution, low-rank projections with learnable weights

Examples:

Compressed Attention (Liu et al., 2018)

Linformer (Wang et al., 2020)

Synthesizers (Tay et al., 2020)



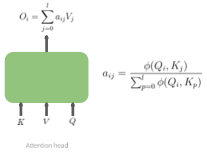
Kernel

Kernels

Recap: attention in its general form uses a similarity function $\phi(Q_i, K_j)$

However, we can simplify things with a decomposable **kernel**:

$$\phi(Q_i, K_j) = \phi(Q_i)^\top \phi(K_j)$$



$$a_{ij} = \frac{\phi(Q_i, K_j)}{\sum_{p=0}^{I} \phi(Q_i, K_p)}$$

Kernel

Kernels

Recap: attention in its general form uses a similarity function $\phi(Q_i, K_j)$

However, we can simplify things with a decomposable **kernel**:

$$\phi(Q_i, K_j) = \phi(Q_i)^\top \phi(K_j)$$

$$O_i = \sum_{j=0}^{I} a_{ij} V_j \qquad a_{ij} = \frac{\phi(Q_i, K_j)}{\sum_{p=0}^{I} \phi(Q_i, K_p)}$$

$$O_i = \frac{\sum_{j=0}^{I} \phi(Q_i)^\top \phi(K_j) V_j}{\sum_{j=0}^{I} \phi(Q_i)^\top \phi(K_j)}$$

$$O_i = \frac{\phi(Q_i)^\top \sum_{j=0}^{I} \phi(K_j) V_j}{\phi(Q_i)^\top \sum_{j=0}^{I} \phi(K_j)}$$

Independent of query!

Kernel

Kernels

Recap: attention in its general form uses a similarity function $\phi(Q_i, K_j)$

However, we can simplify things with a decomposable **kernel**:

$$\phi(Q_i, K_j) = \phi(Q_i)^\top \phi(K_j)$$

In vectorized form:

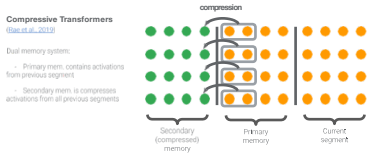
$$O = \phi(Q)\phi(K)^\top V$$

Compute this $d' \times d$ matrix first

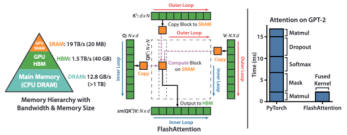
This allows us to compute attention in **linear** time with respect to sequence length!

In Katharopoulos et al., 2020

Recurrence

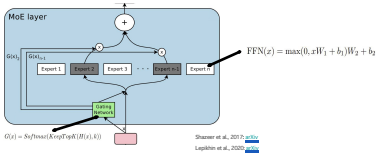


I/O Awareness



FlashAttention (Dao et al., 2019

Mixture-of-Experts



Shazeer et al., 2017: arXiv
Lepikhin et al., 2020: arXiv

Mixture-of-Experts

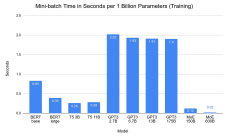
Version 2 (Lepikhin et al., 2020):

$$\mathcal{L} = \ell_{nll} + k * \ell_{aux}$$

Where k is a constant loss weight (a good value is 0.1; usually between 0.01 and 1.0)

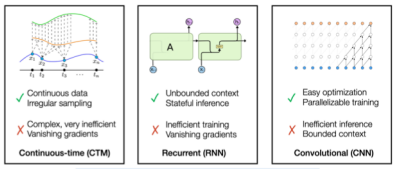
- Random dispatch: Use 2nd expert proportionally to the softmax gate probability.
- Have a frequency cutoff — a token budget — for each expert. If this budget is exceeded the expert degenerated to a zero-matrix. This effectively reduces the output of the MoE layer to zero and thus only the residual connection output around the MoE layer is fed to the next layer.

Mixture-of-Experts



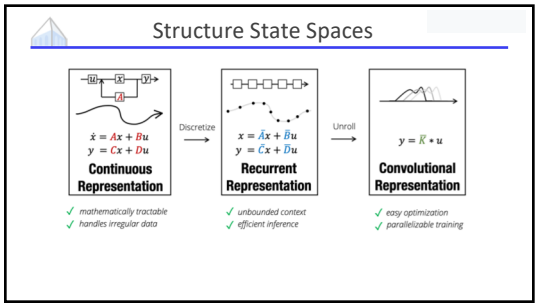
- Works well on diverse data like multilingual machine translation
- Can be difficult to train due to balancing/specialization issues
- Only faster than transformers if you can run it with a large enough batch size to saturate distributed experts
- If you scale the model across a cluster, you will need excellent interconnect performance (TPU v4 Pod, NVIDIA SuperPod)

Structure State Spaces



Existing model families have clear tradeoffs
All struggle with long-range dependencies (LRD)

S4 (Gu et al., 2022)


Structure State Spaces
$\dot{x} = Ax + Bu$
$y = Cx + Du$
Continuous Representation
Discretize
$x = \bar{A}x + \bar{B}u$
$y = \bar{C}x + \bar{D}u$
Recurrent Representation
Unroll
$y = \bar{K} * u$
Convolutional Representation
✓ mathematically tractable
✓ handles irregular data
✓ unbounded context
✓ efficient inference
✓ easy optimization
✓ parallelizable training