推理系统-模型小型化

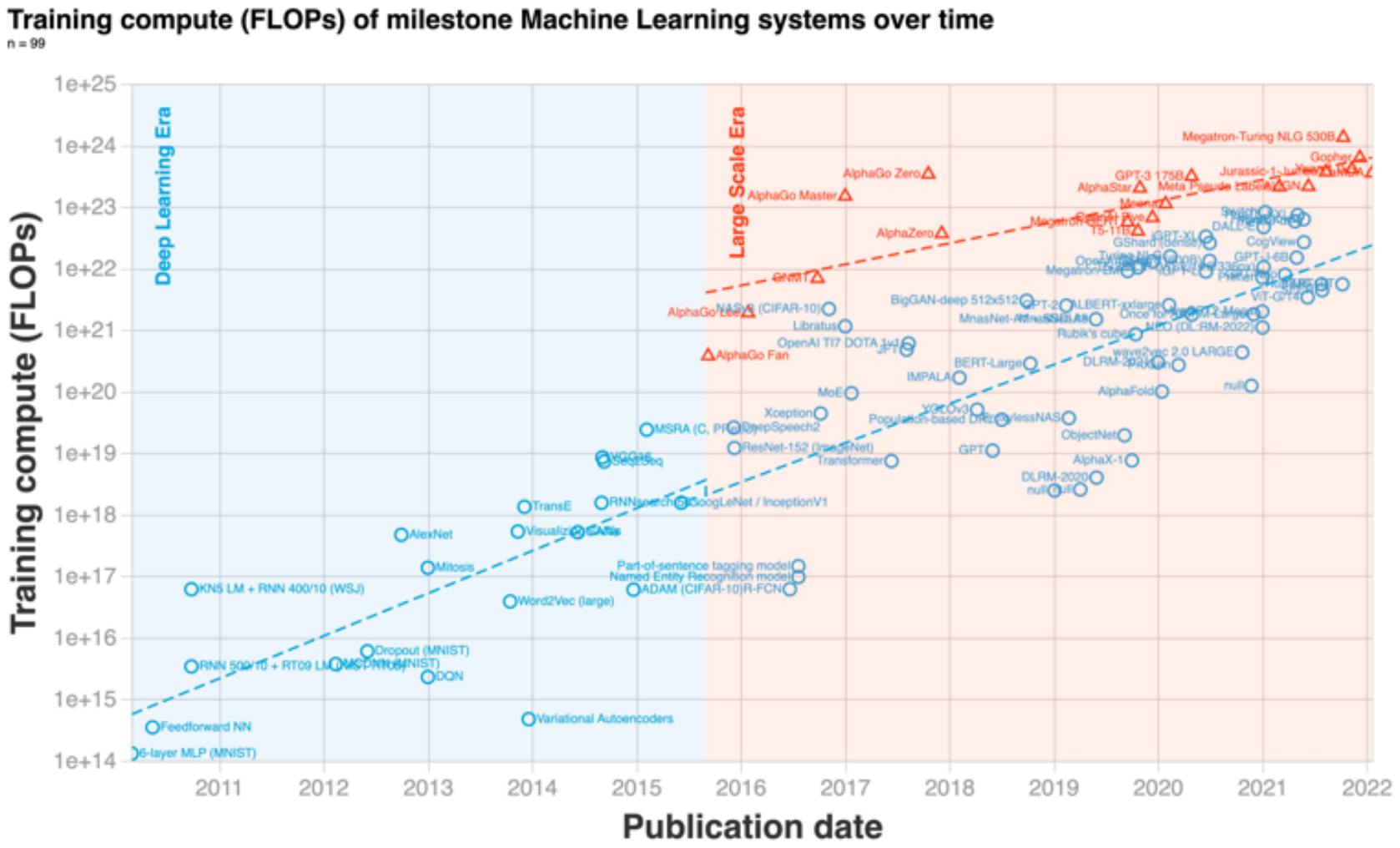
Transformer小型化

ZOMI

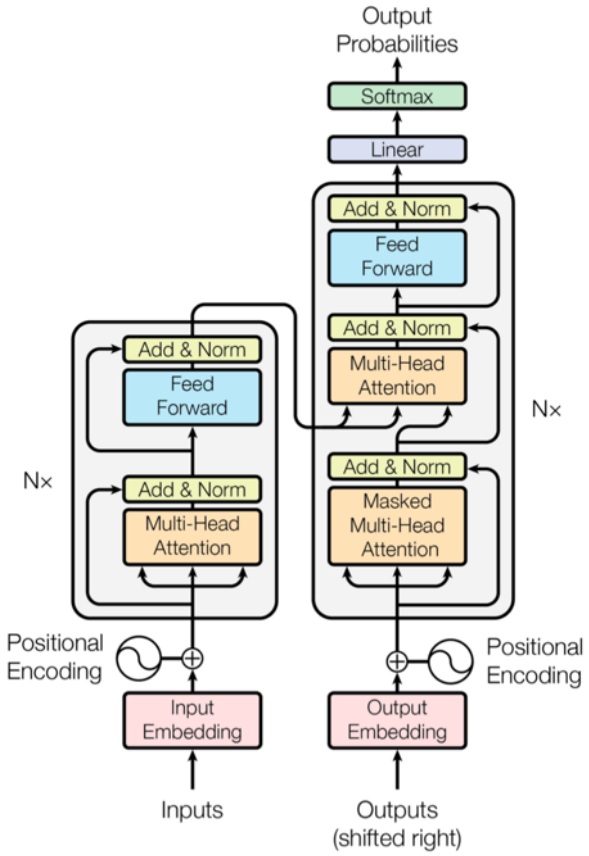
Talk Overview

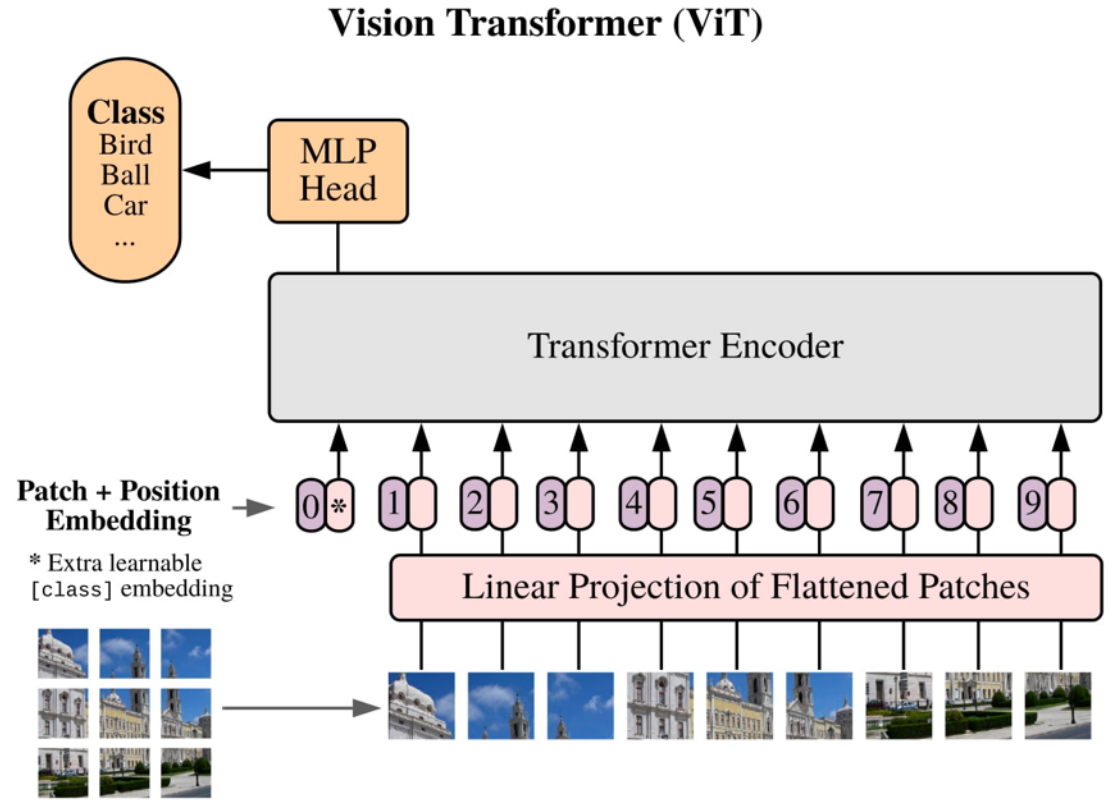
1. **推理系统介绍**
   - 推理系统与推理引擎区别
   - 推理工作流程
   - 推理系统介绍
   - 推理引擎介绍
2. **模型小型化**
   - 基础参数概念
   - CNN小型化结构
   - Transform小型化结构
3. **离线优化压缩**
   - 低比特量化
   - 二值化网络
   - 模型模型剪枝
   - 模型模型蒸馏
4. **部署和运行优化**
   - 图转换优化（算子融合/重排/替换）
   - 并发执行与内存分配
   - 动态batch与bin Packing

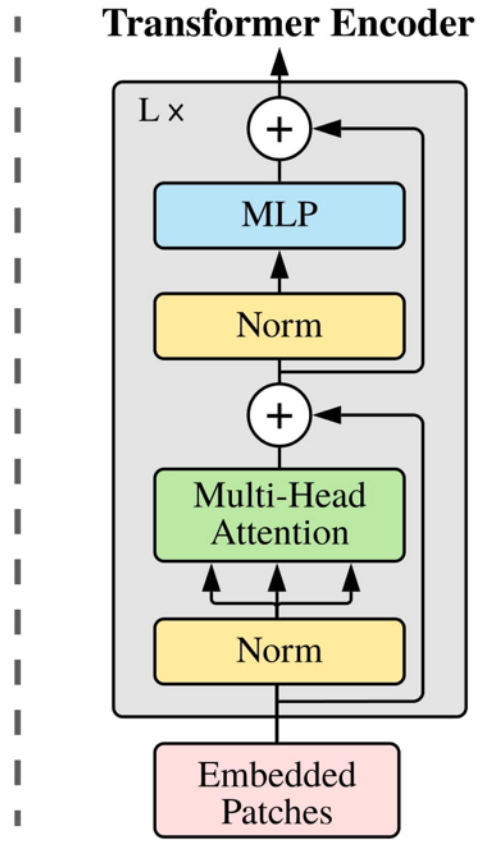
深度学习模型发展



Transformer, Attention is all you need

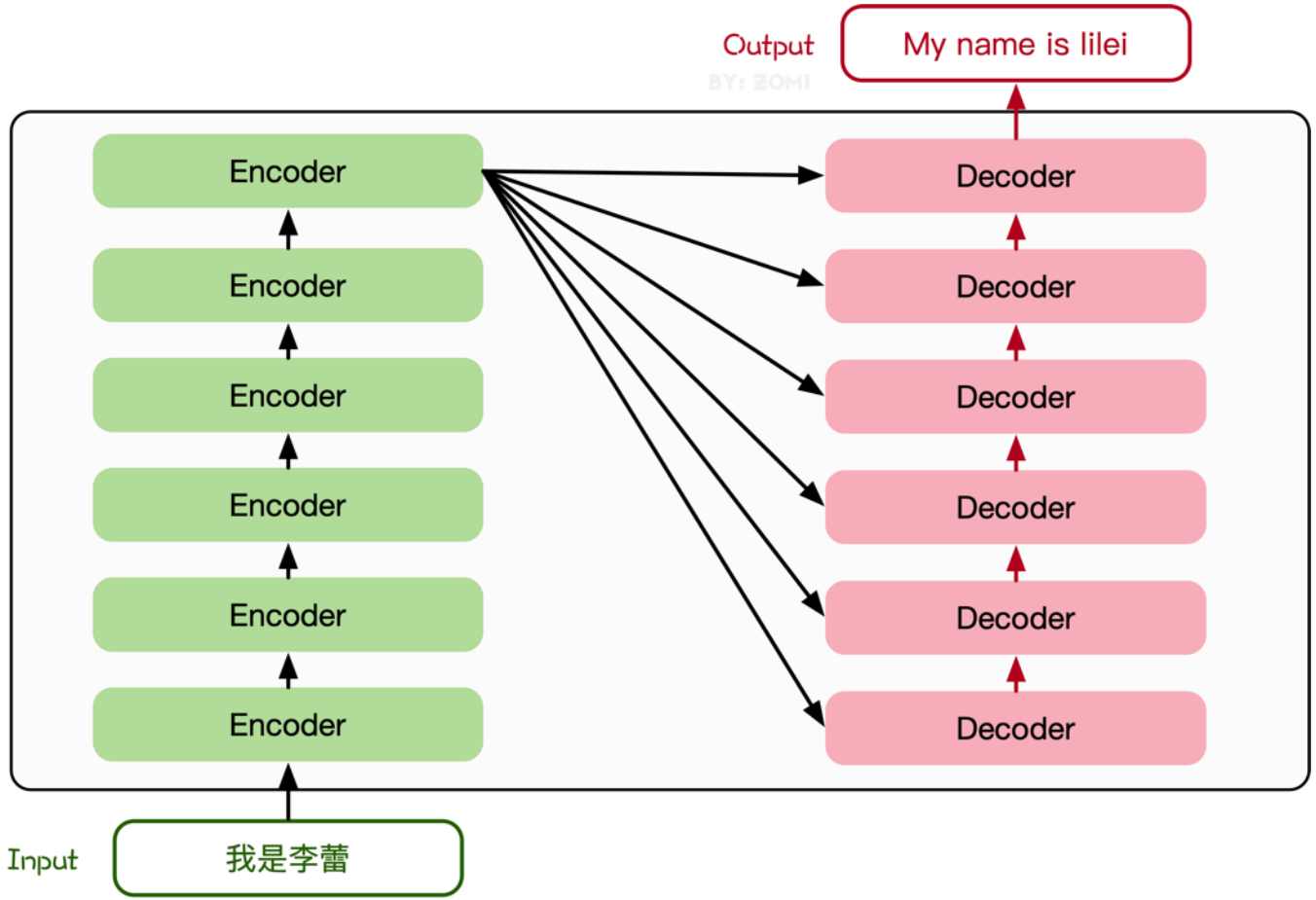






Vaswani, Transformer, 2017

Transformer, Attention is all you need



Transformer, Attention is all you need

Transformer solves Seq2Seq problem, replaces LSTM/RNN with a full attention structure:

- One step calculation to solve the long-term dependency problem;
- The computational complexity of each layer is better;
- Point multiplication results can be directly calculated;

Table 2: The Transformer achieves better BLEU scores than previous state-of-the-art models on the English-to-German and English-to-French newstest2014 tests at a fraction of the training cost.

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [15]	23.75			
Deep-Att + PosUnk [32]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [31]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [8]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [26]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [32]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [31]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [8]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	**$3.3 \cdot 10^{18}$**	
Transformer (big)	**28.4**	**41.0**	$2.3 \cdot 10^{19}$	

Vaswani, Transformer, 2017

Inference

1. Q8BERT: Quantized 8Bit BERT – 2019.10
2. DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter – 2019.10
3. TinyBERT: Distilling BERT for Natural Language Understanding – 2019.09

4. Training data-efficient image transformers & distillation through attention – 2021.3
5. MiniViT: Compressing Vision Transformers with Weight Multiplexing – 2022.04
6. TinyViT: Fast Pretraining Distillation for Small Vision Transformers – 2022.06
7. DynamicViT: Efficient Vision Transformers with Dynamic Token Sparsification - 2022.10

8. Compressing Visual-linguistic Model via Knowledge Distillation – 2021.03
9. MiniVLM: A Smaller and Faster Vision-Language Model – 2021.09

轻量级模型

1. MobileViT（2021）
2. Mobile-Former（2021）
3. EfficientFormer（2022）

轻量化网络总结

如何选择轻量化网络：

1. 不同网络架构，即使 FLOPs 相同，但其 MAC 也可能差异巨大
2. FLOPs 低不等于 latency 低，结合具硬件架构具体分析
3. 多数时候加速芯片算力的瓶颈在于访存带宽
4. 不同硬件平台部署轻量级模型需要根据具体业务选择对应指标

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