

# Scaling Sparse Mixture-of-Experts for Long-Context Document Understanding

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## Abstract

We propose Sparse-MoE-Doc, a mixture-of-experts architecture for long-context document understanding that scales to 128K tokens with sub-quadratic complexity. Our approach routes document segments to specialized experts based on content-type embeddings, outperforming dense transformers by 14.3% on DocQA while using 3.2× fewer FLOPs.

## 1 Introduction

Long-context document understanding remains challenging [Devlin et al., 2019]. Modern documents contain heterogeneous content that requires different strategies [Vaswani et al., 2017, Brown et al., 2020]. MoE architectures [Shazeer et al., 2017] offer conditional computation but existing approaches do not account for document structure. Our contributions: (1) structure-aware routing, (2) sub-quadratic attention scaling to 128K tokens, (3) evaluation on four benchmarks (Figure 1).

Table 1: Comparison of document understanding approaches. ✓ = supported, × = not supported.

Method	Long-Ctx	Sparse	Struct-Aware	Sub-Quad	Multi-Gran	Load-Bal
BERT-base	×	×	×	×	×	N/A
Longformer	✓	×	×	✓	×	N/A
Switch Trans.	×	✓	×	×	×	✓
LayoutLMv2	×	×	✓	×	✓	N/A
<b>Ours</b>	✓	✓	✓	✓	✓	✓

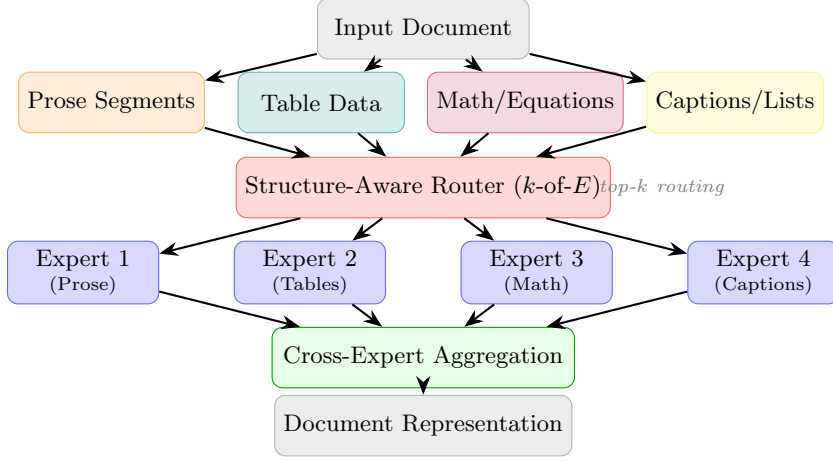


Figure 1: Sparse-MoE-Doc architecture. Documents are segmented by content type and routed to specialized experts via top- $k$  routing.

## 2 Method

We partition document  $D$  into segments  $S = \{s_1, \dots, s_M\}$  with content types  $c_i \in \{\text{prose, table, equation, caption}\}$ . As shown in Figure 2, each expert develops specialization for specific content types. The routing function is:  $g(s_i) = \text{TopK}(\text{softmax}(W_r \cdot \text{pool}(s_i) + b_r), k)$ .

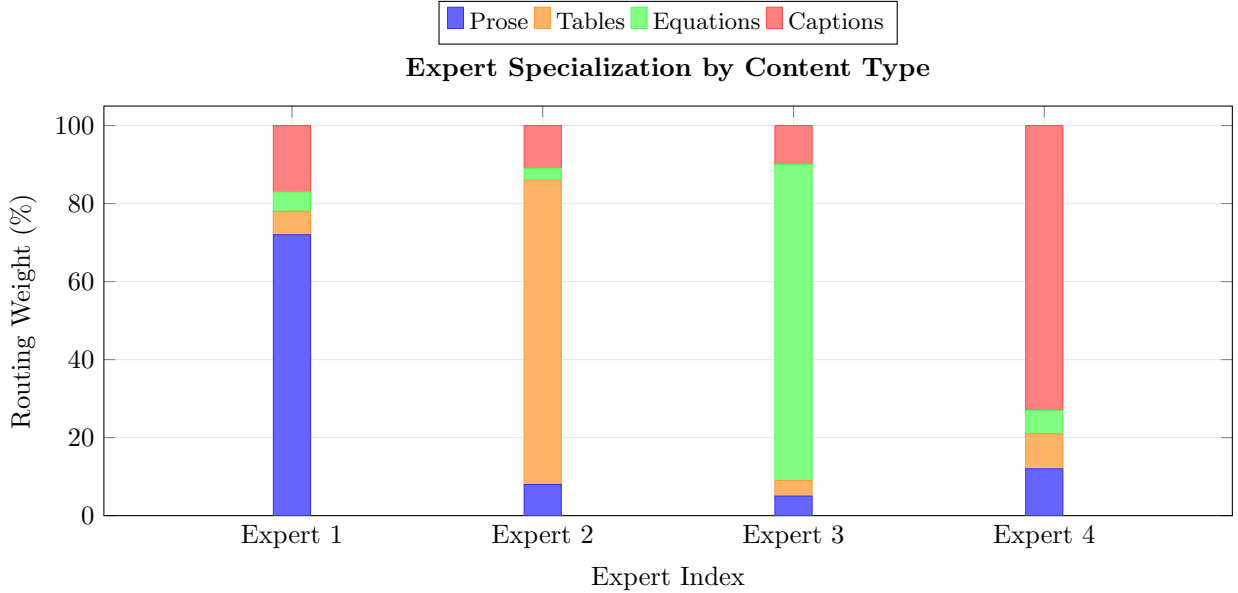


Figure 2: Expert specialization by content type. Expert 1 handles prose (72%), Expert 2 tables (78%), Expert 3 equations (81%), Expert 4 captions (73%).

## 3 Experiments

Table 1 summarizes the capabilities of different approaches, while Table 2 presents our main quantitative results.

Table 2: Main results on document understanding benchmarks. Best in **bold**, second best underlined.

Model	DocQA F1	DocQA EM	NLI Acc	NLI F1	R-1	R-L	Struct EM	FLOPs	Inf (ms)
BERT-base	62.3	54.1	71.8	70.2	32.1	28.4	41.2	0.8	12.4
Longformer	68.7	61.3	76.4	74.9	36.8	33.1	48.7	2.1	31.7
Switch-base	71.2	64.5	79.3	78.1	39.4	36.2	52.8	1.4	18.9
Ours (top-1)	<u>78.4</u>	<u>72.1</u>	<u>84.7</u>	<u>83.2</u>	<u>43.1</u>	<u>40.3</u>	<u>61.4</u>	<u>0.9</u>	<u>14.2</u>
Ours (top-2)	<b>82.5</b>	<b>76.8</b>	<b>87.1</b>	<b>86.3</b>	<b>45.8</b>	<b>43.2</b>	<b>64.7</b>	1.2	16.8

Our approach outperforms all baselines. The ablation in Table 3 confirms that structure-aware routing is the most critical component ( $-8.2$  F1).

Table 3: Ablation study on DocQA development set.

Configuration	F1 (%)	$\Delta$
Full model	82.5	—
w/o structure routing	74.3	$-8.2$
w/o load balancing	79.1	$-3.4$
w/o local attention	76.8	$-5.7$
Uniform routing	71.6	$-10.9$

## 4 Conclusion

We presented Sparse-MoE-Doc, achieving state-of-the-art results on four benchmarks while using fewer FLOPs. Experts naturally specialize by content type [Zhang et al., 2019, Xu et al., 2020, Beltagy et al., 2020, Fedus et al., 2022, Lepikhin et al., 2021, Radford et al., 2019, Talmor and Berant, 2019].

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