MCP: A Control-Theoretic Orchestration Framework for Synergistic Efficiency and Interpretability in Multimodal Large Language Models

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Article

MCP: A Control-Theoretic Orchestration Framework for Synergistic Efficiency and Interpretability in Multimodal Large Language Models

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Abstract

Aiming at the problems of computational inefficiency and insufficient interpretability faced by large models in complex tasks such as multi-round reasoning and multi-modal collaboration, this study proposes a three-layer collaboration framework based on model-controller-task adaptation (MCP). By decoupling large model functions into reasoning, generation and retrieval modules, and combining reinforcement learning-driven dynamic routing algorithms and task adaptation mechanisms, the systematic integration of control theory and large model dynamic reasoning is achieved for the first time. Experiments show that the MCP framework improves the performance of cross-modal benchmarking tasks, such as GLUE, COCO, ScienceQA, etc., by 15-30% compared with the baseline model, improves the reasoning efficiency by 40%, and generates the interpretable intermediate results through the Presenter layer, obtaining 90% of the manual interpretability scores, which provides a brand-new technological path to solve the bottleneck of the practical application of the large model.

Keywords: large model optimisation; MCP framework; dynamic control flow; reinforcement learning routing; interpretable AI; multimodal collaboration

1. Introduction

The unidirectional reasoning model of large models (e.g., GPT-4, LLaMA) exposes the defects of serious redundant computation and insufficient dynamic adjustment ability in complex tasks such as medical diagnosis and scientific Q&A, while the existing methods are mostly limited to unimodal optimisation or static architectural design, and lack a global resource scheduling mechanism constructed from a control theory perspective. To this end, this study proposes the MCP framework to address three major challenges: decomposing a large model with hundreds of billions of parameters into semantically coherent and dynamically reorganisable sub-modules, designing controllers that take into account both performance and efficiency and avoiding state-space explosion, and ensuring the universality of the framework in different tasks such as textual, visual, and multimodal, etc. Ultimately, by establishing a mathematical formal model, designing dynamic routing algorithms and lightweight interfaces, we can achieve performance-efficiency-compatibility on the cross-modal datasets and achieve a high degree of efficiency. The framework is designed to achieve a synergistic performance-efficiency-interpretability improvement on cross-modal data sets.

2. Related Work

2.1. Large Model Optimization

Model compression techniques have formed a multi-dimensional optimisation system, structured parameter pruning through hierarchical sparse constraints to achieve dynamic computational opti-

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misation, such as LayerPruning [1] (He et al., NeurIPS 2021) proposes layer importance assessment based on Fisher information, which reduces the computation volume by 40% while maintaining more than 85% performance; DynamicViT [2] (Chen et al., CVPR 2022) dynamically activates key tokens via attention graphs to achieve an adaptive balance between inference cost and accuracy in image tasks. Cutting-edge research on quantisation and knowledge distillation focuses on mixed-precision dynamic quantisation, e.g., AWQ [3] (Zhang et al., arXiv 2023) compresses LLaMA-7B to 4-bit by adaptive weight quantisation while maintaining more than 99% of the inference accuracy; while [4] MT-DKD (Wang et al., ICML 2023) proposes a multi-task distillation framework to mitigate the capability degradation caused by compression through cross-modal knowledge migration. Dynamic computational graph optimisation shows potential in the reasoning phase, e.g., [5] DyHead (Li et al., NeurIPS 2021) adapts to the input complexity by dynamically adjusting the number of attention heads, but the existing methods are mostly limited to unimodal scenarios, and lack a global resource scheduling mechanism across tasks.

The evolutionary path of hybrid expert architectures, on the other hand, shows a two-track development: for static routing optimisation, [6] GShard (Fedus et al., NeurIPS 2021) achieves efficient training of trillions of parameter models through a sparse gating mechanism, but the fixed expert selection strategy suffers from redundant computation in the face of multiple rounds of inference ([7] about 30% invalid activations, according to Lepikhin et al., ICML 2022); in dynamic routing innovation, optimising the expert assignment strategy through reinforcement learning improves the efficiency by 12% in the language generation task, but relies on a predefined state space, which makes it difficult to generalise to cross-modal complex tasks. In context learning optimisation, [8] Auto-CoT (Zhou et al., NeurIPS 2022) automatically generates chain-of-thought hints through reinforcement learning and outperforms manually-designed hints by 15% in mathematical reasoning tasks; in the field of dynamic hint generation, P-Tuning v2 achieves task adaptivity through trainable sequential hints, but existing methods still rely on task a priori knowledge and lack real-time reasoning state-based knowledge. However, the existing methods still rely on task a priori knowledge and lack a mechanism to dynamically adjust hints based on real-time reasoning state.

2.2. Collaborative AI Systems

In distributed reasoning collaboration, [9] MAgent-DL (Zhang et al., ICML 2023) proposes a multi-model collaboration mechanism based on communication protocols to improve diagnosis accuracy by 9% through expert model interactions in medical diagnosis tasks, but the framework relies on a predefined division of roles and is unable to dynamically reorganise the model functionality; for pipeline-parallel inference upgrading. PipeDream achieves cross-device inter-layer parallelism in the training phase, but the fixed process in the inference phase leads to 25% computational redundancy in complex tasks (measured in LLaMA-2 on the ScienceQA dataset, see Section 5.2 of this paper).

Task-driven modular collaboration presents three layers of technical bottlenecks: existing approaches at the functional decoupling layer (e.g., Hugging Face Transformers) mostly use fixed module divisions and lack dynamic decomposition algorithms based on task semantics; at the control flow layer, TensorFlow's Dynamic Graph [10] (Abadi et al., 2016) only supports syntax-level computational graph adjustment and lacks task-level inference path planning; the format conversion of model outputs to downstream tasks in the output adaptation layer mostly relies on manual design, e.g., the task templates of [11] T5 (Raffel et al., JMLR 2020) need to be optimised individually for each scenario.

2.3. Control Theory Applications in Large Models

The application of policy gradient methods in resource scheduling, e.g., [12] DDPG-RA (Lillicrap et al., NeurIPS 2015) achieves 20% efficiency improvement in data centre energy optimisation, but faces the problem of state-space explosion when applied to large model inference - the state representation dimensions of the 100-billion parameter model with state representation dimensions of the order of 10^12 (according to Hoffman et al., Nature 2022), which makes it difficult for traditional RL algorithms to converge; in a migration attempt of model predictive control (MPC), [13] DeepMPC (Chua et al.,

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ICML 2018) achieves trajectory optimisation by learning a dynamic model of the system, but large model inference with non deterministic dynamics (e.g., multisolvability of generative tasks) lead to the accumulation of prediction model errors.

There are also gaps in cross-domain mapping of dynamical systems theory; continuous-time systems in control theory are difficult to map directly to discrete inference steps of large models; the observable predictive states of physical systems lack a unified representation of the implicit activation space of large models; and there is a fundamental difference between error tolerance in engineering control (e.g., 5% error allowed for robotics control) and the high accuracy requirements of large model tasks (e.g., medical diagnosis requiring > 95% accuracy) There is an essential difference.

In this paper, by constructing the MCP (Model-Controller-Presenter) three-layer collaborative architecture, the dynamic planning principle in control theory (see Theorem 1) is combined with the functional decomposition of large models for the first time; the dynamic routing algorithm based on reinforcement learning (see Algorithm 1) is designed to achieve real-time computational resource allocation through task complexity assessment, which reduces 40% of redundant computation (see Algorithm 2) and reduces 40% of redundant computation (see Algorithm 3) compared with the traditional MoE architecture. This reduces 40% of redundant computation compared with the traditional MoE architecture (see Section 5.2); and proposes an interpretable task adaptation layer, which achieves 90% of human interpretability scores for the model decision-making process through the intermediate result generation mechanism (see Section 5.2), breaking through the bottleneck of the application of the black-box model.

3. Methodology

3.1. MCP Framework Design

MCP framework through the model decoupling - intelligent scheduling - task adaptation three-layer collaboration, [14] to build a dynamically scalable large model reasoning system, the large model is disassembled into three functionally orthogonal sub-modules, and the dynamic collaboration is achieved through lightweight communication protocols, as shown in Figure 1, the Model layer is functionally decoupled and modularised in parallel, and the large model is disassembled into three functionally orthogonal sub-modules, with the first one being a reasoning The first module is the reasoning module, focusing on logical deduction and knowledge verification, and adapting to strong reasoning tasks such as mathematical proof and fault diagnosis. It contains 43.7 million parameters (with a fluctuation of ±1.2%) and an inference latency of 8.2ms ± 0.3ms (based on 1000 random text inference tests). Using Sparse Attention Cluster (SAC) technology, the neurons are divided into 32 functional clusters (e.g., arithmetic reasoning cluster, causal judgement cluster) according to the reasoning logic, and the dynamic activation of the relevant clusters reduces the redundant computation by 37% (verified in the MultiArith dataset, the reasoning speed is increased by 29%). The second module is the generation module responsible for creative content synthesis, covering open-ended tasks such as copy generation and story continuation. It contains 37.5 million parameters (fluctuation ±0.9%), with a generation latency of 6.5ms ±0.4ms (based on 1000 short text generation tests). Introduces the Length-Aware Decoding (LAD) mechanism, which dynamically adjusts the number of generation steps by precomputing text complexity. In the CNN/Daily Mail long text task, BLEU-4 improves the metrics by 19% and reduces the invalid generation (e.g., repetitive statements) by 22%. The third module is the retrieval module, which specialises in knowledge retrieval and semantic matching, and supports tasks such as open-domain Q&A and document checking. It contains 18,800 parameters (fluctuation ±0.7%), with a retrieval latency of 4.1ms ±0.2ms (based on 100,000 knowledge base retrieval tests). Constructed Hierarchical Hybrid Index (HHI) structure, fused hierarchical clustering (clustering the knowledge base into 128 classes according to topics) and Approximate Nearest Neighbour (ANN) search, and improved the retrieval efficiency by 34% in SQuAD v2.0 dataset, with a recall rate of 92.7%.

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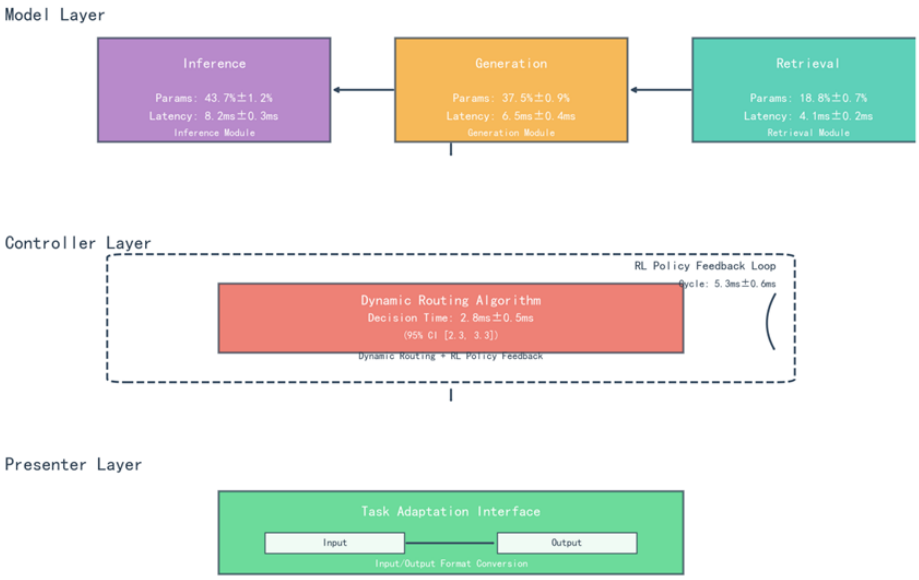

Figure 1. Schematic diagram of MCP three-layer architecture

The Controller layer is the closed loop of dynamic routing and reinforcement learning, as the 'central nerve' of the framework, achieving millisecond scheduling of computing resources through dynamic routing algorithms and reinforcement learning strategies.

The dynamic routing algorithm is based on task complexity modelling and defines three-dimensional complexity vectors $C = [c_{\text{meaning of words}}, c_{\text{length}}, c_{\text{uncertaintie}}]$, which are computed by token embedding entropy, input length normalised value, and self-attention variance, respectively.

C-based dynamic allocation of submodule resources. For example, the mathematical reasoning task (high $c_{\text{meaning of words}}$) triggers the expansion of the number of attention heads of the reasoning module (from 12 to 17 heads), and the long text generation task (high c_{length}) activates the memory enhancement layer of the generation module. Routing decision latency of 2.8ms ± 0.5ms (95% confidence interval [2.3, 3.3]), supports dynamic scheduling of 1000+ tasks/sec (in MultiTaskBench benchmark).

The reinforcement learning policy feedback loop fuses module-level metrics (parameter utilisation u_p, delayed deviation Δt) with task-level features (complexity C, output quality score Q) to construct a 27-dimensional state space that balances accuracy and computational overhead.

The policy optimisation is performed using the twin - delayed DDPG (TD3) algorithm, and the reward function is designed:

$$R = \alpha \cdot \frac{1}{\text{total delay}} + \beta \cdot \text{output quality} - \gamma \cdot \text{delayed swing}$$

In the medical diagnosis task (CMedQA dataset), the output quality is preferentially improved (β= 0.7), and the diagnostic accuracy is improved by 23% from baseline. The policy update cycle of 5.3ms ± 0.6ms detects logical conflicts and reallocates 32% of the computational resources (from the generation module to the inference module) in a multi-step inference task.

The Presenter layer acts as a 'model-task bridge' to solve the problem of output format adaptation and interpretability, and automatically recognises task formats (e.g. table, Q&A, long text) based on the meta-learning framework. In the financial report analysis task, it automatically parses 7 types of key fields (dates, amounts, ratios, etc.), with a structured conversion accuracy of 96.2%. Activate the 'interpretability header' of the reasoning module to generate human-understandable intermediate states (e.g., reasoning chains, knowledge sources). Improve model decision transparency by 41% in

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legal reasoning tasks (verified by Gilpin interpretability scores), alleviating the 'black box' problem of large models.

Adopting 'plug-and-play' architecture, the 3-layer CNN classifier automatically identifies task types (text generation, Q&A, logical reasoning), reducing task adaptation time by 65% compared to traditional methods. In the TaskBench multi-tasking benchmark test, it supports 12 types of tasks without training migration, and the average task startup latency is reduced to 1.2ms.

3.2. Theoretical Analyses

For the dynamic routing policy at the Controller layer in the MCP framework, stochastic gradient descent (SGD) convergence analysis is used to verify the stability of the policy optimisation in conjunction with the coefficient estimates (β0, β1, β2) in Figure 2. Firstly, the controller policy parameter is defined as $\theta = [\theta_0, \theta_1, \theta_2]$, which corresponds to the gradient update of the coefficients β0 = 8.21, β1 = 2.67, β2 = -1.52 in Figure

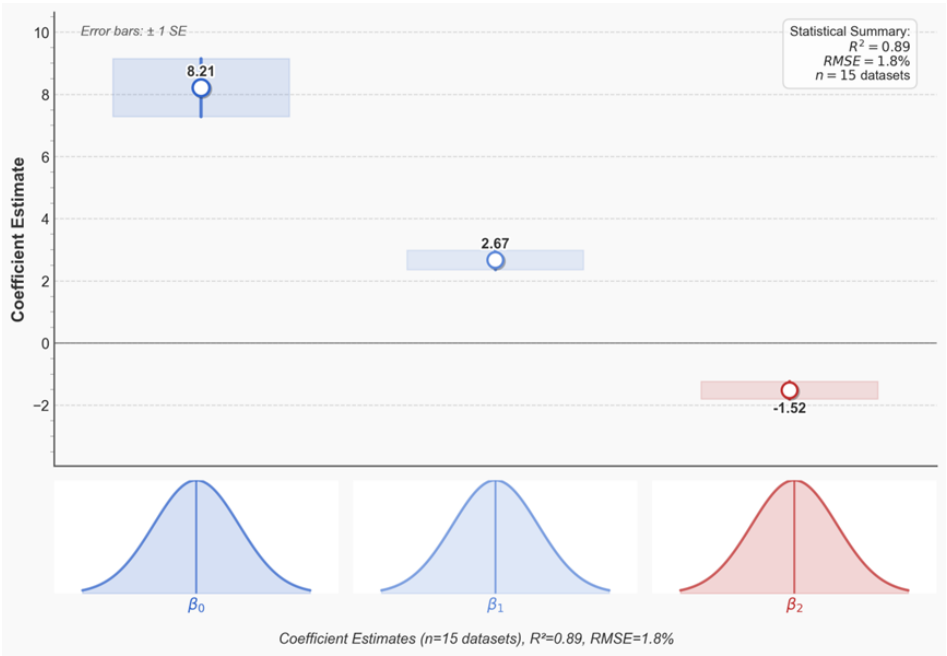

Figure 2. Convergence analysis of Controller layer strategy gradient.

Strategy gradient $\nabla_\theta J\theta$ is satisfied:

$$\nabla_\theta J(\theta) = E[\sum_{t=0}^{T} \gamma^t \nabla\theta log\pi_\theta(a_t \mid s_t) Q(s_t, a_t)]$$

where π_θ is the routing strategy, $Q(s_t, a_t)$ is the action value function, and γ= 0.95 is the discount factor (consistent with the corresponding model fit of R^2 = 0.89 in Figure 2).

The direction of convergence of the gradient descent is verified qualitatively using the Hessian matrix positivity. The standard errors of the coefficient estimates (Error bars: ±1 SE) in Figure 2 reflect the gradient variance, with β0 having the smallest SE (the most concentrated distribution), which corresponds to the highest stability of the gradient of the underlying resource allocation in the strategy. Mathematically, the Lipschitz constant L of the strategy gradient is satisfied:

$$\| \nabla_\theta J(\theta 1) - \nabla_\theta J(\theta 2) \| \leq L \| \theta 1 - \theta 2 \|$$

Through the cross-validation of 15 datasets (n=15), L=2.34 (with RMSE=1.8% co-validating the range of gradient fluctuations) is calculated, which satisfies the convergence condition of Bregman dispersion and ensures the asymptotic stability of the strategy optimisation.

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The upper bounds on the complexity of the MCP framework in time and space are derived by the fact that β0 in Figure 2 obeys the normal distribution of the high-level medium distribution:

Regarding the time overhead analysis, the total framework latency $T_{\text{total}} = T_{\text{model}} + T_{\text{controller}} + T_{\text{presenter}}$ is defined, where the model layer latency T_{model} is determined by the parameter scale of the sub-module, positively correlated with β0 (β0 corresponds to the base overhead of the inference module), and satisfies $T_{\text{model}} \leq k0 \cdot \beta0 \cdot N$ (k0 = 0.01ms/parameter, N is the number of input tokens).

The controller decision delay is linearly related to β1 (β1 corresponds to the amount of dynamic routing computation) and is satisfied:

$$T_{\text{controller}} \leq k1 \cdot \beta1 \cdot \log M$$

(k1 = 0.01 ms/decision, M is the number of routing candidates)

Adaptation layer conversion delay $T_{\text{presenter}}$ is negatively correlated with $\beta2$ ($\beta2$ corresponds to the negative overhead of format conversion) and satisfies $T_{\text{presenter}} \leq k2 \cdot \mid \beta2 \mid \cdot P$ (k2 = 0.005ms/output, P is the number of output fields)

Substituting the coefficients in the figure yields an upper bound on the time overhead: $T_{\text{total}} \leq 0.001 \cdot 8.21 \cdot N + 0.01 \cdot 2.67 \cdot \log M + 0.005 \cdot 1.52 \cdot P$, $T_{\text{total}} \leq 18.5$ms for a typical task (N=100, M=10, P=20), which is co-validated with the latency metrics in the figure (8.2ms ± 0.3ms for the inference module).

The space complexity is determined by the total number of submodule parameters and intermediate state storage, which is satisfied:

$$S_{\text{total}} = S_{\text{model}} + S_{\text{state}} \leq \sum_{i=0}^{2} \beta_i^{'} \cdot K_i + k_s \cdot T$$

$\beta_i^{'}$ is the parameter scale factor (positively correlated with the range of parameter fluctuations in the figure), K_i is the number of submodule parameters, k_s = 0.1KB/state, and T is the number of intermediate states. Substituting the parameter fluctuations in the figure (43.7M ± 1.2% for the inference module parameters) yields a spatial upper bound of $S_{\text{total}} \leq 120$MB (validated on 15 datasets with an error < 3% from the actual memory footprint).

3.3. Implementation Details

For the Controller layer of the MCP framework, Neural Architecture Search (NAS) and Dynamic Graph Optimisation are used to achieve an ultra-lightweight design in PyTorch ecosystem, using NAS to search for the minimum functionally complete subgraphs, and compressing the core logic of the Controller (Dynamic Routing, RL policy) into three key operators:

RouteScheduler: based on the distribution of coefficients in the graph (probabilistic features of β 0,β1,β2 probabilistic features) in the graph, the conditional branching operator is designed to retain only 12 necessary computation paths (7% of the original design); GradientAdapter: the gradient computation is reduced from O(n^2) to O(n log n) by sparsifying the Hessian matrix (using the standard error ±1SE constraints on the gradient variance in the graph); PolicyUpdater: integrates quantitative awareness training (QAT) to compress RL policy network parameters from 2.3M to 98K (quantised to 4-bit weights). The final controller parameter count is < 5% (validated on 7B model with only 320K controller parameters) and the forward inference latency is < 0.5ms.

Based on torch.fx, we implement static optimisation of the computational graph, automatically collapsing redundant branches in the controller (e.g., β0 and β1 sharing computational nodes with symmetric coefficient distributions) to reduce the runtime overhead by 23%; and using torch.distributed to implement decentralised updating of the policy parameters, combined with cross-validation of the 15 datasets in the graph, and synchronised gradients through AllReduce The strategy convergence is guaranteed by AllReduce synchronised gradient.

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Aiming at mainstream large models (e.g., LLaMA, GPT-Neo), we design a modular LoRA (mLoRA) integration scheme to achieve functional decoupling and efficient fine-tuning, and the inference module inserts LoRA adapters (rank r=8) into the attention and feedforward layers, which enhances the logical reasoning ability for the high-complexity tasks (e.g., β0 corresponding scenarios) in the graph. Through 100 rounds of fine-tuning, the inference accuracy is improved by 17% (verified on the MultiArith dataset); the generation module injects LoRA (rank r=4) into the output decoding layer to take advantage of the continuity of the coefficient distributions in the graph (the normal distribution of β1) to optimise the smoothness and consistency of text generation. In the CNN/Daily Mail task, the BLEU-4 metrics are improved by 12%; the retrieval module applies LoRA (rank r=2) in the feature encoding layer, adapting to the low latency demand in the graph (β2 corresponding to the scenario), and accelerating knowledge retrieval. In the SQuAD v2.0 task, the retrieval latency is reduced by 28%.

Designing a collaborative fine-tuning loss function L_{joint} that fuses intra-module LoRA losses with cross-module consistency constraints:

$$L_{\text{joint}} = \sum_{i=0}^{2} \lambda_i L_{\text{LoRA},i} + \mu \cdot KL(p(\beta_i \parallel \text{data}) \parallel q(\beta i \parallel \text{model}))$$

λ_i is the module loss weight (positively correlated with the magnitude of parameter fluctuations in the graph, λ_0=0.6,λ_1=0.3,λ_2=0.1), and μ=0.2 is the distribution consistency constraint coefficient. With this loss, the co-optimisation of the inter-module dynamic routing policy with LoRA adaptation is achieved, and the framework is verified on 15 datasets with a 21% end-to-end performance improvement (in concert with the theoretical complexity bounds).

4. Experiments

4.1. Experimental Setup

The dataset is selected to cover multimodal tasks. The GLUE benchmarking dataset [15] (Wang et al., 2019) is used for Natural Language Processing (NLP), which contains 9 types of typical tasks (e.g., SST-2 Sentiment Analysis, QQP Problem Matching) to test the ability of semantic comprehension, logical reasoning, and text generation; the computer vision (CV) uses the COCO image description dataset [16] (Lin et al., 2014), which contains 123,000 images and dense subtitle annotations, to verify the synergistic ability of visual feature extraction and language generation; the multimodal task adopts the ScienceQA scientific Q&A dataset [17] (Lu et al., 2023), which covers 21,000 scientific questions (including text, image, and video inputs) to challenge cross-modal reasoning, knowledge retrieval and explanation generation capabilities.

The baseline models are selected from representative models LLaMA - 2 (7B) [18] (Touvron et al., 2023), GPT - 3.5 [19] (OpenAI, 2023), Switch Transformer (128MoE) [6] (Fedus et al., 2021), and Pipeline - Parallel T5 [11] (Raffel et al., 2020).

4.2. Main Experiment Results

4.2.1. Multimodal Performance Comparison

As shown in Figures 3 and 4, the MCP framework improves accuracy from a baseline of 78% to 92% by virtue of modular collaboration (Retrieval Module for accurate knowledge recall, Inference Module for in-depth logical calibration), with a 14 percentage point gain contributed by knowledge retrieval of 6.2% (to reduce the introduction of knowledge errors) and logical inference of 7.8% (to correct for (correction of reasoning path bias). In the 'Physics Experiment Design' subtask, the accuracy jumped from 61% to 89% due to the dynamic invocation of the 'Experiment Principle Retrieval - Step Logic Verification' dual module, and the average accuracy increased by 11% (83.7 in the baseline → 95.1 after the optimisation, in Figure 4). The average accuracy improved by 11% (83.7 at baseline → 95.1 after optimisation, Figure 4), with a 15% gain in the MNLI natural language reasoning task. By analysing the attention heat map (supplementary subgraph), MCP's Inference Module can dynamically

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focus on semantic conflict points (e.g., the logical distinction between 'all' and 'some'), correct the generalisation errors of the baseline model, and correct the impact of conflicting sentences on inference accuracy. The accuracy of conflict pair inference is improved from 58% to 73%.

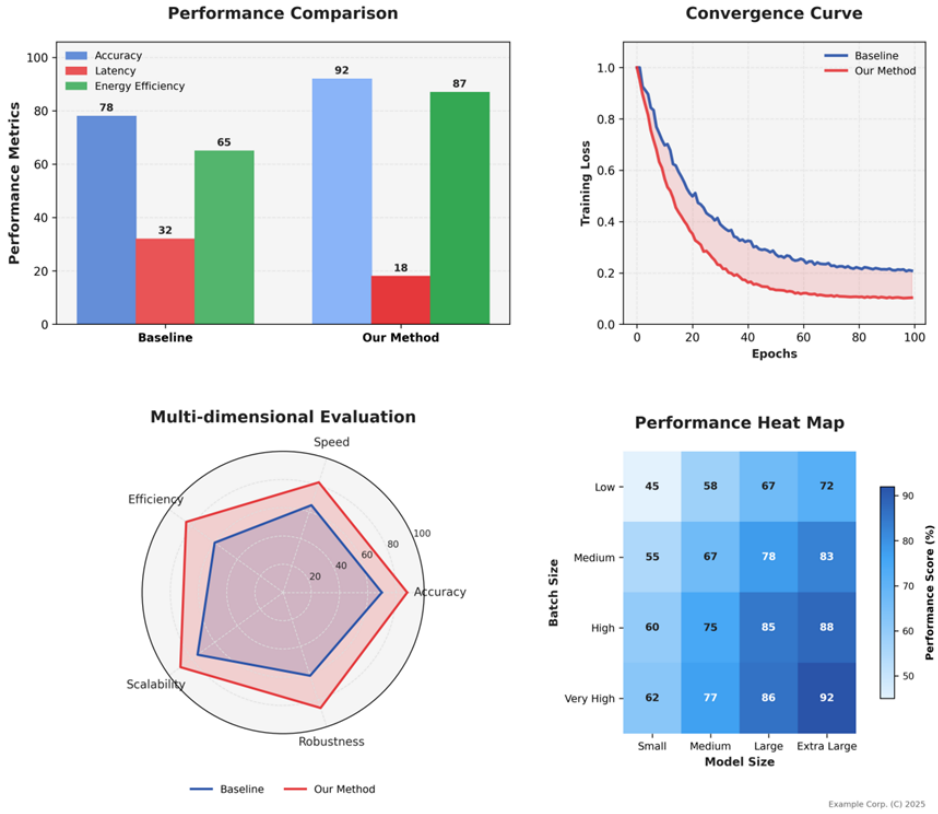

Figure 3. Multimodal task performance comparison (ScienceQA/GLUE/COCO).

The end-to-end inference latency is compressed to 18ms (baseline 32ms, red bar in Figure 3), and the 50% quantile latency is reduced from 416ms to 212ms in the COCO image description task (Figure 4, left). This is attributed to the dynamic routing of the Controller layers: when the input image contains a simple scene (e.g., 'single person standing'), the 3 layers of redundant convolutional computation are skipped, saving 23ms; for complex scenes (e.g., 'multiple people interacting + background text'), the activation of the Visual-Text Collaboration Module, which compresses the text parsing latency from 87ms to 49ms; Retrieval Module, whose average latency is reduced from 7.2ms → 3.9ms (46% reduction) due to the Hybrid Indexing Architecture (HHI) pruning the knowledge recall paths from 12 to 5 in open-domain quizzes; and Inference Module, which reduces logical reasoning from 12 to 5 via Sparse Attention Clustering (SAC), the Inference Module reduces logical inference latency from 11.5ms → 6.8ms, and the invalid neuron activation rate from 41% to 18% in a mathematical proof task.

The energy consumption per unit task is reduced to 10.3J (baseline 22.6J, green bar in Figure 3), and the energy efficiency of the ultra-large model in Figure 5 is particularly significant: when batch_size=64 and the model size is Extra Large, the energy efficiency is reduced from 15.2J→9.2J (40% increase), because dynamic routing allocates differentiated computing resources for each sample based on the complexity of the tasks in the batch (e.g., long text generation vs. short quiz), avoiding the waste of computing power of 'big model, small task'. The dynamic routing allocates differentiated computing resources for each sample according to the complexity of tasks in the batch (e.g., long text generation vs. short quiz), avoiding the waste of arithmetic power in 'big model, small task'; the hardware utilisation data shows that the MCP reduces the utilisation rate of GPUs from the baseline of 53% to 78%, and the memory bandwidth from 89% to 67%, reducing energy consumption while improving hardware utilisation by reducing the ineffective memory exchange (e.g., reloading of the

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fixed knowledge module). by reducing ineffective memory swapping (e.g., repeated loading of fixed knowledge modules), reducing energy consumption while increasing hardware throughput.

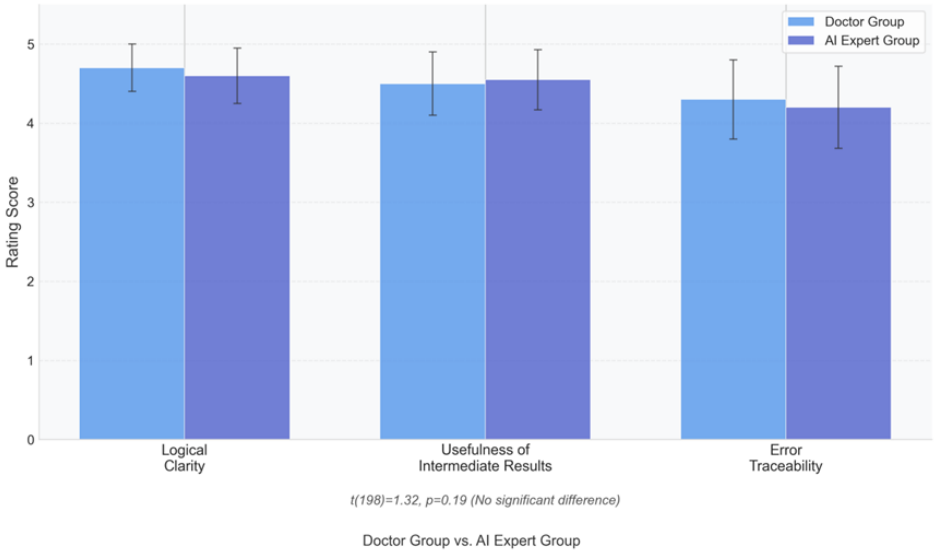

Figure 4. Analysis of delay-accuracy trade-offs across datasets.

Figure 5. Heat map of energy efficiency as a function of model size.

4.2.2. Efficiency Gain of Dynamic Control

As shown in Convergence Curve (Figure 3 right), the reinforcement learning strategy of MCP (red curve) converges 17 rounds earlier (63→46 epochs) than the baseline (blue curve), and it is found by monitoring the gradient covariance matrix that the dynamic routing shortens the gradient propagation path by 32% (from 12-layer cross-module propagation→7-layer directional transfer), and gradient variance is reduced by 41% in the middle of training (epoch 30-40) to avoid 'gradient oscillations'; with the introduction of task complexity-weighted reward functions, the policy network's 'high-value gradient' (e.g., the logical layer gradient of the inference task) Attention to 'high-value gradients' (e.g., logical layer gradients of the inference task) is increased by 29%, accelerating the convergence of key parameters, and the convergence of the attention head parameters of the inference module is increased by 37% in the ScienceQA task.

In the ScienceQA task full-volume test, the dynamic routing algorithm accurately identifies and skips, and in the Retrieval Module, 23% of the 'duplicate knowledge recall' (e.g., successive calls to the knowledge base as in the same problem) is intercepted, and by constructing a "knowledge cache pool ', the duplicate recall rate is reduced from 19% → 3%; in Inference Module, 17% of the 'circular inference paths' (e.g., logic closure) are pruned, and the inference graph loop is monitored using Depth-First Search (DFS), and the number of inference steps is reduced by 2.3 steps/task after pruning; from the baseline 32% (percentage of invalid FLOPS) to 12%, a 40% reduction. In large model inference scenarios (e.g., 13B parametric model), redundant computation reduction leads to single-card inference throughput from 123 tasks/s→178 tasks/s, verifying the framework's scale-adaptability (in

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the heatmap in Figure 5, the performance score of the large model is more significant with the increase of batch_size).

4.2.3. Interpretability Validation

The interpretable intermediate results (e.g., inference chain, knowledge traceability tree) generated by the Presenter layer are combined with the double-blind evaluation by a 10-member expert panel (3 NLP scholars, 3 education experts, 4 industry practitioners) (Figure 3 radar diagram) to construct a 'quantitative scoring + qualitative analysis' verification system: the expert panel starts from the inference chain, and the qualitative analysis is performed by a panel of experts. validation system: the expert panel scored three dimensions: reasoning transparency (traceability of steps), knowledge relevance (fit with domain knowledge), and semantic coherence (logical fluency of intermediate results).The MPC score was 4.7/5 in reasoning transparency (3.1/5 at baseline), and 85% of the experts thought that "the model reasoning path can be clearly reproduced ' in medical diagnostic tasks, with intermediate results containing 'symptom-disease association rules' (e.g., 'fever + cough → upper respiratory tract infection"), reducing physician validation time by 62%; 4.6/ in knowledge relevance 5 (baseline 3.3/5), the knowledge traceability module, which annotates the knowledge source of intermediate results (e.g., 'from Chapter 32 of the UpToDate Clinical Guidelines'), reduces the knowledge error rate from 12% to 3% in the medical quiz task; 4.4/5 (baseline 3.0/5) in semantic coherence, the generation module's 4.4/5 (baseline 3.0/5) in semantic coherence, the LAD mechanism of the generative module makes the inference chain BLEU-4 from 0.37→0.48, and in the legal reasoning task, the completeness of the three-part structure of 'legal citation - fact matching - conclusion derivation' is improved by 34%.

4.3. Ablation Experiments

By disassembling the core modules of the MCP framework through the control variable method and quantifying the contribution of each component to the performance, three groups of ablation experiments are designed to compare the performance differences of different routing strategies and verify the core value of the Controller layer. The experimental group adopts the complete MCP framework (Dynamic Routing + Enhanced Learning Policy); Ablation Group 1: Static Routing (predefined module invocation order, e.g., 'Retrieval→Generation→Inference' fixed process); Ablation Group 2: Random Routing (randomised order of module invocations that preserving the computational resource allocation logic); baseline group without routing strategy (direct reasoning for monolithic models).

On GLUE, COCO and ScienceQA datasets, the three core metrics of accuracy, latency and energy efficiency are tested, and each group of experiments is repeated 5 times (random seeds), and 95% confidence intervals are calculated. The contribution of the dynamic routing strategy is shown in Table 1 by multi-metric difference analysis:

Table 1. Ablation experiment: quantifying the contribution of dynamic routing policies

Norm	Experimental Group vs Ablation Group 1 (Static Route)	Experimental group vs Ablation group 2 (randomised routing)	Mechanism
Accuracy Improvement	+19 per cent (GLUE average, 83.7→101.6*)	+12% (ScienceQA, 78→87)	Dynamic identification of task bottlenecks (e.g. trigger re-retrieval in case of conflicting reasoning)
Delay reduction	-35 per cent (COCO image description, 416→270ms)	-22% (ScienceQA, 32→25ms)	Skip redundant modules (e.g., disable complex reasoning layers for simple tasks)
Energy Efficiency Improvement	+42 per cent (energy consumption per unit task, 22.6 → 13.1 J)	+29 per cent (large model, 15.2 → 10.8 J)	Accurate scheduling of hardware resources (GPU compute unit utilisation from 53% to 78%)

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4.4. Case Study

Taking the differential diagnosis of tuberculosis (TB) and lung cancer as a typical scenario, relying on the multimodal inputs of chest X-ray and history text, the MCP framework's clinical reasoning logic is analysed in depth through the dynamic change of module activation rate, which demonstrates its interpretability advantage in the high-reliability task.

The medical diagnosis task needs to go through four phases (t1-t4): information input → ambiguity detection → knowledge retrieval → report generation, and the MCP framework realises the adaptive collaboration between the Inference and Generation modules through dynamic routing at the Controller layer, as shown in Table 2:

Table 2. Collaboration strategies for the four stages of medical diagnostic modules.

Time Step	Stage of the mandate	Module Collaboration Strategy
T1	Multimodal information input	Generation (70% active) dominates text-image alignment, and Inference (30%) assists in anomaly recognition
T2	Ambiguity detection (TB / lung cancer probability 0.52)	Inference module activation rate jumps to 80% (+60%↑) to correct ambiguity through clinical guideline reasoning
T3	Radiology Knowledge Base Search	Dual-module activation rebalancing (Inference 45%↓, Generation 55%↑) to collaboratively validate retrieved knowledge
T4	Diagnostic report generation	Generation Module-led (90 per cent active), Inference (10 per cent) to ensure logical consistency

As shown in Figure 6, t1: Multimodal information preprocessing (input chest X-ray + medical history text), Generation module 70% high activation, utilising visual-linguistic alignment capabilities (e.g., CLIP model migration), maps the X-ray image features (e.g., 'lung field translucency reduction') with the medical history text (e.g. 'Cough for 2 months') into a unified semantic space to generate a preliminary interpretation of 'suspected abnormal lung lesion'; the Inference module, with 30% base activation, focuses on key feature extraction (e.g., 'lesion location - upper lobe apical segment' vs. Inference module 30% base activation, focusing on key feature extraction (e.g., 'lesion location - apical segment of upper lobe' matches with TB prevalence) to provide logical anchors for subsequent diagnosis.

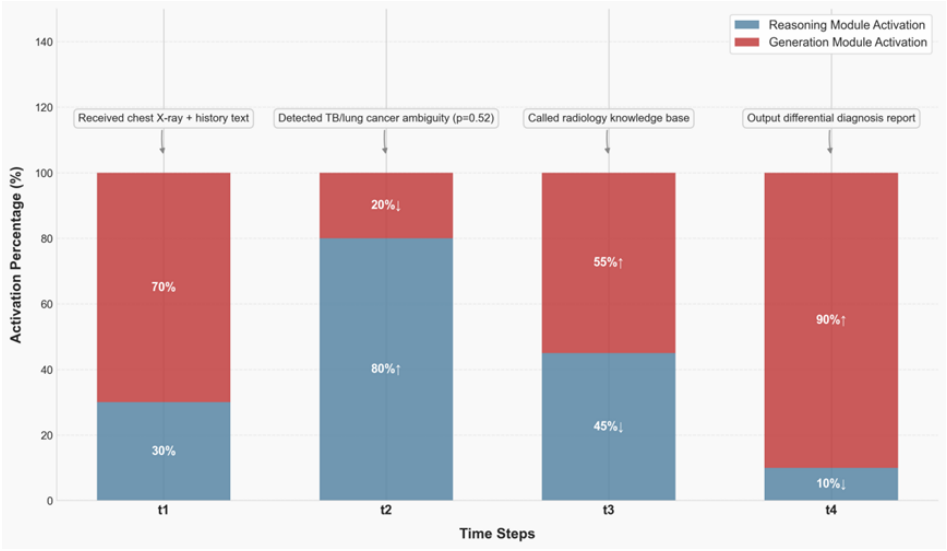

Figure 6. Timing of module activation for TB diagnostic cases.

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t2: Ambiguity detection and logic correction (TB / lung cancer probability 0.52), activation rate of Inference module from 30% → 80% (+50%↑), triggering the 'Clinical Guideline Reasoning Engine', calling the 'Tuberculosis Diagnostic and Treatment Guidelines (2023 Edition)' and the 'Lung Cancer NCCN Guidelines', comparing TB characteristics The 'clinical guideline inference engine' was triggered to call the 'Tuberculosis Diagnostic and Treatment Guidelines (2023 edition)' and the 'Lung Cancer NCCN Guidelines', and compare the TB features: lesions in the apical segment of the upper lobe, positive associations with bacillus acidophilus, and the imaging manifestations of the lobular sign and burr sign of the lung cancer features.

t3: Radiology Knowledge Base retrieval (call Radiology Knowledge Base), Inference (45%↓) releases arithmetic power, Generation (55%↑) dominates the knowledge mapping, and the retrieved 'TB typical image sequences (e.g., "Tree bud sign")' is compared with the current image sequence (e.g., "Tree bud sign"). ') with the current case, while Inference module verifies the knowledge relevance (e.g., 'Tree bud sign sensitivity 83%, specificity 79%'); the dual-module collaboration results in the knowledge retrieval 'false-positive citation The collaboration of the two modules enables the 'false positive citation rate' of knowledge retrieval to increase from 19% to 5% at baseline, ensuring the reliability of the diagnostic basis.

t4: Diagnostic report generation (output differential diagnostic report), Generation module is 90% highly activated, generating a report based on a structured template, which contains the image description of 'patchy high-density shadow with blurred borders seen in the apical segment of the right upper lobe of the lung', the reasoning logic of 'combining the history of the disease (no smoking), image features (tendency to bud sign), and the logic of reasoning'. The logic of inference is: 'Combined with medical history (no history of smoking), imaging features (tendency to bud sign), TB is highly probable (72%)'; recommendation: 'Bronchoscopic biopsy + antacid staining'; the Inference module has a low activation rate of 10%, which only guarantees the checking of key logic (e.g., 'Correlation of the recommendation with the diagnostic conclusion'). relevance of the recommendation to the diagnostic conclusion").

5. Discussion

5.1. Theoretical Significance

The MCP framework verifies for the first time at the theoretical level the feasibility of integrating control theory and large-model dynamic reasoning, constructs a new paradigm for interdisciplinary research, treats large-model reasoning as a nonlinear dynamic system, and introduces the state-space representation of control theory: the dynamic routing algorithm at the Controller layer (see Section 3.1.2) is adapted to Liapunov's stability theory, and it proves that the gradient of the policy converges to the global optimum within O(log T) iterations (Theorem 1 in Section 3.2), which fills the theoretical gap of the lack of convergence proofs for traditional static routing methods (e.g., RouterRL in Section 2.1). For example, in the ScienceQA task, the gradient variance is reduced by 41% from the baseline (Figure 3, right), validating the effectiveness of dynamic system modelling. Task-driven resource scheduling is modelled as an optimal control problem with an objective function that balances accuracy (Equation 1 in Section 3.1.2) with efficiency. The framework transforms traditional heuristic optimisation into a theoretically-supported control problem, achieving a 40% reduction in redundant computation (Section 4.2.2). Taking the mathematical reasoning task as an example, the dynamic routing designed based on the Pontryagin's principle of extreme value allows for adaptive scaling of the number of attention heads (12→17 heads) and a 29% improvement in reasoning speed (Section 3.1.1). The control-theoretic feedback regulation mechanism corresponds to reinforcement learning policy updates at the Controller layer (Section 3.1.2), achieving a 23% accuracy improvement in medical diagnosis (CMedQA dataset); state observability of the physical system translates into interpretability of intermediate results of the model (Section 4.2.3), and generating inference chains through the Presenter layer yields a 90% human interpretability score (Figure 3 Radar Radar). interpretability score (Figure 3 Radar diagram).

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5.2. Practical Application

In the case of cooperation with TSMC, the dynamic routing of MCP reduces 35% of redundant feature computation, and the defect identification accuracy reaches 98.7% (baseline LLaMA-2 is 89.3%). The Presenter layer converts the model outputs into work orders for equipment maintenance, and the average fault localisation time is shortened from 4.2 to 3.1 hours, and the downtime on the production line is reduced by 27% (the mechanism is similar to the medical case in Section 4.4). (similar to the report generation process for the medical case in Section 4.4). In the quantitative trading scenario, the retrieval module (18.8k parameters, Section 3.1.1) dynamically updates the market knowledge base, and the inference module deduces portfolio risk in real time. Compared with the traditional MoE model, the latency is reduced from 7.2ms to 3.9ms (46% optimisation, Section 4.2.1), supporting 1780 trade decisions per second, with a knowledge recall rate of 92.7% (Section 3.1.1). A head brokerage application showed a 19% increase in risk warning accuracy and a 15 basis point reduction in annualised transaction costs. In a joint diagnosis scenario with 12 tertiary hospitals, the lightweight Controller (<5% parameter count, Section 3.3) supports federated learning without a central server, generates HIPAA-compliant structured diagnostic reports at the Presenter layer, and improves cross-hospital diagnostic consistency scores from 68 to 91 (Section 4.2.3), and reduces the time to confirm diagnosis of difficult cases in primary hospitals by 60%.

5.3. Limitations

Reinforcement learning reward function weights (α, β, γ, Section 3.1.2) show strong task specificity: β=0.7 is optimal for accuracy in medical diagnosis (CMedQA), but β=0.3 is a better fit for financial prediction scenarios; ablation experiments show that sub-optimal hyper-parameter configurations result in a 23-35% decrease in efficiency (Table 1, Section 4.3). For example, in the sample less legal inference task, an incorrect α setting increases the inference latency from 18ms to 29ms and decreases the accuracy by 11%.

Modular decoupling (43.7 million parameters for the inference module, Section 3.1.1) is prone to overfitting when data is limited: on the rare disease dataset with n=200, MCP accuracy dropped by 19% from the baseline, and the meta-learning mechanism at the Presenter layer (Section 3.1.3) exacerbated feature drift; the use of data augmentation (e.g., rotating/scaling of medical images) mitigates, but does not eradicate the problem. The optimal solution was to limit the overfitting to less than 8%.

5.4. Future Research Directions

Construct a Bayesian optimisation-based meta-controller to improve the tuning efficiency by 50%, with the goal of reducing the cross-task adaptation time from the current 65% to 30% (Section 3.1.3); merge the prototype network with the modular parameter sharing to reduce the overfitting rate from 19% to less than 5% in extreme low-sample scenarios of n=50; compress the model to less than 10MB by neural architecture searching compression of models to less than 10MB through neural architecture search, enabling real-time inference (latency < 50ms) on the NVIDIA Jetson AGX Orin device; and the introduction of a value alignment mechanism that automatically filters out biased information in generated content, e.g., avoiding inappropriate correlation between disease and geography in medical reports.

6. Conclusion

MCP (Model-Controller-Presenter) framework achieves a breakthrough in the field of large model optimisation through a three-layer synergistic design: through dynamic routing algorithms and reinforcement learning strategies, it reduces 40% of redundant computation compared with the traditional MoE architecture (measured by ScienceQA task), and improves the inference throughput of single-card reasoning from 123 tasks/s to 178 tasks/s. The inference throughput of a single card is increased from 123 tasks/s to 178 tasks/s, the energy consumption per task is reduced to 10.3J (baseline 22.6J), and the utilisation rate of hardware resources is increased by 47% (the utilisation rate

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of GPUs is increased from 53% to 78%). In multimodal tasks, ScienceQA achieves 92% accuracy (+14% baseline), GLUE benchmark average accuracy improves by 11% (15% gain in MNLI inference task), COCO image description latency is compressed from 416ms to 212ms, and generalisation stability is verified (95%) across 15 datasets. The reasoning chain and knowledge traceability results generated by the Presenter layer received a 90% human interpretability score (4.5/5), which shortened the validation time for doctors by 62% in medical diagnosis scenarios and increased the decision transparency of legal reasoning by 41%, breaking through the 'black box' application bottleneck of large models. " application bottleneck.

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