Technical Report

K-EXAONE

Journey to Frontier-Level Performance

of Foundation Models

LG AI Research | 2025 | 236B Parameters

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Model Specifications

K-EXAONE: Frontier-Level Performance

Architecture

Mixture-of-Experts (MoE) with hybrid attention mechanism

236B
Total Params

23B
Activated

Multilingual Coverage

Supporting six languages with balanced performance

한국어 English Español Deutsch 日本語 Tiếng Việt

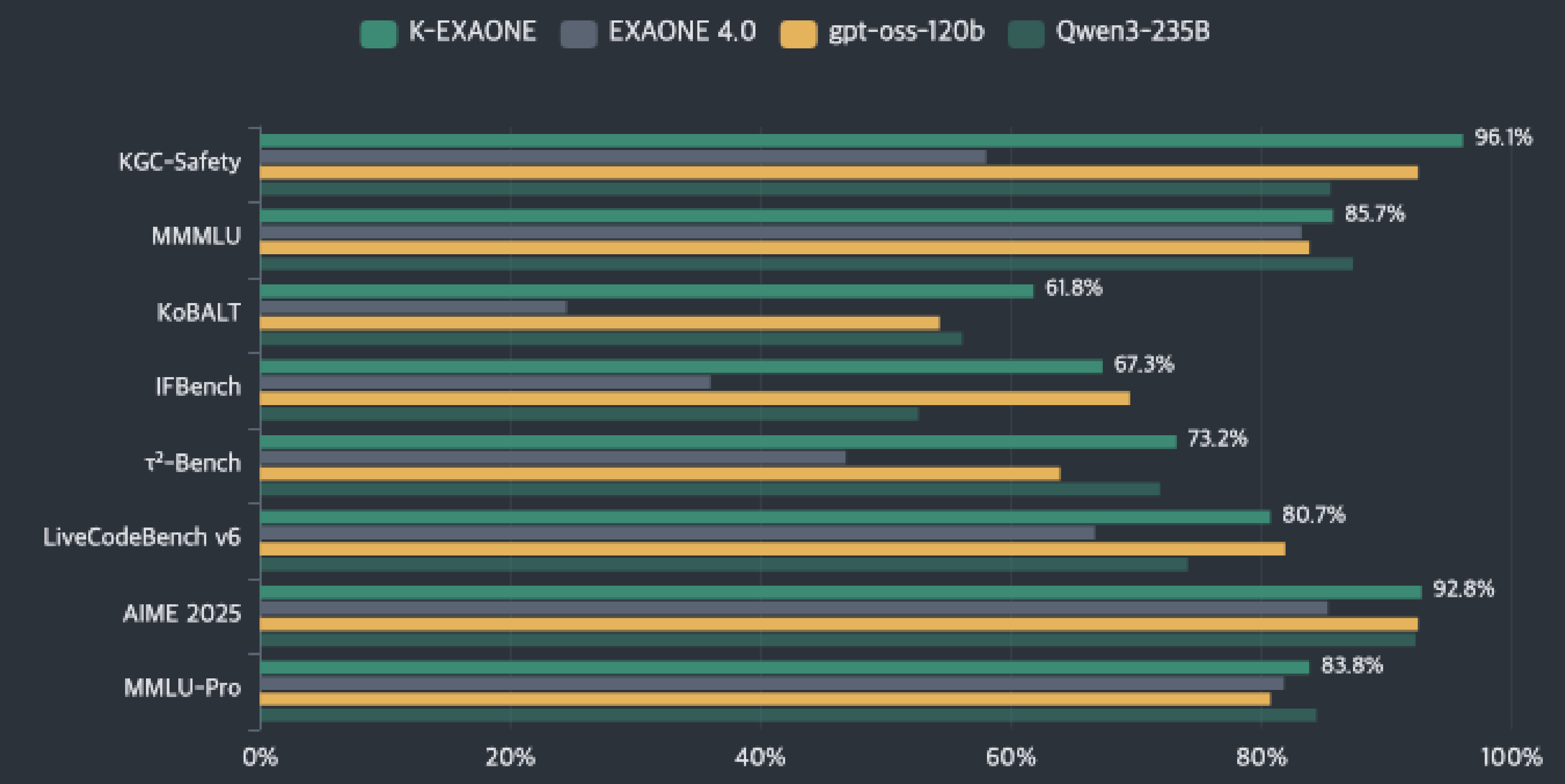
Context Window

256K tokens

Maximum context length

Main Evaluation Results

Performance across eight critical capability categories compared to leading open-weight models



K-EXAONE EXAONE 4.0 gpt-oss-120b Qwen3-235B

Strategic Context

Global LLM Development Landscape & Korea's Response

Global Competition Intensifies

The worldwide LLM development landscape is experiencing unprecedented competition, with leading countries and organizations deploying models with superior performance capabilities.

- **Closed-Source Advantage**
  Proprietary models currently hold competitive edge through massive scale and resources
- **Open-Weight Momentum**
  Rapidly catching up via aggressive scaling, approaching trillion-parameter scale
- **Scaling Imperative**
  Model size scaling crucial for reducing performance gap between closed and open models

Government Strategic Initiative

To address the infrastructure gap, the Korean government initiated a strategic program providing essential GPU resources for large-scale AI model development.

Strategic Resource Provision

Direct GPU allocation to enable development of globally competitive foundation models

Public-Private Partnership

Collaboration between government and industry leaders like LG AI Research

Korea's Infrastructure Challenges

Compared to global leaders, South Korea faces relative shortages in critical AI infrastructure components.

Data Centers

Limited AI-specialized facilities for large-scale training

AI Chips

GPU resource constraints limiting model development scale

LG AI Research Response

LG AI Research actively participated in the government initiative, leveraging support to develop K-EXAONE—a powerful foundation model demonstrating top-tier global performance.

Model Scale	Context Length
236B Params	256K Tokens

Strategic Positioning

K-EXAONE represents Korea's strategic investment in sovereign AI capabilities, designed to advance AI for a better life and position Korea as a global AI leader.

Architectural Innovation

Mixture-of-Experts: Efficient Scaling Architecture

Architectural Paradigm Shift

K-EXAONE represents a fundamental departure from EXAONE's dense modeling paradigm, adopting MoE architecture for resource-efficient scaling of model capacity.

Dense Architecture (EXAONE)

- All parameters activated
- Computationally expensive
- Limited scaling efficiency

MoE Architecture (K-EXAONE)

- Sparse parameter activation
- Resource-efficient scaling
- High representational diversity

Fine-Grained Sparse MoE Design

128	8	+1	9
Total Experts	Routed Experts	Shared Expert	Active Total

Inspired by prior work, K-EXAONE employs fine-grained sparse MoE design. Top-8 experts are activated per token with an additional shared expert, enabling high representational diversity while maintaining resource efficiency.

Parameter Efficiency

Total Parameters

236B

Activated Parameters

23B

Activation Ratio

9.7%

Training Innovations

- **Sequence-Level Load Balancing**
  Improves routing stability and expert utilization
- **Dropless Routing Policy**
  Prevents token dropping, stabilizes gradient flow
- **Multi-Token Prediction (MTP)**
  Enables self-drafting with 1.5× throughput

Context Processing

Hybrid Attention & Long-Context Optimization

Hybrid Attention Architecture

K-EXAONE integrates global and local attention modules, significantly reducing memory consumption and computational overhead compared to full global attention across all layers.

Global Attention (GA)
12 Layers
Full context visibility

Sliding Window (SWA)
36 Layers
Local context processing

KV-Cache Optimization

Sliding Window Size — Reduced 97%

4,096 → 128
Original → Optimized

Minimizes KV-cache usage while preserving modeling capacity, enabling cost-efficient long-context inference with improved deployment accessibility.

Model Configuration

Layers (Total/SWA/GA)
48 / 36 / 12

Attention Heads
Q: 64 / KV: 8

Head Dimensions
128

Maximum Context Length
256K tokens

Stability Features

QK Norm
Layer normalization on query/key vectors mitigating attention logit explosion

SWA-only RoPE
Selective RoPE application preventing interference with global interactions

Inference Efficiency: SWA and GA are natively supported by modern LLM inference engines, improving deployment accessibility and system compatibility.

Tokenization Innovation

Enhanced Tokenizer: From 100K to 150K Vocabulary

Vocabulary Expansion Strategy

The tokenizer was redesigned to increase vocabulary from 100K to 150, improving token efficiency, downstream performance, and multilingual scalability.

Original
100K

→

Enhanced
150K

SuperBPE Strategy

SuperBPE introduces superword tokens, allowing common word sequences to be represented as a single token, reducing overall sequence length.

Superword Token Allocation

English	2 parts
Korean	3 parts
Multilingual	1 part

Superword Tokens
20%
of total vocabulary

Token Efficiency Gains

English	+19.6%
Korean	+29.0%
Multilingual	+49.8%
STEM	+20.1%
Code	+26.7%

Average Improvement
~30%

Unicode Normalization

Original — NFKC
↓
Updated — NFC

Switched to NFC to preserve semantic distinctions in superscripts, subscripts, and symbol-rich text in code and STEM corpora.

Training Pipeline

Three-Stage Pre-training Curriculum

Strategic Curriculum Design

K-EXAONE utilizes a strategic three-stage pre-training curriculum to progressively build capabilities while inheriting EXAONE 4.0's data pipeline with enhanced filtering.

1. **Foundational Knowledge Building**
   Establishes core linguistic understanding and basic world knowledge
2. **Domain Expertise Development**
   Specializes in STEM, code, and multilingual domains
3. **Reasoning Capability Enhancement**
   Develops complex reasoning through thinking-augmented data

Training Resources

Pre-training Data

11T

tokens

Computation

1.52×10^{24}

FLOPs

Multilingual Coverage Expansion

Extended language coverage beyond EXAONE 4.0's Korean, English, and Spanish to include German, Japanese, and Vietnamese.

Language Portfolio

한국어 | English | Español | Deutsch | 日本語 | Tiếng Việt

Used cross-lingual knowledge transfer to generate synthetic corpora, propagating specialized knowledge and reasoning patterns across languages.

Thinking-Augmented Synthesis

Extended EXAONE 4.0's data synthesis pipeline to incorporate explicit reasoning supervision.

- **Document-Grounded Thinking**
  Generating thinking trajectories and combining with source content
- **Step-by-Step Inference**
  Unified samples encoding reasoning behaviors
- **Enhanced Post-Training**
  Improving effectiveness of subsequent alignment

Training Setup

Natively trained with FP8 precision achieving comparable loss curves to BF16. Adopted Muon optimizer with WSD learning rate scheduler and sequence auxiliary loss coefficient of 1.0×10^{-4}.

Long-Context Capabilities

Context Length Extension: 8K → 256K Tokens

Two-Stage Extension Procedure

Base model pre-trained with 8K context, subsequently extended through two carefully managed stages.

1 **Stage 1: 8K → 32K**

First extension stage prioritizing stable performance up to 32K tokens

2 **Stage 2: 32K → 256K**

Second stage emphasizing long-document samples for 256K dependencies

Long-Document Dataset

Full-document sequences consumed within single training instances, encouraging capture of long-range dependencies.

Training Approach

- End-to-end training without truncation
- Stage 1: Up to 32K token sequences
- Stage 2: Emphasis on 256K sequences

Rehearsal Dataset

Mitigates short-context performance degradation during long-context specialization.

Components

- ✓ High-quality pre-training samples
- ✓ Short-context data
- ✓ Consistent training signal anchor

Rehearsal proportion adjusted stage-wise to ensure adequate long-context learning signals.

Synthetic Reasoning Dataset

Strengthens reasoning performance with challenging problems in mathematics, science, and competitive programming.

Math

Science

Programming

Needle-In-A-Haystack (NIAH) Testing: Iterative training repeated until model consistently achieves near-perfect NIAH performance, indicating successful extension to 256K tokens.

Post-Training: Three-Stage Alignment Pipeline

1 Supervised Fine-Tuning

Large-scale SFT to learn following diverse user instructions and producing corresponding responses.

Key Data Sources

- ✓ K-DATA (Korea Data Industry Promotion Agency)
- ✓ Public & institutional data
- ✓ DocQA & translation datasets

2 Reinforcement Learning

RL on reasoning-intensive and verifiable tasks with verifiable rewards using AGAPO optimizer.

Multi-Task Setup

Math	Code
STEM	Instruction-Following

3 Preference Learning

GROUPER (Group-wise SimPER) aligns model with human preferences while preserving reasoning performance.

Alignment Domains

- ✓ Chat & conversational AI
- ✓ Safety & ethical behavior
- ✓ Creative writing

Agentic Tool Use Training

Aggregating real-world agentic tool environments is costly. Instead, K-EXAONE leverages LLMs to build synthetic tool environments.

Synthetic Environment

Tool-use scenarios with verifiable pass criteria for coding and general tool-calling

Verification Process

Evaluating on generated environments to filter unrealistic cases

Web Search with Sub-Agents

When performing web search, K-EXAONE is augmented with two sub-agents for improved context efficiency.

Summarizer Sub-Agent
Distills fetched webpages to avoid processing long, noisy text

Trajectory Compressor
Compresses interaction history into structured JSON record

Optimization Framework

Reinforcement Learning with Verifiable Rewards

AGAPO Optimization Framework

AGAPO (Adaptive Group Advantage Policy Optimization) with off-policy policy-gradient using truncated importance sampling for training efficiency at scale.

Key Features

- ✓ Zero-variance filtering by dropping prompts with identical rewards
- ✓ Group-level advantage computation
- ✓ Global advantage normalization
- ✗ No KL penalty to improve performance

MoE Router Frozen

Throughout RL training to maintain stability

Multi-Task RL Setup

Training covers diverse reasoning domains with verifiable rewards.

- Mathematics
- Coding
- STEM
- Instruction-Following

Mathematical Formulation

RL Objective Function

$$J_{AGAPO}(\theta) = E_{q\sim P(Q)}\, E_{O\sim\pi_{\theta rollout}} \left[(1/G) \Sigma_{i=1}^{G} (1/|o_i|) \Sigma_{t=1}^{|o_i|} sg(\min(\rho_{i,t}, \varepsilon))\, A_{global,i} \log \pi_\theta(o_{i,t} \mid q, o_{i,}) \right]$$

$\rho_{i,t} = \pi_\theta / \pi_{\theta rollout}$

Importance sampling ratio

$A_{group,i}$

Group-level advantage

$A_{global,i}$

Global standardized advantage

Verification Methods

Rule-Based Verifiers

For objective correctness in math, code, etc.

LLM-as-a-Judge

For nuanced evaluation of reasoning quality

Performance Assessment

Comprehensive Evaluation: Nine Benchmark Categories

World Knowledge

MMLU-PRO
83.8

GPQA-DIAMOND
79.1

Mathematics

AIME 2025
92.8

IMO-ANSWERBENCH
76.3

Coding & Agentic

LIVECODEBench v6
80.7

SWE-BENCH VERIFIED
49.4

Agentic Tool Use

τ²-Bench
73.2

TERMINAL-BENCH 2.0
29.0

Instruction Following

IFBENCH
67.3

IFEVAL
89.7

Long Context

AA-LCR
53.5

OPENAI-MRCR
52.3

Korean Capabilities

Strong performance across Korean-centric benchmarks.

KMMLU-PRO	KOBALT
67.3	61.8

Multilinguality

Competitive multilingual knowledge understanding.

MMMLU	WMT24++
85.7	90.5

Safety Evaluation

Competitive performance on safety benchmarks.

WILDJAILBREAK	KGC-SAFETY
79.1	96.1

Evaluation Note: Temperature set to 1.0, top-p to 0.95. Context length 160K for long context benchmarks, 128K for others. MTP disabled at inference.