The Big LLM Architecture Comparison

From DeepSeek-V3 to gpt-oss: A Look At Modern LLM Architecture Design

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JUL 19, 2025

It has been seven years since the original GPT architecture was developed. At first glance, looking back at GPT-2 (2019) and forward to DeepSeek-V3 and Llama 4 (2024-2025), one

might be surprised at how structurally similar these models still are.

Sure, positional embeddings have evolved from absolute to rotational (RoPE), Multi-Head Attention has largely given way to Grouped-Query Attention, and the more efficient SwiGLU has replaced activation functions like GELU. But beneath these minor refinements, have we truly seen groundbreaking changes, or are we simply polishing the same architectural foundations?

Comparing LLMs to determine the key ingredients that contribute to their good (or not-so-good) performance is notoriously challenging: datasets, training techniques, and hyperparameters vary widely and are often not well documented.

However, I think that there is still a lot of value in examining the structural changes of the architectures themselves to see what LLM developers are up to in 2025. (A subset of them are shown in Figure 1 below.)

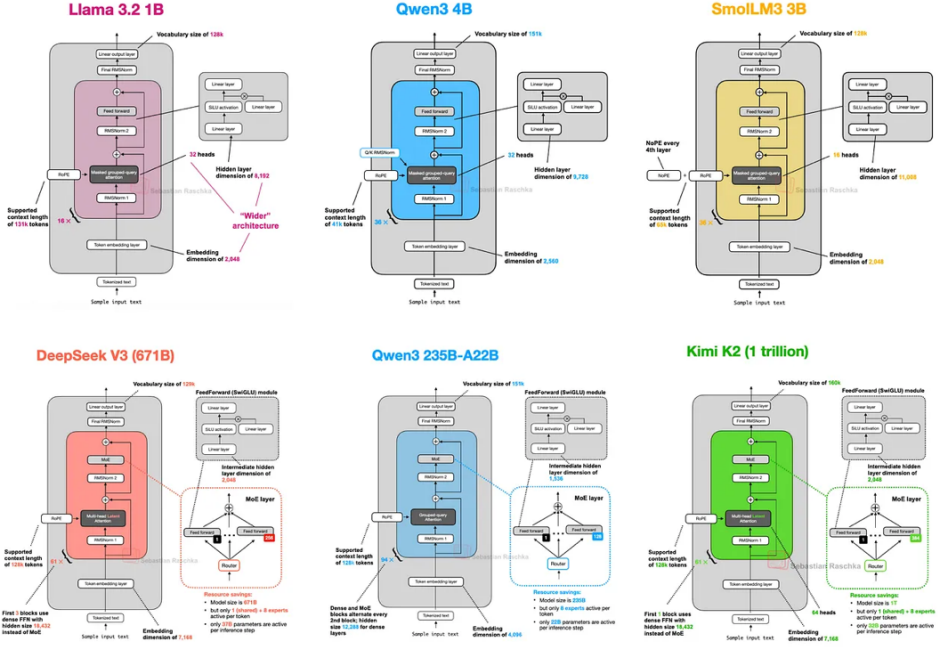


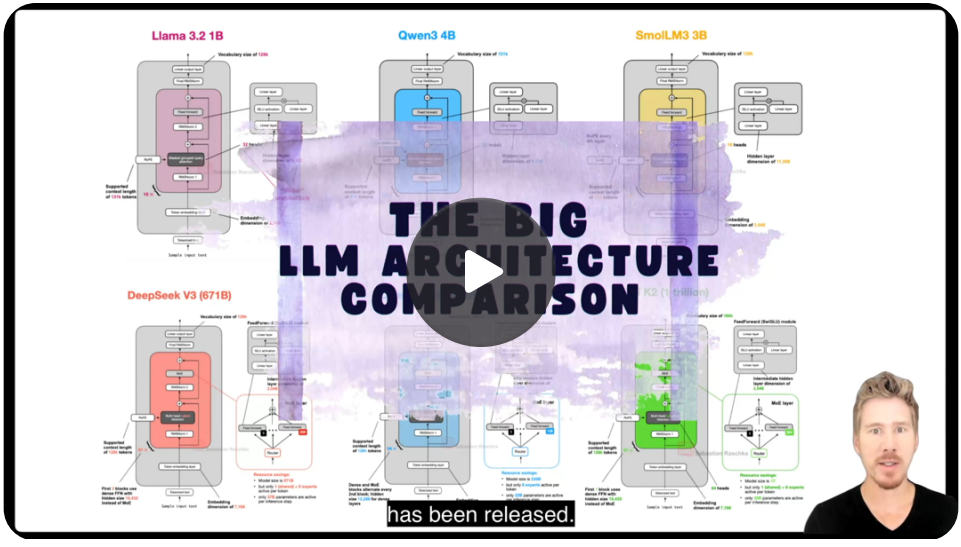
Figure 1: A subset of the architectures covered in this article.

So, in this article, rather than writing about benchmark performance or training algorithms, I will focus on the architectural developments that define today's flagship open models.

(As you may remember, I wrote about multimodal LLMs not too long ago; in this article, I will focus on the text capabilities of recent models and leave the discussion of multimodal capabilities for another time.)

Tip: This is a fairly comprehensive article, so I recommend using the navigation bar to access the table of contents (just hover over the left side of the Substack page).

Optional: The video below is a narrated and abridged version of this article.



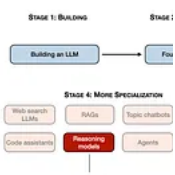
1. DeepSeek V3/R1

As you have probably heard more than once by now, DeepSeek R1 made a big impact when it was released in January 2025. DeepSeek R1 is

a reasoning model built on top of the DeepSeek V3 architecture, which was introduced in December 2024.

While my focus here is on architectures released in 2025, I think it's reasonable to include DeepSeek V3, since it only gained widespread attention and adoption following the launch of DeepSeek R1 in 2025.

If you are interested in the training of DeepSeek R1 specifically, you may also find my article from earlier this year useful:



Understanding Reasoning LLMs

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In this section, I'll focus on two key

architectural techniques introduced in DeepSeek V3 that improved its computational efficiency and distinguish it from many other LLMs:

- Multi-Head Latent Attention (MLA)
- Mixture-of-Experts (MoE)

1.1 Multi-Head Latent Attention (MLA)

Before discussing Multi-Head Latent Attention (MLA), let's briefly go over some background to motivate why it's used. For that, let's start with Grouped-Query Attention (GQA), which has become the new standard replacement for a more compute- and parameter-efficient alternative to Multi-Head Attention (MHA) in

recent years.

So, here's a brief GQA summary. Unlike MHA, where each head also has its own set of keys and values, to reduce memory usage, GQA groups multiple heads to share the same key and value projections.

For example, as further illustrated in Figure 2 below, if there are 2 key-value groups and 4 attention heads, then heads 1 and 2 might share one set of keys and values, while heads 3 and 4 share another. This reduces the total number of key and value computations, which leads to lower memory usage and improved efficiency (without noticeably affecting the modeling performance, according to ablation studies).

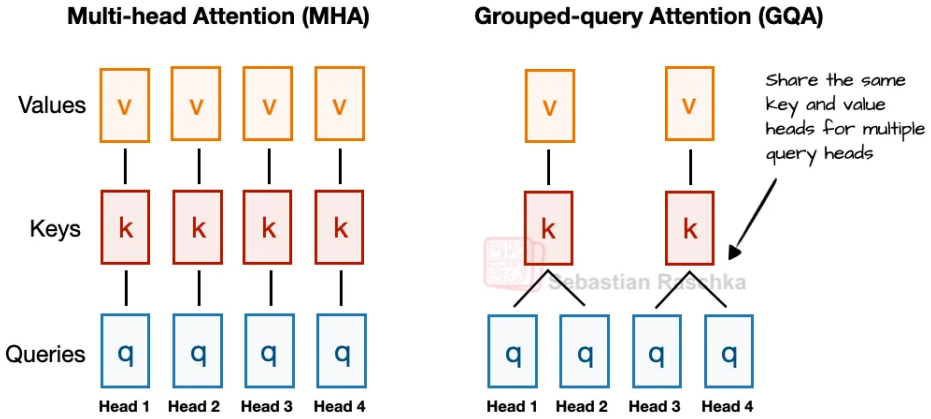


Figure 2: A comparison between MHA and GQA. Here, the group size is 2, where a key and value pair is shared among 2 queries.

So, the core idea behind GQA is to reduce the number of key and value heads by sharing them across multiple query heads. This (1) lowers the model's parameter count and (2) reduces the memory bandwidth usage for key and value tensors during inference since fewer keys and values need to be stored and retrieved from the KV cache.

(If you are curious how GQA looks in code, see my GPT-2 to Llama 3 conversion guide for a version without KV cache and my KV-cache variant here.)

While GQA is mainly a computational-efficiency workaround for MHA, ablation studies (such as those in the original GQA paper and the Llama 2 paper) show it performs comparably to standard MHA in terms of LLM modeling performance.

Now, Multi-Head Latent Attention (MLA) offers a different memory-saving strategy that also pairs particularly well with KV caching. Instead of sharing key and value heads like GQA, MLA compresses the key and value tensors into a lower-dimensional space before storing them

in the KV cache.

At inference time, these compressed tensors are projected back to their original size before being used, as shown in the Figure 3 below. This adds an extra matrix multiplication but reduces memory usage.

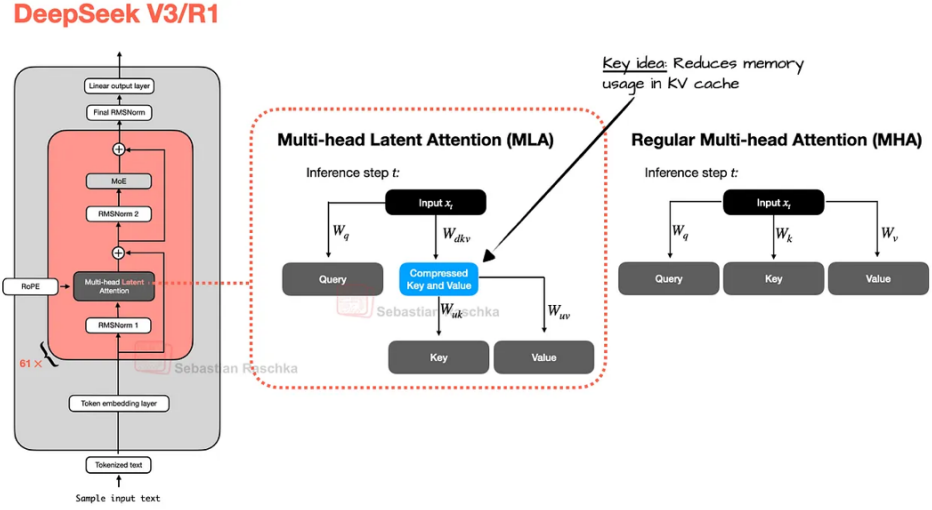
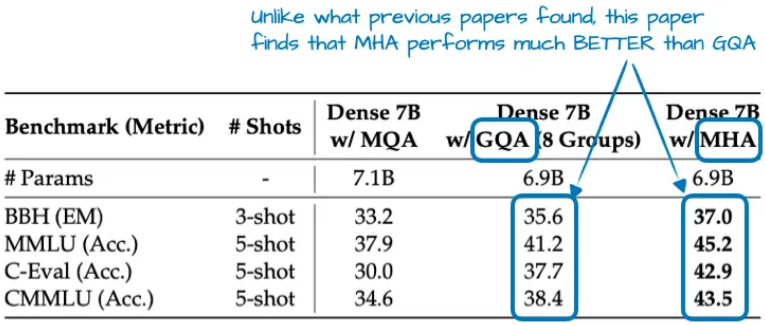


Figure 3: Comparison between MLA (used in DeepSeek V3 and R1) and regular MHA.

(As a side note, the queries are also compressed, but only during training, not inference.)

By the way, MLA is not new in DeepSeek V3, as its DeepSeek-V2 predecessor also used (and even introduced) it. Also, the V2 paper contains a few interesting ablation studies that may explain why the DeepSeek team chose MLA over GQA (see Figure 4 below).



Benchmark (Metric)	# Shots	Dense 7B w/ MQA	Dense 7B w/ GQA (8 Groups)	Dense 7B w/ MHA
# Params	-	7.1B	6.9B	6.9B
BBH (EM)	3-shot	33.2	35.6	**37.0**
MMLU (Acc.)	5-shot	37.9	41.2	**45.2**
C-Eval (Acc.)	5-shot	30.0	37.7	**42.9**
CMMLU (Acc.)	5-shot	34.6	38.4	**43.5**

Table 8 | Comparison among 7B dense models with MHA, GQA, and MQA, respectively. MHA demonstrates significant advantages over GQA and MQA on hard benchmarks.

Benchmark (Metric)	# Shots	Small MoE w/ MHA	Small MoE w/ MLA	Large MoE w/ MHA	Large MoE w/ MLA
# Activated Params	-	2.5B	2.4B	25.0B	21.5B
# Total Params	-	15.8B	15.7B	250.8B	247.4B

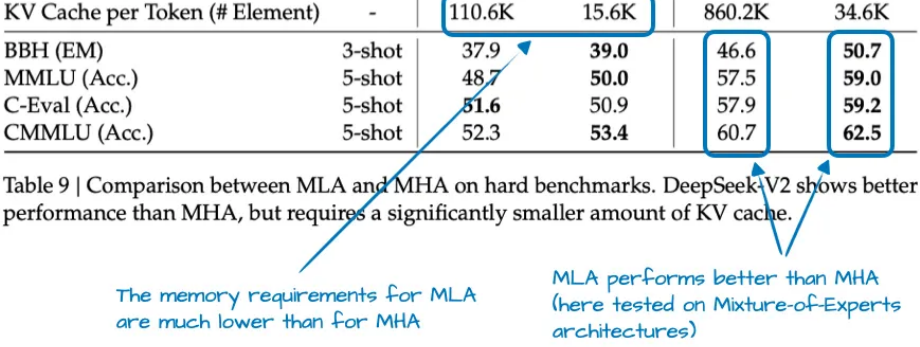


Figure 4: Annotated tables from the DeepSeek-V2 paper, https://arxiv.org/abs/2405.04434

As shown in Figure 4 above, GQA appears to perform worse than MHA, whereas MLA offers better modeling performance than MHA, which is likely why the DeepSeek team chose MLA over GQA. (It would have been interesting to see the "KV Cache per Token" savings comparison between MLA and GQA as well!)

To summarize this section before we move on to the next architecture component, MLA is a

clever trick to reduce KV cache memory use while even slightly outperforming MHA in terms of modeling performance.

1.2 Mixture-of-Experts (MoE)

The other major architectural component in DeepSeek worth highlighting is its use of Mixture-of-Experts (MoE) layers. While DeepSeek did not invent MoE, it has seen a resurgence this year, and many of the architectures we will cover later also adopt it.

You are likely already familiar with MoE, but a quick recap may be helpful.

The core idea in MoE is to replace each FeedForward module in a transformer block

with multiple expert layers, where each of these expert layers is also a FeedForward module. This means that we swap a single FeedForward block for multiple FeedForward blocks, as illustrated in the Figure 5 below.

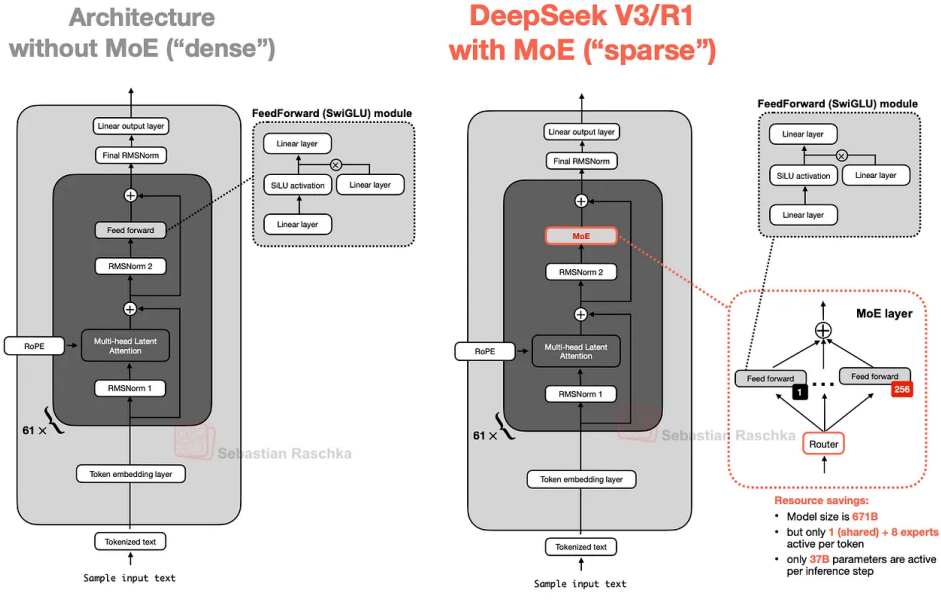


Figure 5: An illustration of the Mixture-of-Experts (MoE) module in DeepSeek V3/R1 (right) compared to an LLM with a standard FeedForward block (left).

The FeedForward block inside a transformer block (shown as the dark gray block in the figure above) typically contains a large number of the model's total parameters. (Note that the transformer block, and thereby the FeedForward block, is repeated many times in an LLM; in the case of DeepSeek-V3, 61 times.)

So, replacing *a single* FeedForward block with *multiple* FeedForward blocks (as done in a MoE setup) substantially increases the model's total parameter count. However, the key trick is that we don't use ("activate") all experts for every token. Instead, a router selects only a small subset of experts per token. (In the interest of time, or rather article space, I'll cover the router in more detail another time.)

Because only a few experts are active at a time, MoE modules are often referred to as *sparse*, in contrast to *dense* modules that always use the full parameter set. However, the large total number of parameters via an MoE increases the capacity of the LLM, which means it can take up more knowledge during training. The sparsity keeps inference efficient, though, as we don't use all the parameters at the same time.

For example, DeepSeek-V3 has 256 experts per MoE module and a total of 671 billion parameters. Yet during inference, only 9 experts are active at a time (1 shared expert plus 8 selected by the router). This means just 37 billion parameters are used per inference step as opposed to all 671 billion.

One notable feature of DeepSeek-V3's MoE design is the use of a shared expert. This is an expert that is always active for every token. This idea is not new and was already introduced in the DeepSeek 2024 MoE and 2022 DeepSpeedMoE papers.

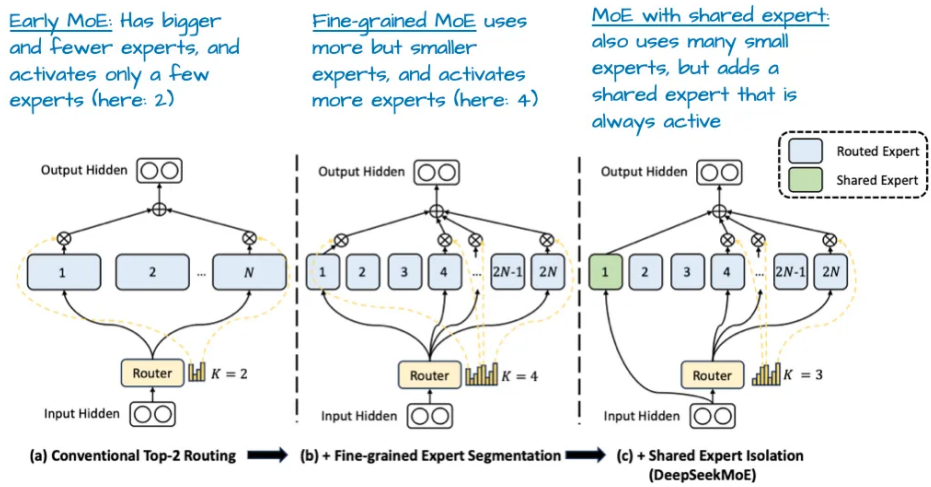


Figure 6: An annotated figure from "DeepSeekMoE: Towards Ultimate Expert Specialization in Mixture-of-Experts Language Models", https://arxiv.org/abs/2401.06066

The benefit of having a shared expert was first noted in the DeepSpeedMoE paper, where they found that it boosts overall modeling performance compared to no shared experts. This is likely because common or repeated patterns don't have to be learned by multiple individual experts, which leaves them with more room for learning more specialized patterns.

1.3 DeepSeek Summary

To summarize, DeepSeek-V3 is a massive 671-billion-parameter model that, at launch, outperformed other open-weight models, including the 405B Llama 3. Despite being larger, it is much more efficient at inference time thanks to its Mixture-of-Experts (MoE)

architecture, which activates only a small subset of (just 37B) parameters per token.

Another key distinguishing feature is DeepSeek-V3's use of Multi-Head Latent Attention (MLA) instead of Grouped-Query Attention (GQA). Both MLA and GQA are inference-efficient alternatives to standard Multi-Head Attention (MHA), particularly when using KV caching. While MLA is more complex to implement, a study in the DeepSeek-V2 paper has shown it delivers better modeling performance than GQA.

2. OLMo 2

The OLMo series of models by the non-profit Allen Institute for AI is noteworthy due to its

transparency in terms of training data and code, as well as the relatively detailed technical reports.

While you probably won't find OLMo models at the top of any benchmark or leaderboard, they are pretty clean and, more importantly, a great blueprint for developing LLMs, thanks to their transparency.

And while OLMo models are popular because of their transparency, they are not that bad either. In fact, at the time of release in January (before Llama 4, Gemma 3, and Qwen 3), OLMo 2 models were sitting at the Pareto frontier of compute to performance, as shown in Figure 7 below.

The Pareto frontier (yellow region) represents the most efficient models that achieve the highest benchmarl

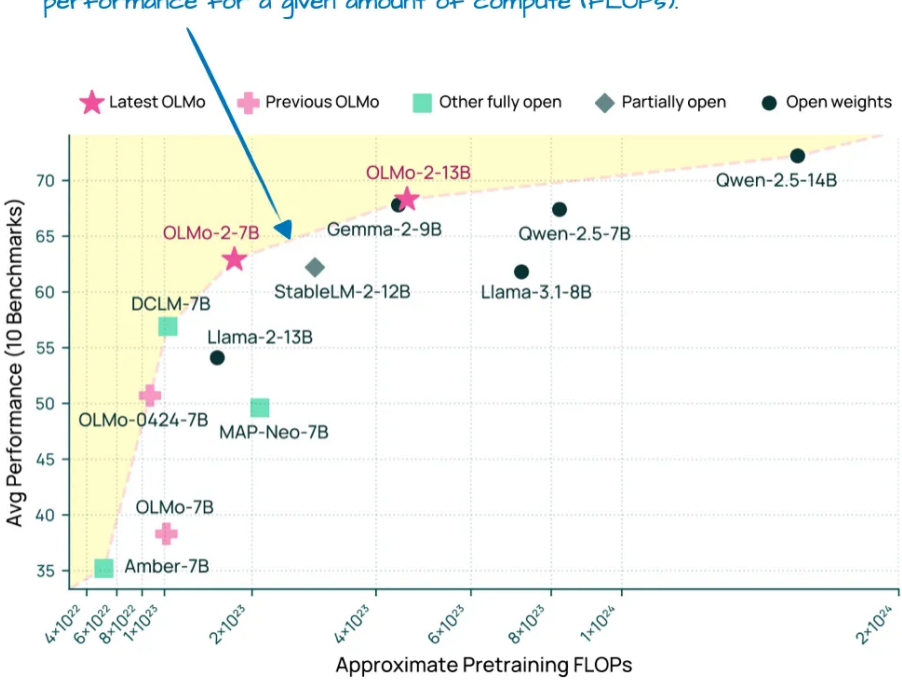


Figure 7: Modeling benchmark performance (higher is better) vs pre-training cost (FLOPs; lower is better) for different LLMs. This is an annotated figure from the OLMo 2 paper, https://arxiv.org/abs/2501.00656

As mentioned earlier in this article, I aim to focus only on the LLM architecture details (not training or data) to keep it at a manageable

length. So, what were the interesting architectural design choices in OLMo2 ? It mainly comes down to normalizations: the placement of RMSNorm layers as well as the addition of a QK-norm, which I will discuss below.

Another thing worth mentioning is that OLMo 2 still uses traditional Multi-Head Attention (MHA) instead of MLA or GQA.

2.1 Normalization Layer Placement

Overall, OLMo 2 largely follows the architecture of the original GPT model, similar to other contemporary LLMs. However, there are some noteworthy deviations. Let's start with the normalization layers.

Similar to Llama, Gemma, and most other LLMs, OLMo 2 switched from LayerNorm to RMSNorm.

But since RMSNorm is old hat (it's basically a simplified version of LayerNorm with fewer trainable parameters), I will skip the discussion of RMSNorm vs LayerNorm. (Curious readers can find an RMSNorm code implementation in my GPT-2 to Llama conversion guide.)

However, it's worth discussing the placement of the RMSNorm layer. The original transformer (from the "Attention is all you need" paper) placed the two normalization layers in the transformer block *after* the attention module and the FeedForward module, respectively.

This is also known as Post-LN or Post-Norm.

GPT and most other LLMs that came after placed the normalization layers *before* the attention and FeedForward modules, which is known as Pre-LN or Pre-Norm. A comparison between Post- and Pre-Norm is shown in the figure below.

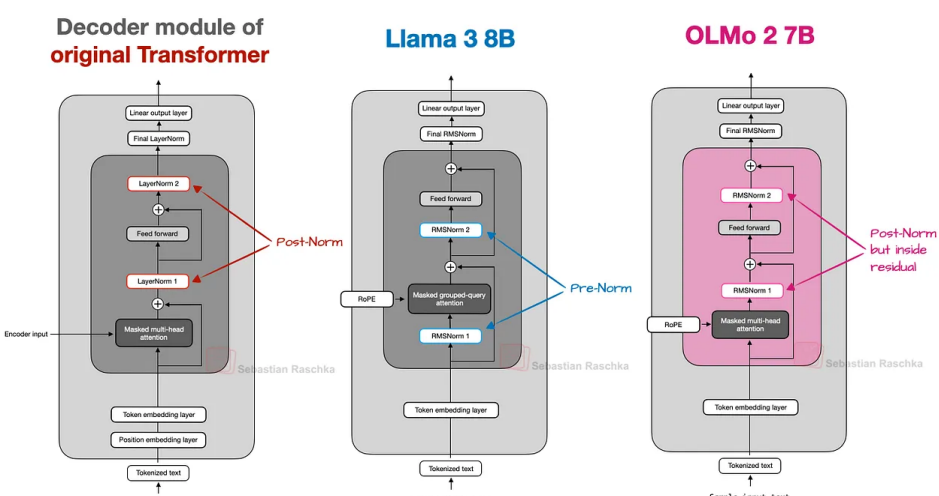


Figure 8: A comparison of Post-Norm, Pre-Norm, and OLMo 2's flavor of

Post-Norm.

In 2020, Xiong et al. showed that Pre-LN results in more well-behaved gradients at initialization. Furthermore, the researchers mentioned that Pre-LN even works well without careful learning rate warm-up, which is otherwise a crucial tool for Post-LN.

Now, the reason I am mentioning that is that OLMo 2 adopted a form of Post-LN (but with RMSNorm instead of LayerNorm, so I am calling it *Post-Norm*).

In OLMo 2, instead of placing the normalization layers before the attention and FeedForward layers, they place them after, as shown in the figure above. However, notice that in contrast to the original transformer architecture, the

normalization layers are still inside the residual layers (skip connections).

So, why did they move the position of the normalization layers? The reason is that it helped with training stability, as shown in the figure below.

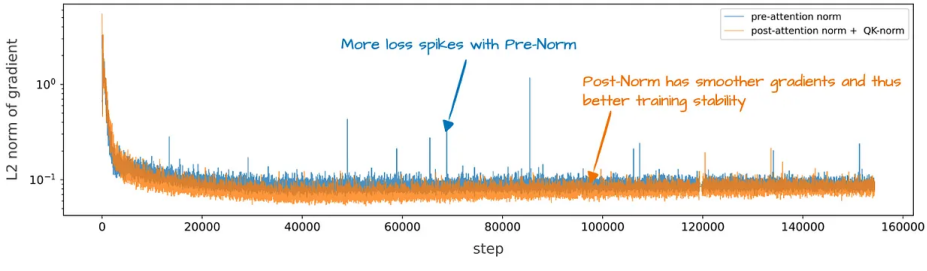


Figure 9: A plot showing the training stability for Pre-Norm (like in GPT-2, Llama 3, and many others) versus OLMo 2's flavor of Post-Norm. This is an annotated figure from the OLMo 2 paper, https://arxiv.org/abs/2501.00656

Unfortunately this figure shows the results of the reordering together with QK-Norm, which is a separate concept. So, it's hard to tell how much the normalization layer reordering contributed by itself.

2.2 QK-Norm

Since the previous section already mentioned the QK-norm, and other LLMs we discuss later, such as Gemma 2 and Gemma 3, also use QK-norm, let's briefly discuss what this is.

QK-Norm is essentially yet another RMSNorm layer. It's placed inside the Multi-Head Attention (MHA) module and applied to the queries (q) and keys (k) before applying RoPE. To illustrate this, below is an excerpt of a Grouped-Query Attention (GQA) layer I wrote

for my Qwen3 from-scratch implementation (the QK-norm application in GQA is similar to MHA in OLMo):

```
class
GroupedQueryAttention(nn.Module):
    def __init__(
        self, d_in, num_heads,
num_kv_groups,
        head_dim=None,
qk_norm=False, dtype=None
    ):
        # ...

        if qk_norm:
            self.q_norm =
RMSNorm(head_dim, eps=1e-6)
            self.k_norm =
RMSNorm(head_dim, eps=1e-6)
        else:
            self.q_norm =
```

```
self.k_norm = None

    def forward(self, x, mask,
cos, sin):
        b, num_tokens, _ =
x.shape

        # Apply projections
        queries = self.W_query(x)
        keys = self.W_key(x)
        values = self.W_value(x)

        # ...

        # Optional normalization
        if self.q_norm:
            queries =
self.q_norm(queries)
        if self.k_norm:
            keys =
self.k_norm(keys)

        # Apply RoPE
        queries =
```

```
apply_rope(queries, cos, sin)
        keys = apply_rope(keys,
cos, sin)

        # Expand K and V to match
number of heads
        keys =
keys.repeat_interleave(self.group
_size, dim=1)
        values =
values.repeat_interleave(self.gro
up_size, dim=1)

        # Attention
        attn_scores = queries @
keys.transpose(2, 3)
        # ...
```

As mentioned earlier, together with Post-Norm, QK-Norm stabilizes the training. Note that QK-Norm was not invented by OLMo 2 but goes

back to the 2023 Scaling Vision Transformers paper.

2.3 OLMo 2 Summary

In short, the noteworthy OLMo 2 architecture design decisions are primarily the RMSNorm placements: RMSNorm after instead of before the attention and FeedForward modules (a flavor of Post-Norm), as well as the addition of RMSNorm for the queries and keys inside the attention mechanism (QK-Norm), which both, together, help stabilize the training loss.

Below is a figure that further compares OLMo 2 to Llama 3 side by side; as one can see, the architectures are otherwise relatively similar except for the fact that OLMo 2 still uses the traditional MHA instead of GQA. (However, the

OLMo 2 team released a 32B variant 3 months later that uses GQA.)

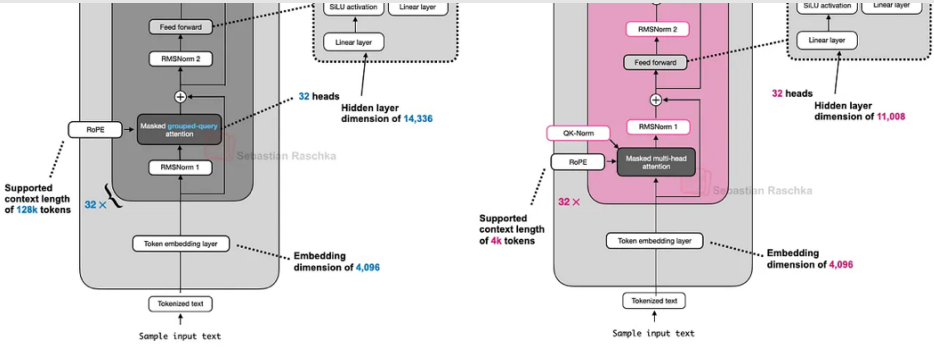


Figure 10: An architecture comparison between Llama 3 and OLMo 2.

3. Gemma 3

Google's Gemma models have always been really good, and I think they have always been a bit underhyped compared to other popular

models, like the Llama series.

One of the distinguishing aspects of Gemma is the rather large vocabulary size (to support multiple languages better), and the stronger

sizes: 1B, 4B, and 12B.

The 27B size hits a really nice sweet spot: it's much more capable than an 8B model but not as resource-intensive as a 70B model, and it runs just fine locally on my Mac Mini.

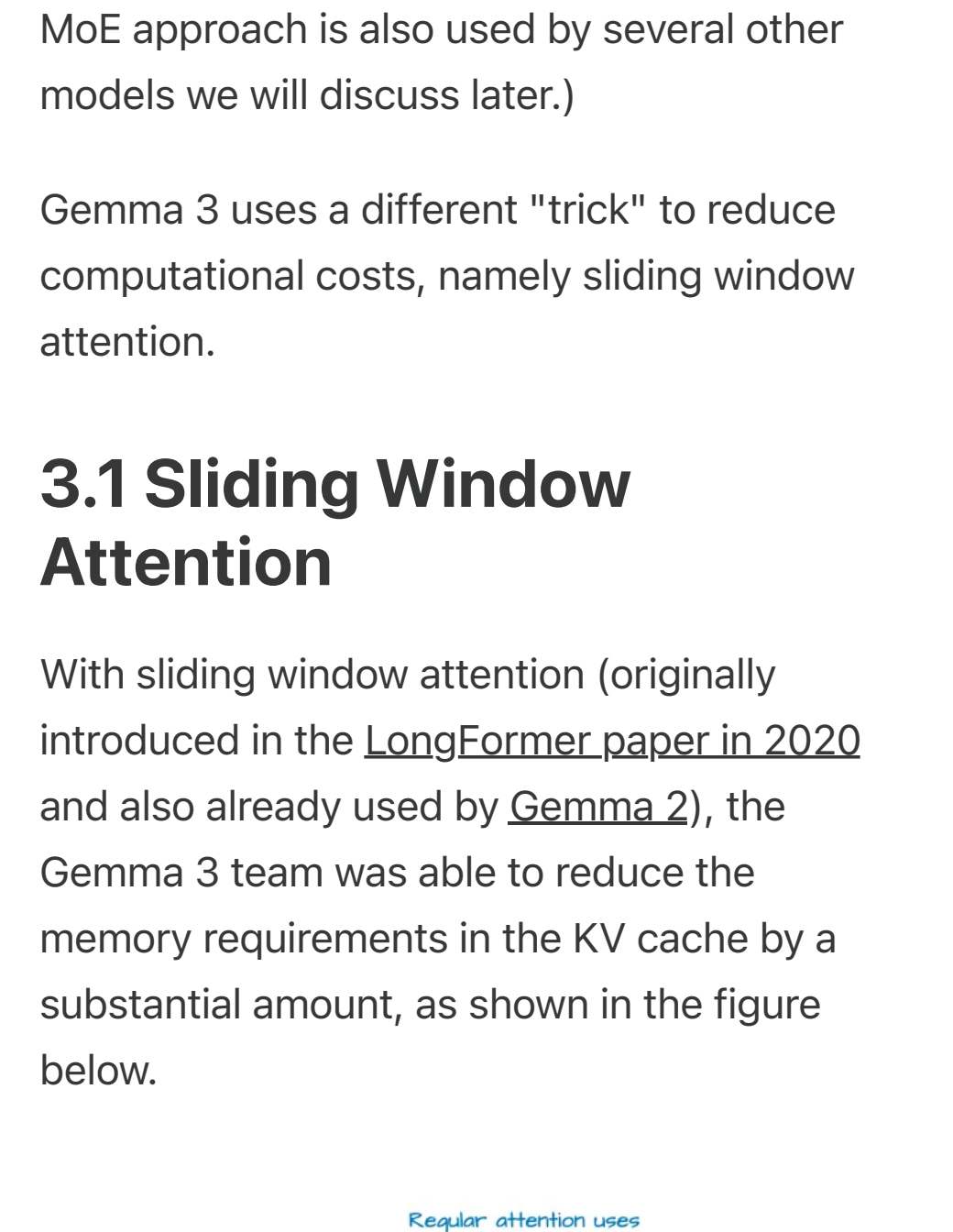
So, what else is interesting in Gemma 3? As discussed earlier, other models like Deepseek-V3/R1 use a Mixture-of-Experts (MoE) architecture to reduce memory requirements at inference, given a fixed model size. (The

MoE approach is also used by several other models we will discuss later.)

Gemma 3 uses a different "trick" to reduce computational costs, namely sliding window attention.

3.1 Sliding Window Attention

With sliding window attention (originally introduced in the LongFormer paper in 2020 and also already used by Gemma 2), the Gemma 3 team was able to reduce the memory requirements in the KV cache by a substantial amount, as shown in the figure below.



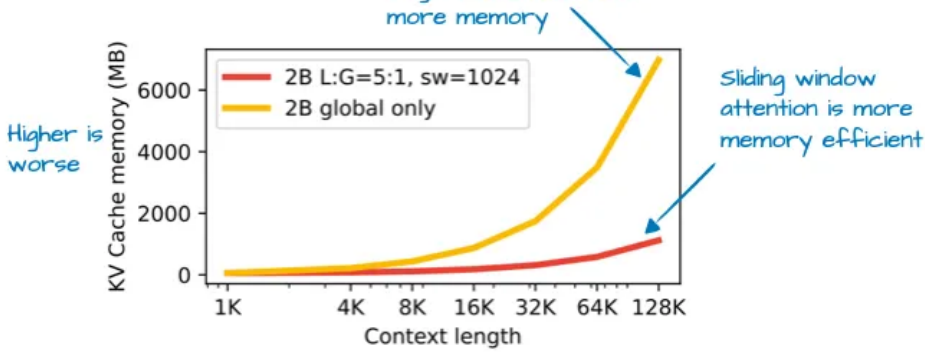


Figure 11: An annotated figure from Gemma 3 paper (https://arxiv.org/abs/2503.19786) showing the KV cache memory savings via sliding window attention.

So, what is sliding window attention? If we think of regular self-attention as a *global* attention mechanism, since each sequence element can access every other sequence element, then we can think of sliding window attention as *local* attention, because here we restrict the context size around the current query position. This is illustrated in the figure

below.

Figure 12: A comparison between regular attention (left) and sliding window attention (right).

Please note that sliding window attention can be used with both Multi-Head Attention and Grouped-Query Attention; Gemma 3 uses grouped-query attention.

As mentioned above, sliding window attention

is also referred to as *local* attention because the local window surrounds and moves with the current query position. In contrast, regular attention is *global* as each token can access all other tokens.

Now, as briefly mentioned above, the Gemma 2 predecessor architecture also used sliding window attention before. The difference in Gemma 3 is that they adjusted the ratio between global (regular) and local (sliding) attention.

For instance, Gemma 2 uses a hybrid attention mechanism that combines sliding window (local) and global attention in a 1:1 ratio. Each token can attend to a 4k-token window of nearby context.

Where Gemma 2 used sliding window attention in every other layer, Gemma 3 now has a 5:1 ratio, meaning there's only 1 full attention layer for every 5 sliding windows (local) attention layers; moreover, the sliding window size was reduced from 4096 (Gemma 2) to just 1024 (Gemma 3). This shifts the model's focus towards more efficient, localized computations.

According to their ablation study, the use of sliding window attention has minimal impact on modeling performance, as shown in the figure below.

Figure 13: An annotated figure from Gemma 3 paper (https://arxiv.org/abs/2503.19786) showing that sliding window attention has little to no impact on the LLM-generated output perplexity.

While sliding window attention is the most notable architecture aspect of Gemma 3, I want to also briefly go over the placement of the normalization layers as a follow-up to the previous OLMo 2 section.

3.2 Normalization Layer Placement in Gemma 3

A small but interesting tidbit to highlight is that Gemma 3 uses RMSNorm in both a Pre-Norm and Post-Norm setting around its grouped-

query attention module.

This is similar to Gemma 2 but still worth highlighting, as it differs from (1) the Post-Norm used in the original transformer ("Attention is all you need"), (2) the Pre-Norm, which was popularized by GPT-2 and used in many other architectures afterwards, and (3) the Post-Norm flavor in OLMo 2 that we saw earlier.

Figure 14: An architecture comparison between OLMo2 and Gemma 3; note the additional normalization layers in Gemma 3.

I think this normalization layer placement is a relatively intuitive approach as it gets the best of both worlds: Pre-Norm and Post-Norm. In my opinion, a bit of extra normalization can't hurt. In the worst case, if the extra normalization is redundant, this adds a bit of inefficiency through redundancy. In practice, since RMSNorm is relatively cheap in the grand scheme of things, this shouldn't have any noticeable impact, though.

3.3 Gemma 3 Summary

Gemma 3 is a well-performing open-weight LLM that, in my opinion, is a bit underappreciated in the open-source circles. The most interesting part is the use of sliding window attention to improve efficiency (it will be interesting to combine it with MoE in the future).

Also, Gemma 3 has a unique normalization layer placement, placing RMSNorm layers both before and after the attention and FeedForward modules.

3.4 Bonus: Gemma 3n

A few months after the Gemma 3 release,

Google shared Gemma 3n, which is a Gemma 3 model that has been optimized for small-device efficiency with the goal of running on phones.

One of the changes in Gemma 3n to achieve better efficiency is the so-called Per-Layer Embedding (PLE) parameters layer. The key idea here is to keep only a subset of the model's parameters in GPU memory. Token-layer specific embeddings, such as those for text, audio, and vision modalities, are then streamed from the CPU or SSD on demand.

The figure below illustrates the PLE memory savings, listing 5.44 billion parameters for a standard Gemma 3 model. This likely refers to the Gemma 3 4-billion variant.

Figure 15: An annotated figure from Google's Gemma 3n blog (https://developers.googleblog.com/en/introducing-gemma-3n/) illustrating the PLE memory savings.

The 5.44 vs. 4 billion parameter discrepancy is because Google has an interesting way of reporting parameter counts in LLMs. They often exclude embedding parameters to make

the model appear smaller, except in cases like this, where it is convenient to include them to make the model appear larger. This is not unique to Google, as this approach has become a common practice across the field.

Another interesting trick is the MatFormer concept (short for Matryoshka Transformer). For instance, Gemma 3n uses a single shared LLM (transformer) architecture that can be sliced into smaller, independently usable models. Each slice is trained to function on its own, so at inference time, we can run just the part you need (instead of the large model).

4. Mistral Small 3.1

Mistral Small 3.1 24B, which was released in

March shortly after Gemma 3, is noteworthy for outperforming Gemma 3 27B on several benchmarks (except for math) while being faster.

The reasons for the lower inference latency of Mistral Small 3.1 over Gemma 3 are likely due to their custom tokenizer, as well as shrinking the KV cache and layer count. Otherwise, it's a standard architecture as shown in the figure below.

Figure 16: An architecture comparison between Gemma 3 27B and Mistral 3.1 Small 24B.

Interestingly, earlier Mistral models had utilized sliding window attention, but they appear to have abandoned it in Mistral Small 3.1 if we consider the default setting (`"sliding_window": null`) in the official Model Hub configuration file. Also, the model card makes no mention of it.

So, since Mistral uses regular Grouped-Query Attention instead of Grouped-Query Attention with a sliding window as in Gemma 3, maybe there are additional inference compute savings due to being able to use more optimized code (i.e., FlashAttention). For instance, I speculate that while sliding window attention reduces

memory usage, it doesn't necessarily reduce inference latency, which is what Mistral Small 3.1 is focused on.

5. Llama 4

The extensive introductory discussion on Mixture-of-Experts (MoE) earlier in this article pays off again. Llama 4 has also adopted an MoE approach and otherwise follows a relatively standard architecture that is very similar to DeepSeek-V3, as shown in the figure below. (Llama 4 includes native multimodal support, similar to models like Gemma and Mistral. However, since this article focuses on language modeling, we only focus on the text model.)

Figure 17: An architecture comparison between DeepSeek V3 (671-billion parameters) and Llama 4 Maverick (400-billion parameters).

While the Llama 4 Maverick architecture looks very similar to DeepSeek-V3 overall, there are some interesting differences worth highlighting.

First, Llama 4 uses Grouped-Query Attention similar to its predecessors, whereas

DeepSeek-V3 uses Multi-Head Latent Attention, which we discussed at the beginning of this article. Now, both DeepSeek-V3 and Llama 4 Maverick are very large architectures, with DeepSeek-V3 being approximately 68% larger in its total parameter count. However, with 37 billion active parameters, DeepSeek-V3 has more than twice as many active parameters as Llama 4 Maverick (17B).

Llama 4 Maverick uses a more classic MoE setup with fewer but larger experts (2 active experts with 8,192 hidden size each) compared to DeepSeek-V3 (9 active experts with 2,048 hidden size each). Also, DeepSeek uses MoE layers in each transformer block (except the first 3), whereas Llama 4 alternates MoE and dense modules in every other transformer block.

Given the many small differences between architectures, it is difficult to determine their exact impact on final model performance. The main takeaway, however, is that MoE architectures have seen a significant rise in popularity in 2025.

6. Qwen3

The Qwen team consistently delivers high-quality open-weight LLMs. When I helped co-advising the LLM efficiency challenge at NeurIPS 2023, I remember that the top winning solutions were all Qwen2-based.

Now, Qwen3 is another hit model series at the top of the leaderboards for their size classes.

There are 7 dense models: 0.6B, 1.7B, 4B, 8B, 14B, and 32B. And there are 2 MoE models: 30B-A3B, and 235B-A22B.

(By the way, note that the missing whitespace in "Qwen3" is not a typo; I simply try to preserve the original spelling the Qwen developers chose.)

6.1 Qwen3 (Dense)

Let's discuss the dense model architecture first. As of this writing, the 0.6B model may well be the smallest current-generation open-weight model out there. And based on my personal experience, it performs really well given its small size. It has great token/sec throughput and a low memory footprint if you are planning to run it locally. But what's more,

it's also easy to train locally (for educational purposes) due to its small size.

So, Qwen3 0.6B has replaced Llama 3 1B for me for most purposes. A comparison between these two architectures is shown below.

Figure 18: An architecture comparison between Qwen3 0.6B and Llama 3 1B; notice that Qwen3 is a deeper architecture with more layers, whereas

Llama 3 is a wider architecture with more attention heads.

If you are interested in a human-readable Qwen3 implementation without external third-party LLM library dependencies, I recently implemented Qwen3 from scratch (in pure PyTorch).

The computational performance numbers in the figure above are based on my from-scratch PyTorch implementations when run on an A100 GPU. As one can see, Qwen3 has a smaller memory footprint as it is a smaller architecture overall, but also uses smaller hidden layers and fewer attention heads. However, it uses more transformer blocks than Llama 3, which leads to a slower runtime (lower tokens/sec generation speed).

6.2 Qwen3 (MoE)

As mentioned earlier, Qwen3 also comes in two MoE flavors: 30B-A3B and 235B-A22B. Why do some architectures, like Qwen3, come as regular (dense) and MoE (sparse) variants?

As mentioned at the beginning of this article, MoE variants help reduce inference costs for large base models. Offering both dense and MoE versions gives users flexibility depending on their goals and constraints.

Dense models are typically more straightforward to fine-tune, deploy, and optimize across various hardware.

On the other hand, MoE models are optimized for scaling inference. For instance, at a fixed

inference budget, they can achieve a higher overall model capacity (i.e., knowledge uptake during training due to being larger) without proportionally increasing inference costs.

By releasing both types, the Qwen3 series can support a broader range of use cases: dense models for robustness, simplicity, and fine-tuning, and MoE models for efficient serving at scale.

To round up this section, let's look at Qwen3 235B-A22B (note that the A22B stands for "22B active parameters) to DeepSeek-V3, which has almost twice as many active parameters (37B).

Figure 19: An architecture comparison between DeepSeek-V3 and Qwen3 235B-A22B.

As shown in the figure above, the DeepSeek-V3 and Qwen3 235B-A22B architectures are remarkably similar. What's noteworthy, though, is that the Qwen3 model moved away from using a shared expert (earlier Qwen models, such as Qwen2.5-MoE did use a shared expert).

Unfortunately, the Qwen3 team did not disclose any reason as to why they moved

away from shared experts. If I had to guess, it was perhaps simply not necessary for training stability for their setup when they increased the experts from 2 (in Qwen2.5-MoE) to 8 (in Qwen3). And then they were able to save the extra compute/memory cost by using only 8 instead of 8+1 experts. (However, this doesn't explain why DeepSeek-V3 is still keeping their shared expert.)

Update. Junyang Lin, one of the developers of Qwen3, responded as follows:

> At that moment we did not find significant enough improvement on shared expert and we were worrying about the optimization for inference caused by shared expert. No straight answer to this question honestly.

7. SmolLM3

SmolLM3 is perhaps not as nearly as popular as the other LLMs covered in this article, but I thought it is still an interesting model to include as it offers really good modeling performance at a relatively small and convenient 3-billion parameter model size that sits between the 1.7B and 4B Qwen3 model, as shown in the figure below.

Moreover, it also shared a lot of the training details, similar to OLMo, which is rare and always appreciated!

Figure 20: An annotated figure from the SmolLM3 announcement post, https://huggingface.co/blog/smollm3, comparing the SmolLM3 win rate to Qwen3 1.7B and 4B as well as Llama 3 3B and Gemma 3 4B.

As shown in the architecture comparison figure below, the SmolLM3 architecture looks fairly standard. The perhaps most interesting aspect is its use of NoPE (No Positional Embeddings), though.

Figure 21: A side-by-side architecture comparison between Qwen3 4B and SmolLM3 3B.

7.1 No Positional Embeddings (NoPE)

NoPE is, in LLM contexts, an older idea that goes back to a 2023 paper (The Impact of Positional Encoding on Length Generalization in Transformers) to remove explicit positional information injection (like through classic

absolute positional embedding layers in early GPT architectures or nowadays RoPE).

In transformer-based LLMs, positional encoding is typically necessary because self-attention treats tokens independently of order. Absolute position embeddings solve this by adding an additional embedding layer that adds information to the token embeddings.

Figure 22: A modified figure from my Build A Large Language Model (From Scratch) book

(https://www.amazon.com/Build-Large-Language-Model-Scratch/dp/1633437167) illustrating absolute positional embeddings.

RoPE, on the other hand, solves this by rotating the query and key vectors relative to their token position.

In NoPE layers, however, no such positional signal is added at all: not fixed, not learned, not relative. Nothing.

Even though there is no positional embedding, the model still knows which tokens come before, thanks to the causal attention mask. This mask prevents each token from attending to future ones. As a result, a token at position t can only see tokens at positions $\leq t$, which preserves the autoregressive ordering.

So while there is no positional information that is explicitly added, there is still an implicit sense of direction baked into the model's structure, and the LLM, in the regular gradient-descent-based training, can learn to exploit it if it finds it beneficial for the optimization objective. (Check out the NoPE paper's theorems for more information.)

So, overall, the NoPE paper not only found that no positional information injection is necessary, but it also found that NoPE has better length generalization, which means that LLM answering performance deteriorates less with increased sequence length, as shown in the figure below.

Figure 23: An annotated figure from the NoPE paper (https://arxiv.org/abs/2305.19466) showing better length generalization with NoPE.

Note that the experiments shown above were conducted with a relatively small GPT-style model of approximately 100 million parameters and relatively small context sizes. It is unclear how well these findings generalize to larger, contemporary LLMs.

For this reason, the SmolLM3 team likely only "applied" NoPE (or rather omitted RoPE) in every 4th layer.

8. Kimi K2 and Kimi K2 Thinking

Kimi K2 recently made big waves in the AI community due to being an open-weight model with an incredibly good performance. According to benchmarks, it's on par with the best proprietary models like Google's Gemini, Anthropic's Claude, and OpenAI's ChatGPT models.

A notable aspect is its use of a variant of the relatively new Muon optimizer over AdamW. As far as I know, this is the first time Muon was

used over AdamW for any production model of this size (previously, it has only been shown to scale up to 16B). This resulted in very nice training loss curves, which probably helped catapult this model to the top of the aforementioned benchmarks.

While people commented that the loss was exceptionally smooth (due to the lack of spikes), I think it's not exceptionally smooth (e.g., see the OLMo 2 loss curve in the figure below; also, the L2 norm of the gradient would probably be a better metric to track training stability). However, what's remarkable is how well the loss curve decays.

However, as mentioned in the introduction of this article, training methodologies are a topic for another time.

Figure 24: Annotated figures from the Kimi K2 announcement blog article (https://moonshotai.github.io/Kimi-K2/) and the OLMo 2 paper (https://arxiv.org/abs/2305.19466).

The model itself is 1 trillion parameters large, which is truly impressive.

It may be the biggest LLM of this generation as of this writing (given the constraints that Llama 4 Behemoth is not released, proprietary LLMs don't count, and Google's 1.6 trillion Switch Transformer is an encoder-decoder architecture from a different generation).

It's also coming full circle as Kimi K2 uses the DeepSeek-V3 architecture we covered at the beginning of this article except they made it larger, as shown in the figure below.

Figure 25.1: An architecture comparison between DeepSeek V3 and Kimi K2.

As shown in the figure above, Kimi K2 is basically the same as DeepSeek V3, except that it uses more experts in the MoE modules and fewer heads in the Multi-head Latent Attention (MLA) module.

Kimi K2 is not coming out of nowhere. The earlier Kimi 1.5 model discussed in the Kimi k1.5: Scaling Reinforcement Learning with LLMs paper, was impressive as well. However, it had the bad luck that the DeepSeek R1 model paper was published on exactly the

same date on January 22nd. Moreover, as far as I know, the Kimi 1.5 weights were never publicly shared.

So, most likely the Kimi K2 team took these lessons to heart and shared Kimi K2 as an open-weight model, before DeepSeek R2 was released. As of this writing, Kimi K2 is the most impressive open-weight model.

Update: On Nov 6, 2025 the Kimi K2 team also released their new "Thinking" model variant. The architecture is unchanged from Kimi K2 above, except that they extended the context size from 128k to 256k.

According to the benchmarks shared by the Kimi team, the model exceeds the performance of the leading proprietary LLMs.

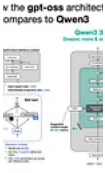
(Unfortunately, there is no direct comparison to DeepSeek R1.

Figure 25.2: DeepSeek R1 versus Kimi K2 Thinking architecture (top) and Kimi

K2 Thinking benchmarks (bottom).

9. GPT-OSS

OpenAI's released gpt-oss-120b and gpt-oss-20b, their first open-weight models since GPT-2 in 2019, about one week after I wrote this article. Since OpenAI's open-weight models have been so widely anticipated, I updated this article to include them. I will keep this section brief, but I have written another, much more detailed article dedicated to the gpt-oss models here:



From GPT-2 to gpt-oss: Analyzing the Architectural Advances

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Before summarizing the interesting tidbits, let's start with an overview of the two models, gpt-oss-20b and gpt-oss-120b, as shown in Figure 26 below.

Figure 26: Architecture overview of the two gpt-oss models.

Looking at Figure 26, the architecture contains all the familiar components we have seen in other architectures discussed previously. For instance, Figure 27 puts the smaller gpt-oss

architecture next to Qwen3 30B-A3B, which is also an MoE model with a similar number of active parameters (gpt-oss has 3.6B active parameters, and Qwen3 30B-A3B has 3.3B).

Figure 27: Architecture comparison between gpt-oss and Qwen3

One aspect not shown in Figure 27 is that gpt-oss uses sliding window attention (similar to Gemma 3, but in every other layer instead of

using a 5:1 ratio).

9.1 Width Versus Depth

Figure 27 shows that gpt-oss and Qwen3 use similar components. But if we look at the two models closely, we see that Qwen3 is a much deeper architecture with its 48 transformer blocks instead of 24.

On the other hand, gpt-oss is a much wider architecture:

- An embedding dimension of 2880 instead of 2048
- An intermediate expert (feed forward) projection dimension of also 2880 instead of 768

It's also worth noting that gpt-oss uses twice

as many attention heads, but this doesn't directly increase the model's width. The width is determined by the embedding dimension.

Does one approach offer advantages over the other given a fixed number of parameters? As a rule of thumb, deeper models have more flexibility but can be harder to train due to instability issues, due to exploding and vanishing gradients (which RMSNorm and shortcut connections aim to mitigate).

Wider architectures have the advantage of being faster during inference (with a higher tokens/second throughput) due to better parallelization at a higher memory cost.

When it comes to modeling performance, there's unfortunately no good apples-to-

apples comparison I am aware of (where parameter size and datasets are kept constant) except for an ablation study in the Gemma 2 paper (Table 9), which found that for a 9B parameter architecture, a wider setup is slightly better than a deeper setup. Across 4 benchmarks, the wider model achieved a 52.0 average score, and the deeper model achieved a 50.8 average score.

9.2 Few Large Versus Many Small Expert

As shown in Figure 27 above, it's also noteworthy that gpt-oss has a surprisingly small number of experts (32 instead of 128), and only uses 4 instead of 8 active experts per token. However, each expert is much larger than the experts in Qwen3.

This is interesting because the recent trends and developments point towards more, smaller models as being beneficial. This change, at a constant total parameter size, is nicely illustrated in Figure 28 below from the DeepSeekMoE paper.

Figure 28: An annotated figure from "DeepSeekMoE: Towards Ultimate Expert Specialization in Mixture-of-Experts Language Models",

https://arxiv.org/abs/2401.06066

Notably, unlike DeepSeek's models, neither gpt-oss nor Qwen3 uses shared experts, though.

9.3 Attention Bias and Attention Sinks

Both gpt-oss and Qwen3 use grouped query attention. The main difference is that gpt-oss restricts the context size via sliding window attention in each second layer, as mentioned earlier.

However, there's one interesting detail that caught my eye. It seems that gpt-oss uses bias units for the attention weights, as shown in Figure 29 below.

Figure 29: gpt-oss models use bias units in the attention layers. See code example here.

I haven't seen these bias units being used since the GPT-2 days, and they are commonly regarded as redundant. Indeed, I found a recent paper that shows mathematically that this is at least true for the key transformation (`k_proj`). Furthermore, the empirical results show that there is little difference between with and without bias units (see Figure 30 below).

Figure 30: Table from https://arxiv.org/pdf/2302.08626 showing the average test loss when the models were trained from scratch with and without bias units.

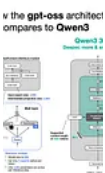
Another detail you may have noticed is the definition of `sinks` in the code screenshot in Figure 30. In general models, attention sinks are special "always-attended" tokens placed at the start of the sequence to stabilize attention, which is especially useful in long-context scenarios. I.e., if the context gets very long, this special attended token at the

beginning is still attended to, and it can learn to store some generally useful information about the entire sequence. (I think it was originally proposed in the Efficient Streaming Language Models with Attention Sinks paper.)

In the gpt-oss implementation, *attention sinks* are not actual tokens in the input sequence. Instead, they are learned per-head bias logits that are appended to the attention scores (Figure 31). The goal is the same as with the above-mentioned attention sinks, but without modifying the tokenized inputs.

Figure 31: The use of attention sinks in gpt-oss; based on the Hugging Face code here.

For more information about gpt-oss, and how it compares to GPT-2, please see my other gpt-oss article:



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10. Grok 2.5

A few weeks after this article first went online, xAI released the weights of their 270B-parameter Grok 2.5 model.

I thought it would be worth including here, since Grok 2.5 was xAI's flagship production model last year. Up to this point, all models we discussed were released as open-weight models from the start. For example, gpt-oss is likely not an open-weight clone of GPT-4 but rather a custom model trained specifically for the open-source community.

With Grok 2.5, we get a rare look at a real production system, even if it is last year's.

Architecturally, Grok 2.5 looks fairly standard overall (Figure 32), but there are a few noteworthy details.

Figure 32: Grok 2.5 next to a Qwen3 model of comparable size

For instance, Grok 2.5 uses a small number of large experts (eight), which reflects an older trend. As discussed earlier, more recent designs such as those in the DeepSeekMoE

paper favor a larger number of smaller experts (this is also present in Qwen3).

Another interesting choice is the use of what amounts to a shared expert. The additional SwiGLU module shown on the left in Figure 32 functions as an always-on, shared expert. It is not identical to the classic shared-expert design since its intermediate dimension is doubled, but the idea is the same. (I still find it interesting that Qwen3 omitted shared experts, and it will be interesting to see if that changes with Qwen4 and later models.)

11. GLM-4.5

GLM-4.5 is another major release this year.

It is an instruction/reasoning hybrid similar to Qwen3, but even better optimized for function calling and agent-style contexts.

Figure 33: GLM-4.5 benchmark from the official GitHub repository at https://github.com/zai-org/GLM-4.5

As shown in Figure 34, GLM-4.5 comes in two

variants. The flagship 355-billion-parameter model outperforms Claude 4 Opus on average across 12 benchmarks and trails only slightly behind OpenAI's o3 and xAI's Grok 4. There is also GLM-4.5-Air, a more compact 106-billion-parameter version that delivers performance only marginally below the 355-billion model.

Figure 35 compares the 355-billion architecture to Qwen3.

Figure 34: GLM-4.5 next to a similarly-sized Qwen3 model.

The designs are largely similar, but GLM-4.5 adopts a structural choice first introduced by DeepSeek V3: 3 dense layers precede the Mixture-of-Experts (MoE) blocks. Why? Starting with several dense layers improves convergence stability and overall performance in large MoE systems. If MoE routing is introduced immediately, the instability of sparse expert selection can interfere with early syntactic and semantic feature extraction. So, one might say that by keeping the initial layers dense ensures the model forms stable low-level representations before routing decisions begin to shape higher-level processing.

Also, GLM-4.5 uses a shared expert similar to DeepSeek-V3 (and unlike Qwen3).

(Interestingly, GLM-4.5 also retains the attention bias mechanism used in GPT-2 and gpt-oss.)

12. Qwen3-Next

On 11 September 2025, the Qwen3 team released Qwen3 Next 80B-A3B (Figure 35), available in both Instruct and Thinking variants. While its design builds on the previously discussed Qwen3 architecture, I included it here as a separate entry to keep the figure numbering consistent and to draw attention to some of its design changes.

12.1 Expert Size and Number

The new Qwen3 Next architecture stands out because, despite being 3× smaller than the previous 235B-A22B model (Figure 35), it introduces four times as many experts and even adds a shared expert. Both of these design choices (a high expert count and the inclusion of a shared expert) were future directions I had highlighted prior to this release, particularly in the video version of the article that I linked at the top.

Figure 35: The original Qwen3 model released in May (left) next to the Qwen3 Next model released in September (right).

12.2 Gated DeltaNet + Gated Attention Hybrid

The other highlight is that they replace the regular attention mechanism by a Gated DeltaNet + Gated Attention hybrid, which helps enable the native 262k token context length in terms of memory usage (the previous 235B-A22B model model supported 32k natively, and 131k with YaRN scaling.)

So how does this new attention hybrid work? Compared to grouped-query attention (GQA), which is still standard scaled dot-product attention (sharing K/V across query-head groups to cut KV-cache size and memory bandwidth as discussed earlier but whose decode cost and cache still grow with sequence length), their hybrid mechanism mixes *Gated DeltaNet* blocks with *Gated Attention* blocks with in a 3:1 ratio as shown in Figure 36.

Figure 36: The Gated DeltaNet + Gated Attention hybrid mechanism. Note that these are arranges in a 3:1 ratio, meaning that 3 transformer blocks with Gated DeltaNet are followed by 1 transformer block with Gated Attention. The right subfigure is from the official Qwen3 blog: https://qwen.ai/blog?id=4074cca80393150c248e508aa62983f9cb7d27cd&from=research.latest-advancements-list

We can think of the gated attention block as standard scaled-dot-product attention that can be used in GQA, but it has a few tweaks on top. The main differences between *gated attention* and plain GQA block are:

1. an output gate (sigmoid-controlled, usually per-channel) that scales the attention result before it is added back to the residual;
2. zero-centered RMSNorm for QKNorm, rather than a standard RMSNorm;
3. partial RoPE (on a subset of dimensions).

Note that these are essentially just stability changes to GQA.

The Gated DeltaNet is a more significant change. In the DeltaNet block, q, k, v and two gates (α, β) are produced by linear and lightweight convolutional layers with normalization, and the layer replaces attention with a fast-weight *delta rule* update.

However, the tradeoff is that DeltaNet offers less precise content-based retrieval than full attention, which is why one gated attention layer remains.

Given that attention grows quadratically, the DeltaNet component was added to help with memory efficiency. In the "linear-time, cache-free" family, the DeltaNet block is a essentially an alternative to Mamba. Mamba keeps a state with a learned state-space filter (essentially a dynamic convolution over time). DeltaNet keeps a tiny fast-weight memory updated with α and β and reads it with q, with small convolutions only used only to help form q, k, v, α, β.

12.3 Multi-Token Prediction

The two subsections above describe two design decisions geared towards efficiency. Since all good things come in threes, the Qwen3 added another technique on top: Multi-Token Prediction (MTP).

Multi-token prediction trains the LLM to predict several future tokens, instead of a single one, at each step. Here, at each position *t*, small extra heads (linear layers) output logits for *t+1…t+k*, and we sum cross-entropy losses for these offsets (in the MTP paper the researchers recommended *k=4*). This additional signal speeds up training, and inference may remain at generating one token at a time. However, the extra heads can be used in speculative multi-token decoding, which is what Qwen3-Next seems to do,

however, the details are still a bit sparse:

> Qwen3-Next introduces a native Multi-Token Prediction (MTP) mechanism, which not only yields an MTP module with a high acceptance rate for Speculative Decoding but also enhances the overall performance.Additionally, Qwen3-Next specifically optimizes the multi-step inference performance of MTP, further improving the acceptance rate of Speculative Decoding in real scenarios through multi-step training that maintains consistency between training and inference. Souce: Qwen3-Next blog post

13. MiniMax-M2

Recently, open-weight LLM developers shared flavors of their core architectures optimized for efficiency. One example is Qwen3-Next (see previous section), which replaces some of the full attention blocks with a fast gated DeltaNet module. Another example is DeepSeek V3.2, which uses sparse attention, a linear attention variant that trades off some modeling performance for improved computational performance (I plan to cover this mechanism in more detail in an upcoming article).

Now, MiniMax-M1 falls into a similar category to the models above, in that it uses a linear attention variant (lightning attention) that offers improved efficiency over regular (full) attention. I originally didn't cover MiniMax M1 as it wasn't quite as popular as some of the

other models discussed here. However, their new MiniMax-M2 release is currently considered the best open-weight model (according to benchmark performance), which makes it too big to ignore.

Figure 37: MiniMax-M2 benchmark performance compared to other popular open-weight and proprietary LLMs. Image from the official model hub release readme file.

As shown in the overview figure below, I

grouped MiniMax-M2 with the other decoder-style transformer LLMs as it does not use the efficient lightning attention variant proposed in MiniMax-M1. Instead, the developers went back to using full attention, likely to improve modeling (and benchmark) performance.

Figure 38: A timeline of the main LLMs covered in this article, next to some of the attention-hybrid models that constitute more efficient alternatives, trading off some modeling performance with improved efficiency.

Overall, MiniMax-M2 is surprisingly similar to Qwen3. Besides changing the number of layers, sizes, etc., it uses the same components overall.

13.1 Per-Layer QK-Norm

Perhaps the one noteworthy highlight here is that MiniMax-M2 uses a so-called "per_layer" QK-Norm instead of the regular QK-Norm. A closer look at the code reveals that it is implemented like this inside the attention mechanism:

```
self.q_norm =
MiniMaxText01RMSNormTP(self.head_
dim * self.total_num_heads,
eps=...)
```

```
self.k_norm =
MiniMaxText01RMSNormTP(self.head_
dim * self.total_num_kv_heads,
eps=...)
```

Here, the `hidden_size` equals the concatenated heads (`num_heads * head_dim`), so the RMSNorm has a scale vector with distinct parameters for every head (and each head dim).

So, the "`per_layer`" means that the RMSNorm (used for QK-Norm as explained earlier) is defined in each transformer block (as in regular QK-Norm), but, in addition, instead of reusing it across attention heads, it's a unique QK-Norm for each attention head.

The model configuration file also includes a

sliding-window attention setting (similar to Gemma 3 in section 3), but, as in Mistral 3.1 (discussed in section 4), it is disabled by default.

Otherwise, besides the per-layer QK-Norm, the architecture is very similar to Qwen3, as shown in the figure below.

Figure 39: Comparison between Qwen3 and MiniMax-M2.

13.2 MoE Sparsity

Other interesting tidbits, as shown in the figure below, include the fact that they don't use a shared expert (similar to Qwen3 but unlike Qwen3-Next). As mentioned earlier, in my opinion, shared experts are useful because they reduce redundancy among the other experts.

Also, as apparent from the figure above, MiniMax-M2 is twice as "sparse" as Qwen3. I.e., at roughly the same size as Qwen3 235B-A22B, MiniMax-M2 has only 10B instead of 22B active experts per token (that is, 4.37% of the parameters are used in each inference step in MiniMax-M2, whereas Qwen3 uses 9.36% active tokens).

13.3 Partial RoPE

Lastly, similar to MiniMax-M1, MiniMax-M2 uses a "partial" instead of regular RoPE inside the attention modules to encode positional information. Similar to regular RoPE, the rotations are applied to the queries and keys after applying QK-Norm.

Partial RoPE here means only the first `rotary_dim` channels of each head get rotary position encodings, and the remaining `head_dim - rotary_dim` channels remain unchanged.

In the official M1 README file, the developers mention

> Rotary Position Embedding (RoPE) applied

> to half of the attention head dimension with a base frequency of 10,000,000

We can picture it as follows:

```
Full RoPE:      [r r r r r r r r]
Partial RoPE:   [r r r r – – – –]
```

where in the conceptual illustration above, the "r"s show rotated (position-encoded) dimensions, and the dashes are the untouched dimensions.

What's the point of this? In the M1 paper, the developers stated that

> ...implementing RoPE on half of the softmax attention dimensions enables length

> extrapolation without performance degradation.

My speculation is that this prevents "too much" rotation for long sequences, and particularly those that are longer than the longest documents in the training dataset. I.e., the rationale here could be that no rotation is better than a "bad" or "too extreme" rotation that the model hasn't seen before in training.

14. Kimi Linear

There's recently been a revival in linear attention mechanisms to improve the efficiency of LLMs.

The attention mechanism introduced in the

Attention Is All You Need paper (2017), aka scaled-dot-product attention, remains the most popular attention variant in today's LLMs. Besides traditional multi-head attention, it's also used in the more efficient flavors like grouped-query attention, sliding window attention, and multi-head latent attention.

14.1 Traditional Attention and Quadratic Costs

The original attention mechanism scales quadratically with the sequence length:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^\top}{\sqrt{d}}\right)V$$

This is because the query (Q), key (K), and value (V) are *n*-by-*d* matrices, where *d* is the

embedding dimension (a hyperparameter) and *n* is the sequence length (i.e., the number of tokens).

You can find more details on attention in my other article:

Understanding and Coding Self-Attention, Multi-Head Attention, Causal-Attention, and Cross-Attention in LLMs

JANUARY 14, 2024

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Figure 40: Illustration of the quadratic cost in attention due to sequence length n.

14.2 Linear attention

Linear attention variants have been around for a long time, and I remember seeing tons of papers in the 2020s. For example, one of the earliest I recall is the 2020 Transformers are RNNs: Fast Autoregressive Transformers with

Linear Attention paper, where the researchers approximated the attention mechanism:

$$\text{ion}(Q, K, V) = \text{softmax}\left(\frac{QK^\top}{\sqrt{d}}\right)V \approx \phi(Q)\big(\phi($$

Here, ϕ(·) is a kernel feature function, set to ϕ(x) = elu(x) + 1 .

This approximation is efficient because it avoids explicitly computing the n \times n attention matrix QK^T . Instead of performing all pairwise token interactions (which cost O(n^2d) time and memory).

I don't want to dwell too long on these older attempts. But the bottom line was that they reduced both time and memory complexity from O(n^2) to O(n) to making attention much more efficient for long sequences.

However, they never really gained traction as they degraded the model accuracy, and I have never really seen one of these variants applied in an open-weight state-of-the-art LLM.

14.3 Linear Attention Revival

In the second half of this year, there was a bit of a revival of linear attention variants. The first notable model was MiniMax-M1 with lightning attention, a 456B parameter mixture-of-experts (MoE) model with 46B active parameters, which came out back in June.

Then, in August, the Qwen3 team followed up with Qwen3-Next, which I discussed in more detail above. Then, in September, the

DeepSeek Team announced DeepSeek V3.2. All three models (MiniMax-M1, Qwen3-Next, DeepSeek V3.2) replace the traditional quadratic attention variants in most or all of their layers with efficient linear variants.

Interestingly, there was a recent plot twist, where the MiniMax team released their new 230B parameter M2 model (discussed in section 13) without linear attention, going back to regular attention. The team stated that linear attention is tricky in production LLMs. It seemed to work fine with regular prompts, but it had poor accuracy in reasoning and multi-turn tasks, which are not only important for regular chat sessions but also agentic applications.

This could have been a turning point where

linear attention may not be worth pursuing after all. However, it gets more interesting. In October, the Kimi team released their new Kimi Linear model with linear attention.

Figure 41: An overview of the linear attention hybrid architectures.

Side note: I could have grouped Qwen3-Next and Kimi Linear with the other transformer-state space model (SSM) hybrids in the overview figure. Personally, I see these other transformer-SSM hybrids as SSMs with

transformer components, whereas I see the models discussed here (Qwen3-Next and Kimi Linear) as transformers with SSM components. However, since I have listed IBM Granite 4.0 and NVIDIA Nemotron Nano 2 in the transformer-SSM box, an argument could be made for putting them into a single category.

14.4 Kimi Linear vs. Qwen3-Next

Kimi Linear shares several structural similarities with Qwen3-Next. Both models rely on a hybrid attention strategy. Concretely, they combine lightweight linear attention with heavier full attention layers. Specifically, both use a 3:1 ratio, meaning for every three transformer blocks employing the linear Gated

DeltaNet variant, there's one block that uses full attention as shown in the figure below.

Figure 42: Qwen3-Next and Kimi Linear side by side.

Gated DeltaNet is a linear attention variant with inspiration from recurrent neural networks, including a gating mechanism from the Gated

Delta Networks: Improving Mamba2 with Delta Rule paper. In a sense, Gated DeltaNet is a DeltaNet with Mamba-style gating, and DeltaNet is a linear attention mechanism. Due to the overview-nature of this article, DeltaNet would be good topic for a separate article in the future.

Note that the omission of the RoPE box in the Kimi Linear part of the figure above is intentional. Kimi applies NoPE (No Positional Embedding) in multi-head latent attention MLA) layers (global attention). As the authors state, this lets MLA run as pure multi-query attention at inference and avoids RoPE retuning for long-context scaling (the positional bias is supposedly handled by the Kimi Delta Attention blocks). For more information on MLA, and multi-query attention,

which is a special case of grouped-query attention, please see my The Big LLM Architecture Comparison article.

In addition, I've written more about Gated DeltaNet here.

14.5 Kimi Delta Attention

Kimi Linear modifies the linear attention mechanism of Qwen3-Next by the Kimi Delta Attention (KDA) mechanism, which is essentially a refinement of Gated DeltaNet. Whereas Qwen3-Next applies a scalar gate (one value per attention head) to control the memory decay rate, Kimi Linear replaces it with a channel-wise gating for each feature dimension. According to the authors, this gives more control over the memory, and this, in

turn, improves long-context reasoning.

In addition, for the full attention layers, Kimi Linear replaces Qwen3-Next's gated attention layers (which are essentially standard multi-head attention layers with output gating) with Multi-Head Latent Attention (MLA). This is the same MLA mechanism we discussed earlier in the DeepSeek V3/R1 section but with an additional gate. (To recap, MLA compresses the key/value space to reduce the KV cache size.)

There's no direct comparison to Qwen3-Next, but compared to the Gated DeltaNet-H1 model from the Gated DeltaNet paper (which is essentially Gated DeltaNet with sliding-window attention), Kimi Linear achieves higher modeling accuracy while maintaining the same

token-generation speed.

Figure 43: Annotated figure from the Kimi Linear paper showing that Kimi Linear is as fast as GatedDeltaNet, and much faster than an architecture with multi-head latent attention (like DeepSeek V3/R1), while having a higher benchmark performance.

Furthermore, according to the ablation studies in the DeepSeek-V2 paper, MLA is on par with regular full attention when the hyperparameters are carefully chosen.

And the fact that Kimi Linear compares favorably to MLA on long-context and reasoning benchmarks makes linear attention variant once again promising for larger state-of-the-art models. That being said, Kimi Linear is 48B-parameter large, but it's 20x smaller than Kimi K2. It will be interesting to see if the Kimi team adopts this approach for their upcoming K3 model.

15. Olmo 3 Thinking

Allen AI released their new Olmo 3 7B and 32B models on November 20. (The official spelling was changed from OLMo to Olmo, so I will be adopting that in this section.)

As mentioned earlier, Olmo models are always interesting because they are fully open-source. Here, that means that the team also shares detailed training reports, multiple checkpoints, information about the training data, and so forth. In other words, Olmo models are fully transparent.

This time, the Olmo suite also comes in an additional reasoning model flavor (next to base and instruct models), and there are lots of interesting details about the training in Olmo 3's technical report. However, since this is an article about architectural comparisons, this

section focuses only on Olmo 3's architecture.

The closest model to compare Olmo 3 to would be Qwen3, as the Qwen3 series has two models of similar size, and the Qwen3 models have a similar performance.

First, let's take a look at the smaller of the two, Olmo 3 7B.

Figure 44: Olmo 3 7B and Qwen3 8B

side by side.

As we can see, the Olmo 3 architecture is relatively similar to Qwen3. However, it's worth noting that this is essentially likely inspired by the Olmo 2 predecessor, not Qwen3.

Similar to Olmo 2, Olmo 3 still uses post-norm instead of pre-norm, as they found in the Olmo 2 paper that it stabilizes the training.

Interestingly, the 7B model still uses multi-head attention similar to Olmo 2. However, to make things more efficient and shrink the KV cache size, they now use sliding window attention (e.g., similar to Gemma 3).

Next, let's look at the 32B model.

Figure 45: Olmo 3 32B and Qwen3 32B side by side.

Overall, it's the same architecture but just scaled up. Also, the proportions (e.g., going from the input to the intermediate size in the feed forward layer, and so on) roughly match the ones in Qwen3.

My guess is the architecture was initially somewhat smaller than Qwen3 due to the smaller vocabulary, and they then scaled up

the intermediate size expansion from 5x in Qwen 3 to 5.4 in Olmo 3 to have a 32B model for a direct comparison.

Also, note that the 32B model uses grouped query attention.

Perhaps a last small detail is that Olmo 3 uses YaRN for context extension for the supported context length of 64k, but only for the global (non-sliding-window-attention) layers. (YaRN is essentially a careful RoPE rescaling technique, which helps preserve model quality better at long context sizes.)

In Qwen3, YaRN is optional to extend the native context from 32k tokens to 131k tokens.

If you are interested in additional architecture

details, I implemented Olmo 3 from scratch in a standalone notebook here.

Figure 46: Olmo 3 from-scratch implementation

16. DeepSeek V3.2

This article started with DeepSeek V3, which was released back in December 2024. There have been multiple DeepSeek releases back then, but I largely skipped them as they were not big flagship-model releases like DeepSeek V3 and DeepSeek R1.

Figure 47: A timeline of the DeepSeek model releases since DeepSeek V3. The main models are shown in red.

However, DeepSeek V3.2 was a really big release as it is on par with the current GPT-5.1 and Gemini 3.0 Pro models on certain benchmarks.

The architecture is overall similar to DeepSeek V3 but they added a sparse attention mechanism to improve efficiency.

Figure 48: The DeepSeek model architecture with multi-head latent and

sparse attention.

I originally planned to write a short section about DeepSeek V3.2 for this article, but it turned into a >5000 word write-up, so I moved it to a separate article, which I linked below:

A Technical Tour of the DeepSeek Models from V3 to V3.2

SEBASTIAN RASCHKA, PHD • DEC 3

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After all these years, LLM releases remain exciting, and I am curious to see what's next!

This magazine is a personal passion project,

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If you'd like to support my work, please consider my Build a Large Language Model (From Scratch) book or its follow-up, Build a Reasoning Model (From Scratch). (I'm confident you'll get a lot out of these; they explain how LLMs work in depth you won't find elsewhere.)

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Apart from the architectural differences, what would be interesting to know is on which text data the LLMs have been trained on. From my pov, it's really unfortunate that this info is typically not disclosed, even for open-source LLMs. Not just the amount of training data (e.g. number of tokens) but also the data quality as factors for a true scientific comparison.

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Amazing article! This is evidence that we haven't hit a wall yet with LLMs as all these labs haven't converged to the same architectures.

Cohere Labs is also doing some great work for open source and have some interesting work. I feel a lot of people don't know who they are as they are trying to appeal to businesses/governments.

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