

Автоформатировать

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  "status": "Production Ready",  
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        "Quick Start Code"  
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```

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Автоформатировать

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[{"id": "1", "name": "Mixture-of-Experts Layer", "description": "A neural network architecture where multiple smaller models (experts) are combined to handle different tasks or branches of the input data.", "parameters": {"deployment_stages": {"stage_1_prototyping": "2 weeks", "stage_2_optimization": "2 weeks", "stage_3_scaling": "4 weeks", "stage_4_production": "ongoing"}}, "usage_scenarios": {"scenario_a_small": {"branches": 10, "total_params_b": 12.5, "gpu": "1x A100 80GB", "training_days": 30}, "scenario_b_medium": {"branches": 30, "total_params_b": 25.5, "gpu": "2x A100 80GB", "training_days": 45}, "scenario_c_large": {"branches": 100, "total_params_b": 147, "gpu": "4x A100 80GB", "training_days": 90}}, "learning_rates": {"moe_layers": "1e-4", "gating_networks": "5e-4", "lora_adapters": "5e-4", "task_heads": "1e-3", "warmup_steps": 500, "total_steps": 50000}, "quality_assurance": {"checks": ["Base encoder frozen", "Aux loss decreasing", "Expert utilization balanced", "Branch-specific accuracy monitored", "Gradient clipping enabled", "Checkpoints saved regularly"]}, "monitoring_metrics": ["Total loss", "Aux loss", "Per-branch accuracy", "Expert utilization", "Training speed", "Memory usage"]}, {"id": "2", "name": "LoRA", "description": "A low-rank adaptation technique for large language models, which aims to reduce memory usage and computation costs by updating only a small fraction of the model's parameters.", "parameters": {}, "usage_scenarios": {}, "learning_rates": {}, "quality_assurance": {}, "monitoring_metrics": {}}, {"id": "3", "name": "BERT", "description": "A pre-trained neural network model for natural language processing, specifically designed for tasks like question answering and text classification.", "parameters": {"learning_rate": "1e-5", "batch_size": 16, "epochs": 10}, "usage_scenarios": {"scenario_a": {"tokens": 1000000, "gpu": "1x V100 16GB", "training_time": "1 week"}, "scenario_b": {"tokens": 5000000, "gpu": "2x V100 16GB", "training_time": "2 weeks"}, "scenario_c": {"tokens": 10000000, "gpu": "4x V100 16GB", "training_time": "4 weeks"}}, "learning_rates": {"learning_rate": "1e-5"}, "quality_assurance": {"checks": ["Model converges", "Loss decreases over time", "Accuracy improves with training steps"]}, "monitoring_metrics": ["Total loss", "Cross-entropy loss", "Accuracy", "Training speed", "Memory usage"]}], [{"text": "Overall, the Mixture-of-Experts Layer and LoRA demonstrate how different architectural choices and optimization techniques can be used to build efficient and effective large-scale AI systems. The Mixture-of-Experts Layer allows for parallel processing and scaling, while LoRA provides a more memory-efficient alternative for fine-tuning large models like BERT."}]
```

Автоформатировать

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        url: "https://arxiv.org/pdf/2407.06204.pdf"
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        "title": "A Survey on Mixture of Experts in Large Language Models",
        "authors": "Shen et al.",
        "year": 2024,
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    {
        "title": "Multi-Task Reinforcement Learning Enables Parameter Scaling",
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