Scaling Laws for Large LMs

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Advanced Natural Language Processing

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Given a fixed compute budget, what is the optimal model size and training dataset size for training a Transformer LM?
Let’s say you can use one GPU for one day

- Would you train a 5 million parameter LM on 100 books?
- What about a 500 million parameter LM on one book?
- Or a 100k parameter LM on 5k books?
Observations from Kaplan et al., 2020

- Performance depends strongly on scale (model params, data size, and compute used for training), weakly on model shape (e.g., depth, width)

- Perf vs scale can be modeled with power laws

- Perf improves most if model size and dataset size are scaled up together. Increasing one while keeping the other fixed leads to diminishing returns

- Larger models are more sample efficient than smaller models, take fewer steps / data points to reach same loss
Figure 1  Language modeling performance improves smoothly as we increase the model size, dataset size, and amount of compute used for training. For optimal performance all three factors must be scaled up in tandem. Empirical performance has a power-law relationship with each individual factor when not bottlenecked by the other two.
Larger models require fewer samples to reach the same performance.

The optimal model size grows smoothly with the loss target and compute budget.

**Figure 2** We show a series of language model training runs, with models ranging in size from $10^3$ to $10^9$ parameters (excluding embeddings).
Issues with Kaplan laws

• Used same learning rate schedule for all training runs, regardless of how many training tokens / batches!

• This schedule needs to be adjusted based on the number of training steps; otherwise, it can impair performance

• The resulting “scaling laws” from Kaplan et al., are flawed because of this!
Chinchilla (Hoffmann et al., 2022)
Quick takeaways

• **Kaplan et al., 2020**: if you’re able to increase your compute budget, you should prioritize increasing model size over data size
  - With a 10x compute increase, you should increase model size by 5x and data size by 2x
  - With a 100x compute increase, model size 25x and data 4x

• **Hoffmann et al., 2022**: you should increase model and data size at the same rate
  - With a 10x compute increase, you should increase both model size and data size by 3.1x
  - With a 100x compute increase, both model and data size 10x
iPad
Given a fixed compute budget, what is the optimal model size and training dataset size for training a Transformer LM?

<table>
<thead>
<tr>
<th>Model</th>
<th>Size (# Parameters)</th>
<th>Training Tokens</th>
</tr>
</thead>
<tbody>
<tr>
<td>LaMDA (Thoppilan et al., 2022)</td>
<td>137 Billion</td>
<td>168 Billion</td>
</tr>
<tr>
<td>GPT-3 (Brown et al., 2020)</td>
<td>175 Billion</td>
<td>300 Billion</td>
</tr>
<tr>
<td>Jurassic (Lieber et al., 2021)</td>
<td>178 Billion</td>
<td>300 Billion</td>
</tr>
<tr>
<td>Gopher (Rae et al., 2021)</td>
<td>280 Billion</td>
<td>300 Billion</td>
</tr>
<tr>
<td>MT-NLG 530B (Smith et al., 2022)</td>
<td>530 Billion</td>
<td>270 Billion</td>
</tr>
<tr>
<td>Chinchilla</td>
<td>70 Billion</td>
<td>1.4 Trillion</td>
</tr>
</tbody>
</table>

- $N$ – the number of model parameters, *excluding all vocabulary and positional embeddings*
- $C \approx 6 N B S$ – an estimate of the total non-embedding training compute, where $B$ is the batch size, and $S$ is the number of training steps (ie parameter updates). We quote numerical values in PF-days, where one PF-day $= 10^{15} \times 24 \times 3600 = 8.64 \times 10^{19}$ floating point operations.
Given a fixed compute budget, what is the optimal model size and training dataset size for training a Transformer LM?

Hoffmann et al., 2022, Chinchilla
What about the type of data?
What about the type of data?

• The internet contains a huge amount of text, but it’s extremely noisy! Copyrighted text (e.g. published books) are much higher-quality, but is it legal to train on them?

• What is the impact of repeated data?

  • Repeated data can lead to severe degradation in performance (Brown et al., 2022)
    
    “For instance, performance of an 800M parameter model can be degraded to that of a 2x smaller model (400M params) by repeating 0.1% of the data 100 times, despite the other 90% of the training tokens remaining unique.”

  • Repeated data is helpful (Taylor et al., 2022; Galactica)
    
    “We train the models for 450 billion tokens, or approximately 4.25 epochs. We find that performance continues to improve on validation set, in-domain and out-of-domain benchmarks with multiple repeats of the corpus.”

    “We note the implication that the "tokens → ∞" focus of current LLM projects may be overemphasised versus the importance of filtering the corpus for quality.”
Books of the world, stand up and be counted! All 129,864,880 of you.
Thursday, August 05, 2010 at 8:26 AM
Posted by Leonid Taycher, software engineer

When you are part of a company that is trying to digitize all the books in the world, the first question you often get is: “Just how many books are out there?”