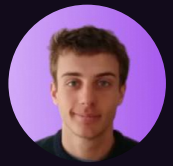
Pruna AI

Evaluation for Language Models



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Founder, President & Chief Scientist

Overview

Quality evaluation

- Perplexity
- Task-specific metrics (e.g. accuracy for question-answering)
- Robustness *[Reliability]*
- Uncertainty *[Reliability]*

Efficiency evaluation

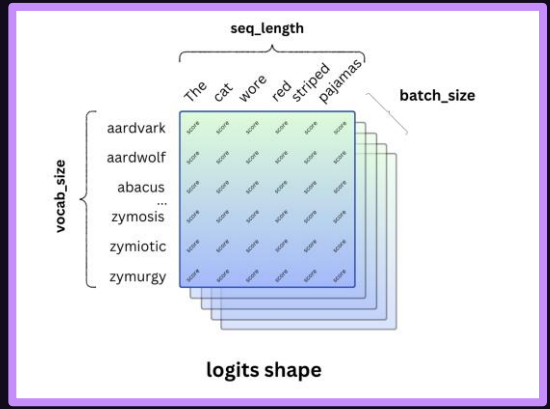
- #Parameters, #Activations *[Memory]*
- Disk, Inference, training memory *[Memory]*
- MAC, FLOP, FLOPS, OP, OPS *[Compute]*
- Scaling laws
- Latency *[Memory] [Compute]*
- Memory vs Compute bound
- Throughput *[Memory] [Compute]*
- *Money* *[Memory] [Compute]*
- Energy *[Memory] [Compute]*

Quality Evaluation

Perplexity

The perplexity measures how well a model can explain/predict data samples.

Definition: Given a dataset $D = \{x_1, \dots, x_N\}$, the perplexity of the (probabilistic) model $P_\theta(.)$ is $e^{-\frac{1}{N}\sum_{i=1}^{N} log(P_\theta(x_i))}$. The negative exponent indicates an average likelihood per token. Hence, the lower the perplexity is, the better the model is at explaining the dataset D.



Remarks

- It only needs a text corpus with any additional labels.
- It is an efficient and powerful proxy quality metric to evaluate the capacity of a model on a given data domain.
- Perplexity does not perfectly correlate with task specific metrics e.g. reasoning or long-term understanding.
- Using longer context length helps reducing perplexity.

Reference:
- https://www.comet.com/site/blog/perplexity-for-llm-evaluation/
- https://kilthub.cmu.edu/articles/journal_contribution/Evaluation_Metrics_For_Language_Models/6605324/1?file=12095765

Accuracy

The accuracy measures capacity of a model for question answering task.

Definition: Given a dataset $D = \{(x_1, y_1), \ldots, (x_N, y_N)\}$, the accuracy corresponds to the number of correct answer over the total number of answers. Formally, for a (probabilistic) model $P_\theta(.)$, it is $\frac{\sum_{i=1}^{N} 1_{argmax(P(x_i)==y_i}}{N}$

Remarks

- It requires a labelled questions/answers dataset.
- It is easy to evaluate on multi choice questions.
- It is complicated to evaluate on open questions.

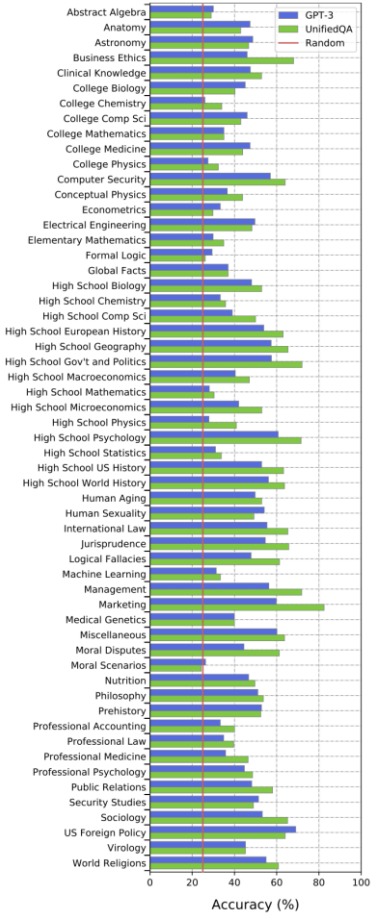


Figure 6: GPT-3 (few-shot) and UnifiedQA results.

Reference:

- https://www.confident-ai.com/blog/llm-evaluation-metrics-everything-you-need-for-llm-evaluation

Efficiency Evaluation

Memory Metrics

Category	Definition	Formula
Number of parameters	Number of weights in the model.	$\#parameters$
Number of active activations	Number of activations *active* in the model.	$\#activations$
Storage memory	Memory required to store the model.	$\#parameters \times avg\ bit\ width$
Inference memory	Memory required to run inference on the model.	$\#parameters \times avg\ parameter\ bit\ width + \#activations \times avg\ activation\ bit\ width$
Training memory	Memory required to run training on the model.	$\#parameters \times avg\ parameter\ bit\ width + \#activations \times avg\ activation\ bit\ width + \#parameters \times avg\ gradient\ bit\ width$

Layer	# Parameters
Linear Layer	$c_i \times c_o$
Convolution	$c_i \times c_o \times k_h \times k_w$
Grouped Convolution	$\frac{c_i \times c_o \times k_h \times k_w}{g}$
Depthwise Convolution	$c_o \times k_h \times k_w$

c_i: #input channels
c_o : #output channels
k_h : kernel height
k_w : kernel width
g : #groups

Remarks

- The storage, inference, training memory metrics measured in **Bytes or Bits** are the **closest to the real-world constraints**. The rest are proxy metrics.
- The real storage, inference, training memory requirements is **distributed across memory levels** (e.g. disk, cpu, gpu).
- The real storage, inference, training memory requirements depends on **implementation efficiency** (e.g. variables can be shared).
- The size of SOTA models overall increase with time. Scaling model size leads to better performance.

Reference:

- https://epoch.ai/data/notable-ai-models
- https://arxiv.org/abs/2203.15556
- https://arxiv.org/pdf/2007.10319

Compute Metrics

Category	Definition	Formula
MAC (Multiply-Accumulate)	A multiplication followed by an addition.	$\#(multiplication + addition)$
FLOP (Floating Point Operation)	A single floating-point arithmetic operation (addition, multiplication, etc.).	$\#multiplications + \#additions$
FLOPS (Floating Point Operations Per Second)	The number of FLOPs that a system can process per second.	$\frac{FLOPs}{Execution\ time}$
OP (Operation)	A single general computation operation (e.g., MACs, FLOPs, comparisons, etc.).	$\#multiplications + \#additions + \#comparisons + \ ...$
OPS (Operations Per Second)	The number of OPs that a system can process per second.	$\frac{OPs}{Execution\ time}$

Layer	MACs (batch size = 1)
Linear Layer	$c_i \times c_o$
Convolution	$c_i \times c_o \times k_h \times k_w \times h_o \times w_o$
Grouped Convolution	$\frac{c_i \times c_o \times k_h \times k_w \times h_o \times w_o}{g}$
Depthwise Convolution	$c_o \times k_h \times k_w \times h_o \times w_o$
Attention calculation	$s \times s \times c_i$

c_i, c_o : #input/ #output channels
h_i, h_o : #input/ #output heights
w_i, w_o : #input/ #output widths
k_h, k_w: kernel height/width
s : sequence length
g : #groups

Remarks

- Multiplication and addition are key operations for matrix-vector (GEMV) and matrix-matrix multiplications (GEMM).
- Performance of models can be improved by investing more compute during training or inference.

Reference:

- https://medium.com/@pashashaik/a-guide-to-hand-calculating-flops-and-macs-fa5221ce5ccc
- https://epoch.ai/data/notable-ai-models

Scaling Laws

Training-time scaling laws: The test performance L of a model architecture scales with the model size N, training dataset size D, training cost C.

$$L = L_0 + \left(\frac{x_0}{x}\right)^{\alpha}$$

Henighan & Kaplan scaling laws

$$\begin{cases} C = C_0 ND \\ L = \frac{A}{N^{\alpha}} + \frac{B}{D^{\beta}} + L_0 \end{cases}$$

Chinchilla scaling laws

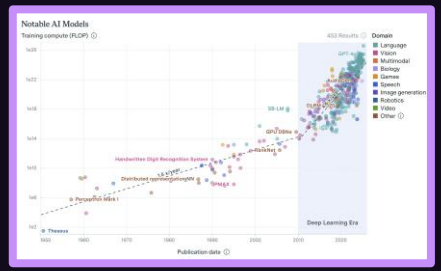
$$y = a + \left(bx^{-c_0}\right) \prod_{i=1}^{n} \left(1 + \left(\frac{x}{d_i}\right)^{1/f_i}\right)^{-c_i * f_i}$$

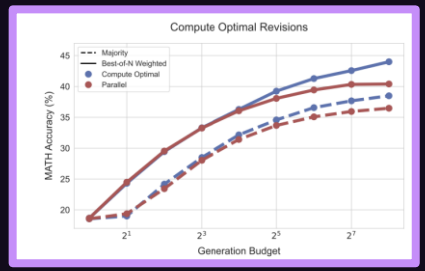
Broken scaling laws

Test-time scaling laws: The test performance L of a model scales with the test compute cost C.

Remarks

- It is possible to trade training compute against test compute.
- There are many other scaling laws accounting for more factors (e.g. precision, distillation, …).





Reference:

- https://arxiv.org/abs/2210.14891
- https://arxiv.org/abs/2010.14701
- https://arxiv.org/abs/2203.15556

Latency

Definition: It is the time to obtain the prediction of one single output.

High latency – 5 sec/image

Low latency – 0.5 sec/image

Remarks

- It is important for the user experience.
- It can be directly improved:
  - with more efficient models.
  - with more performant hardware.
  - with more hardware if computation is well distributed.

Latency vs Memory/Compute

Latency is the consequence of time spend for memory access and computation time.

$$Latency \approx \max(T_{memory}, T_{compute})$$

$$T_{compute} = \frac{\#Operations\ by\ the\ model}{\#Operation\ processed\ per\ time\ unit\ by\ the\ hardware}$$

$$T_{memory} = T_{activation} + T_{weights}$$

$$T_{activation} = \frac{Input\ activation\ size + output\ activation\ size}{Memory\ bandwith\ of\ the\ hardware}$$

$$T_{weights} = \frac{Model\ size}{Memory\ bandwith\ of\ the\ hardware}$$

Remarks

- Latency depends on both the hardware and the model.
- Both memory access and compute can take time and energy!

Integer	
Add	
8 bit	0.03pJ
32 bit	0.1pJ
Mult	
8 bit	0.2pJ
32 bit	3.1pJ

FP	
FAdd	
16 bit	0.4pJ
32 bit	0.9pJ
FMult	
16 bit	1.1pJ
32 bit	3.7pJ

Memory	
Cache	(64bit)
8KB	10pJ
32KB	20pJ
1MB	100pJ
DRAM	1.3-2.6nJ

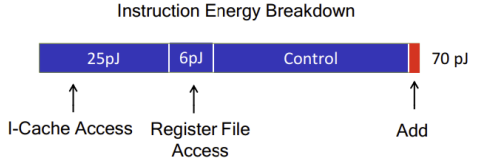


Figure 1.1.9: Rough energy costs for various operations in 45nm 0.9V.

Reference:

- https://gwern.net/doc/cs/hardware/2014-horowitz-2.pdf

Memory vs Compute Bound

Arithmetic intensity of the model

$$\frac{\#Operations\ by\ the\ model}{input\ activation\ size + output\ activation\ size + model\ size}$$

Ops/byte ratio of the hardware

$$\frac{\#Operation\ processed\ per\ time\ unit\ by\ the\ hardware}{Memory\ bandwith\ of\ the\ hardware}$$

When is the memory the limiting factor?

$$T_{memory} > T_{compute} \leftrightarrow Arithmetic\ int. < \frac{ops}{byte} ratio$$

When is the compute the limiting factor?

$$T_{memory} < T_{compute} \leftrightarrow Arithmetic\ int. > \frac{ops}{byte} ratio$$

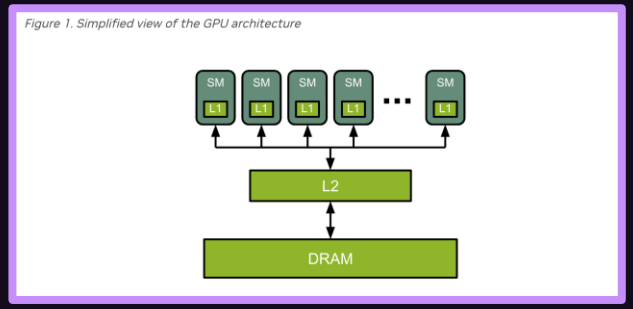


Table 1. Examples of neural network operations with their arithmetic intensities. Limiters assume FP16 data and an NVIDIA V100 GPU.

Operation	Arithmetic Intensity	Usually limited by...
Linear layer (4096 outputs, 1024 inputs, batch size 512)	315 FLOPS/B	arithmetic
Linear layer (4096 outputs, 1024 inputs, batch size 1)	1 FLOPS/B	memory
Max pooling with 3x3 window and unit stride	2.25 FLOPS/B	memory
ReLU activation	0.25 FLOPS/B	memory
Layer normalization	< 10 FLOPS/B	memory

Example: V100 Peak compute rate of 125 FP16 Tensor TFLOPS, an off-chip memory bandwidth of approx. 900 GB/s, and an on-chip L2 bandwidth of 3.1 TB/s, giving it a ops:byte ratio between 40 and 139, depending on the source of an operation's data (on-chip or off-chip memory).

Reference:

- https://docs.nvidia.com/deeplearning/performance/dl-performance-gpu-background/index.html#understand-perf

Throughput

Definition: It is the number of output that can be predicted per time unit.

Low throughput – 1 image/sec

High throughput – 4 image/sec

Remarks

- It is important to scale to a large set of queries/users.
- It can be directly improved
  - with more efficient models.
  - with more hardware.
  - with better hardware for a whole server.

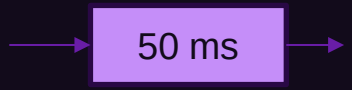
Latency vs Throughput

Latency and throughput are equivalent for sequential input processing.

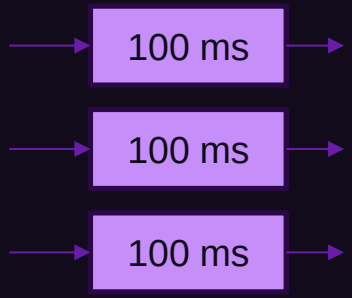
Example: A smartphone process frame after frame.

Latency and throughput are not equivalent for batched input processing.

Example: A server process a batch of user queries.



Latency → 50 ms
Throughput → 20 samples/s



Latency → 100 ms
Throughput → 30 samples/s

Money

Definition: It is the money required for the prediction of a single output.

If you use cloud machines, it approximately corresponds to

$$\frac{hardware\ price\ per\ time\ unit\ \times usage\ time}{number\ of\ processed\ samples}$$

If you use internal machines, it approximately corresponds to

$$\frac{hardware\ energy\ consumption\ per\ time\ unit \times energy\ price\ per\ time\ unit \times\ usage\ time}{\#processed\ samples} + \frac{hardware\ price}{\#processed\ samples\ in\ hardware\ lifetime}$$

Remarks

- It can be improved via more efficient models.
- More performant hardware, or more hardware are not guaranteed to improve it. It depends on the price to hardware compute power ratio.

Energy

Definition: It is the energy required for the prediction of a single output.

It approximately corresponds to

$$\frac{hardware\ energy\ consumption\ per\ time\ unit \times\ usage\ time}{\#processed\ samples} + \frac{energy\ for\ hardware\ production}{\#processed\ samples\ in\ hardware\ lifetime}$$

Remarks

- It can be improved via more efficient models.
- More performant hardware, or more hardware are not guaranteed to improve it. It depends on the price to hardware compute power ratio.