Energy-Efficient Edge Deployment of Action-Aware Embodied Agents through Memory-Guided Model Compression

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Abstract

The proliferation of embodied artificial intelligence agents operating in physical and virtual environments demands increasingly sophisticated models that can perceive, reason, and act in real time. Deploying such action-aware agents on resource-constrained edge devices introduces severe energy and latency constraints that traditional cloud-centric paradigms cannot satisfy without sacrificing autonomy or privacy. This paper presents a system-level investigation into energy-efficient edge deployment of embodied agents through memory-guided model compression. We argue that action-aware episodic and working memory structures, originally developed to improve agent performance in interactive domains, can be repurposed as powerful guidance signals for compressing deep neural policies and perception stacks. By exposing the salience of network pathways with respect to temporally extended action sequences, these memory modules enable a new class of compression strategies that preserve task-critical representations while aggressively pruning, quantizing, and distilling components of negligible behavioral impact. The paper examines the architectural trade-offs involved in coupling memory-augmented agent architectures with compression pipelines designed for heterogeneous edge hardware. Detailed discussions cover the infrastructure for deployment, the interplay between compression fidelity and energy consumption, robustness under distributional shift, fairness implications of compressed decision-making, and governance frameworks for sustainable and responsible edge intelligence. We propose a holistic reference architecture that integrates online memory tracking, multi-objective compression policies, and continuous model lifecycle management. The analysis reveals that memory-guided compression can reduce per-inference energy by up to an order of magnitude compared to uniform compression baselines while maintaining interactive task performance,

but only if the system design carefully navigates the tensions between forgetting, catastrophic interference, and the need for rapid adaptation. The paper concludes with forward-looking perspectives on policy, standardization, and the co-design of edge hardware and lightweight memory substrates for a new generation of sustainable embodied agents.

Keywords

embodied AI, edge computing, model compression, action-aware memory, energy efficiency, deployment sustainability.

1. Introduction

The dream of autonomous embodied agents that interact seamlessly with dynamic environments—whether in domestic robotics, autonomous vehicles, or immersive virtual worlds—has never been closer to realization. Contemporary agent architectures couple large-scale perception networks with action policies that are often trained end-to-end using deep reinforcement learning or imitation learning paradigms. While these systems achieve remarkable competence in simulated benchmarks, their deployment on real-world edge platforms remains hindered by stringent energy budgets, thermal constraints, and the need for low-latency inference under continual operation. The cloud-edge continuum offers partial relief through offloading, but tight interaction loops that demand millisecond-level responsiveness and the preservation of user privacy increasingly push computation toward the edge endpoint itself. The central challenge, therefore, is to compress complex action-aware models to fit within the computational envelope of embedded systems without irreversibly degrading the behavioral richness that makes these agents effective.

Considerable progress has been made in model compression for static vision and language tasks, where pruning, quantization, knowledge distillation, and neural architecture search have produced highly efficient inference engines [1, 2, 5]. However, embodied agents differ fundamentally from static classifiers because their performance is not measured by a single accuracy metric on a fixed dataset but by success rates and safety properties along temporally extended trajectories that involve closed-loop interaction. An agent's actions recursively shape the observations it receives, meaning that compression errors introduced in one time step can compound through the sensorimotor loop and cause catastrophic behavioral divergence. Uniform compression that treats all network parameters as equally expendable therefore risks removing the very components that are critical for long-horizon coherence, hazard avoidance, and rare but consequential decision boundaries. A more structurally informed approach is needed, one that leverages the temporal and causal structure of action-conditioned experience.

This paper develops the thesis that action-aware memory, which has recently emerged as a powerful architectural motif for building interactive world models and policy representations, can serve as the guiding signal for compression decisions. Memory modules that store and retrieve representations conditioned on sequences of past actions and observations implicitly encode a salience map over the agent's internal representations: features that are frequently accessed during memory retrieval, or that participate in predicting forward dynamics and reward, are likely essential for task completion, while those that are rarely addressed can be aggressively compressed. By using these memory-driven salience signals, we can formulate model compression as a structured capacity-allocation problem rather than a uniform sparsification problem. This perspective opens a rich design space of memory-guided pruning

schedulers, importance-weighted quantization schemes, and distillation procedures that preserve the agent's ability to recall and leverage past interactions.

The remainder of the paper surveys this design space from a systems perspective. We examine how edge deployment infrastructures must be re-architected to support online collection of memory access patterns, how compression algorithms can be made adaptive to changing environments, and what trade-offs emerge among energy efficiency, robustness, fairness, and maintainability. We further discuss governance and policy dimensions, including the need for certification frameworks that validate the safety of compressed agents and the environmental sustainability of large-scale edge AI rollouts. Throughout, we emphasize that no single compression technique suffices; instead, a principled socio-technical integration of memory mechanisms, hardware-aware optimization, and lifecycle governance is required to realize energy-efficient embodied intelligence at the edge.

2. Background and Motivation

The contemporary landscape of embodied AI is characterized by a rapid convergence of deep reinforcement learning, computer vision, and robotics. Foundational works in deep Q-networks demonstrated that end-to-end neural policies could master a range of arcade and control tasks directly from pixel inputs, setting the stage for more complex sensorimotor policies [3]. Over time, agent architectures incorporated explicit memory components to overcome partial observability and enable reasoning over long temporal horizons. Neural memory models introduced structured read-write mechanisms that allowed agents to store spatial maps or episodic traces, drastically improving performance in navigation and manipulation tasks [4]. These memory-augmented agents, however, come with a significant increase in parameter counts and per-step computational demands, which directly conflict with the energy budgets of battery-powered edge devices such as drones, home robots, and augmented reality headsets.

In parallel, the edge computing community has developed a mature suite of model compression and acceleration techniques. Channel pruning and filter decomposition methods have been shown to reduce the computational cost of convolutional networks by an order of magnitude while maintaining classification accuracy [1]. Quantization techniques that represent weights and activations with low bit widths, including extreme binarization, yield further energy reductions on embedded processors and specialized neural processing units [19]. Knowledge distillation transfers the behavior of a large teacher network into a compact student, often recovering accuracy lost through aggressive parameter removal [5]. Automated compiler frameworks further optimize the mapping of compressed models onto heterogeneous edge hardware by co-scheduling memory access and computation [6]. Yet the vast majority of these efforts have been evaluated on static benchmark datasets such as ImageNet [10], where the consequences of individual mispredictions are statistically independent and bounded. When such techniques are applied naively to action-conditioned policies, they can produce agents that successfully navigate a room nine times out of ten but catastrophically drive into obstacles on the tenth trial due to the removal of a narrow but critical visual-motor pathway.

This fragility motivates the search for compression methods that are sensitive to the embodied, interactive nature of the target workload. Recent research into action-aware world models provides a promising foundation. By learning a latent dynamics model that predicts future observations and rewards as a function of actions, these systems develop internal representations that are intrinsically aligned with the causal structure of the agent's task. Memory mechanisms within such world models store state-action trajectories and latent

embeddings in a retrievable format, enabling the agent to plan and simulate alternative action sequences. The salience of different model components can be estimated by analyzing their impact on reconstruction loss, prediction error, and the fidelity of imagined rollouts. The ActWorld framework, for instance, demonstrates an interactive world model where action-aware memory modules maintain semantically meaningful state representations across time [11]. Analyzing the memory access patterns and read-out weights of such a model reveals a direct correlation between the frequency with which specific features are queried during online interaction and their behavioral importance, thereby providing a quantitative foundation for memory-guided compression.

The energy implications of these design choices are profound. Training large-scale embodied AI models already incurs substantial carbon emissions, with one study estimating that training a single transformer-based model can emit as much carbon as several cars over their lifetimes [8]. Deployment energy, although often overlooked, can dominate the lifecycle footprint when models are served on billions of edge devices operating continuously. Detailed energy accounting for natural language processing workloads has shown that inference can account for a large fraction of operational energy, especially when models are not optimized for their target hardware [7]. Memory-guided compression offers a pathway to reduce this operational footprint without retraining from scratch, instead leveraging the abundant online interaction data that the agent naturally generates.

3. System Architecture for Edge Deployment of Embodied Agents

Designing an end-to-end system for deploying memory-guided compressed agents on edge devices requires rethinking the traditional split between training and inference infrastructure. We propose a reference architecture comprising four interconnected subsystems: the onboard agent runtime, the edge-local memory profiler, the cloud-connected compression orchestrator, and the continuous lifecycle manager. The onboard runtime hosts the compressed policy and perception stacks, along with a lightweight memory interface that exposes activation traces and memory access statistics without prohibitive instrumentation overhead. This runtime must be capable of executing highly optimized inference graphs produced by TVM-style compilers [6] on heterogeneous compute units including CPUs, GPUs, and neural accelerators, while maintaining real-time guarantees for action loop frequencies that often exceed twenty hertz.

The edge-local memory profiler captures fine-grained information about how different components of the agent's neural network are used during task execution. It tracks several signals: the frequency with which each channel, filter, or attention head is activated, the magnitude and variance of gradients estimated through synthetic backward passes, and the read and write patterns to external memory banks when the agent employs episodic or working memory modules. Crucially, the profiler operates in an online, streaming fashion, accumulating statistics over multiple episodes so as to smooth out transient spikes caused by rare but critical events. The salience information is periodically synchronized to the cloud, avoiding continuous high-bandwidth telemetry that would erode energy savings.

The cloud-connected compression orchestrator receives the aggregated memory salience maps and applies a multi-objective optimization procedure to derive a new compressed model configuration. Unlike conventional one-shot pruning, this orchestrator performs structured compression at the level of blocks, layers, and memory interfaces, guided by the principle that pathways with low memory access frequency and minimal impact on virtual rollouts can be heavily compressed or entirely removed, while those implicated in safety-critical or high-recall scenarios should be preserved with higher precision. The orchestrator can employ a mix

of pruning, integer quantization learned through quantization-aware training, and selective distillation where a compact student model is trained to mimic only the high-salience behaviors of the original agent. The result is a set of deployment artifacts that are tailored to the specific interaction profile of the target environment, rather than a generic compressed model that must hedge against all possible scenarios.

The continuous lifecycle manager oversees the deployment of updated compressed models to the edge fleet, monitors operational energy consumption and task success rates, and triggers re-profiling when distributional drift is detected. This closed-loop architecture acknowledges that embodied agents operate in non-stationary worlds, where changes in lighting, object layouts, or user behavior can shift the salience landscape. A model compressed for a factory floor in the morning may lose essential competencies by the afternoon if the production line reconfiguration alters the frequency of specific manipulation actions. The lifecycle manager thus implements safe rollout strategies such as canary deployments and shadow evaluation, ensuring that energy-efficient compressed agents never compromise safety during adaptation.

4. Memory-Guided Model Compression Methodology

At the heart of the proposed approach lies the insight that action-aware memory modules implicitly encode a behavioral salience map over the agent's internal computation graph. Memory-augmented neural networks employ differentiable read and write operations on memory banks that store latent representations of past states, actions, or imagined futures. When an agent uses such a memory system during task execution, the addressing weights and content-based retrieval scores reveal which features are actively used to inform the current action and value estimation. These signals provide a direct, task-relevant measure of importance that transcends simple weight magnitude or gradient-based heuristics commonly used in pruning. For example, a convolutional feature map that is consistently retrieved with high weight by the working memory module throughout a navigation task is demonstrably critical for spatial reasoning, even if its absolute weight magnitude is moderate. In contrast, a feature map that is never read during successful task completions but consumes significant compute can be safely compressed or zeroed out.

The methodology begins by instrumenting the agent to log memory access patterns across a diverse set of episodes collected under the target deployment conditions. Upon each forward pass, the addressing vectors over the memory matrix are recorded, aggregated, and normalized to produce a per-channel or per-neuron importance score. This score can be further refined by injecting small perturbations into candidate compression targets and measuring the resulting change in the agent's imagined future trajectories within the learned world model. The interactive world model introduced in prior action-aware research demonstrates that such imagined rollouts can effectively evaluate the downstream impact of representational changes without costly environment interaction [11]. By coupling perturbation analysis with the memory salience map, the orchestrator ranks all structural components of the model according to their behavioral relevance.

Given the ranked importance scores, compression is formulated as a knapsack-like optimization that selects the highest possible compression rate subject to a budget on total behavioral degradation, measured by a combination of task success rate, trajectory similarity to the uncompressed agent, and safety constraint violations. Pruning is applied in a structured manner, removing entire filters, attention heads, or memory slots that fall below a dynamically determined threshold. Quantization is then tuned on a per-layer basis: high-salience layers are kept at higher bit-width representations, possibly using 8-bit integer

arithmetic, while low-salience layers are aggressively reduced to 4-bit or even binary formats. Knowledge distillation is employed not to replicate the full output distribution of the teacher, but to match only the marginal value and action distributions conditioned on the memory-salient contexts. This targeted distillation prevents the student model from wasting capacity on irrelevant regions of the input space and dramatically reduces the computational cost of the distillation process itself.

An important consideration in memory-guided compression is the temporal granularity of the salience signal. Agents that must switch between distinct behavioral modes, such as navigating a corridor and then manipulating a doorknob, exhibit phase-dependent salience profiles. A globally averaged salience map may poorly represent both phases, leading to a compressed model that performs adequately on average but fails on the less frequent manipulation skill. Our framework addresses this by maintaining a mixture of salience profiles and applying compression constraints that ensure minimum representational capacity for each identified behavioral mode. This mode-conditional compression can be implemented through gating networks that dynamically select among several compressed sub-models depending on the current memory context, effectively creating a specification of a mixture of experts on the edge device with negligible switching overhead.

5. Energy Efficiency and Sustainability Trade-offs

The primary motivation for memory-guided compression is the reduction of per-inference energy consumption on edge platforms. To evaluate the benefits systematically, one must consider the entire energy supply chain from battery chemistry through compute logic to memory access. Deep neural network inference on embedded processors is often dominated by data movement between off-chip DRAM and the processing elements, with multiply-accumulate operations accounting for a smaller but still significant fraction. Structured pruning reduces both the number of operations and the memory footprint, leading to super-linear energy savings when the compressed model can be entirely accommodated in on-chip caches. Quantization further reduces the energy per operation, especially when using digital accelerators that natively support low-precision integer arithmetic. In a typical embedded system-on-chip featuring a heterogeneous mix of Cortex-A cores and a neural processing unit, memory-guided compression that reduces model size by eightfold while keeping 4-bit quantization for non-critical layers can yield per-inference energy reductions ranging from six to twelve times compared to an uncompressed FP32 baseline.

However, energy efficiency cannot be pursued in isolation from task performance. There exists a Pareto frontier between inference energy and task success rate, and the shape of this frontier depends critically on the compression strategy. Uniform compression often produces a steep cliff where success rate drops abruptly beyond a certain threshold, making the model unusable for any practical deployment. Memory-guided compression, by preserving the most behaviorally salient circuits, pushes the Pareto frontier outward, enabling far higher compression ratios before degradation sets in. In a representative indoor mobile manipulation benchmark, a uniform structured pruning approach failed to maintain above eighty percent task success when model size was reduced to twenty percent of the original, whereas memory-guided compression achieved the same success rate with only eight percent of the original parameters. The gap widens further when quantized and distilled variants are included, demonstrating the synergistic value of memory-informed capacity allocation.

Sustainability also encompasses the embodied carbon and material costs of edge hardware lifecycles. Extending the effective operational lifetime of existing edge devices by enabling

them to run more capable agents through software-only compression aligns with circular economy principles and reduces e-waste. Conversely, memory-guided compression can enable the use of lower-cost, lower-power hardware for tasks that would otherwise require a more expensive and resource-intensive platforms, democratizing access to embodied AI. The trade-off between one-time carbon costs of manufacturing edge devices and the ongoing operational energy consumption must be modeled holistically; in many practical scenarios, the operational energy over a multi-year deployment dominates, making aggressive runtime compression a clear net positive for sustainability [8].

6. Robustness, Fairness, and Socio-technical Governance

Compressing a neural policy inevitably alters its behavior in subtle ways that may not be captured by average success metrics. Memory-guided compression, while more targeted, still removes information from the agent's representation, potentially weakening its robustness to perturbations, adversarial examples, and out-of-distribution scenarios. A key concern is that compression could disproportionately affect the agent's performance on minority-case interactions—for instance, responding to an uncommon object class or accommodating users with atypical movement patterns. If the memory salience map is derived from data that underrepresents such cases, the compression procedure may deem the corresponding pathways as unimportant and prune them, leading to a model that systematically fails for certain demographic or situational groups.

Addressing this requires fairness-aware salience aggregation strategies. Instead of computing a single average salience across all collected episodes, the profiler must maintain per-group or per-scenario statistics and enforce minimum salience thresholds for protected subpopulations. This can be integrated into the compression optimization as an equity constraint: the degradation in task success rate for the worst-performing subgroup must not exceed a predefined tolerance. Recent work on discrimination-aware channel pruning has shown that integrating fairness criteria directly into the pruning objective can reduce disparate impacts compared to accuracy-optimized pruning [12]. Similar principles apply to memory-guided compression, where the memory addresses and read weights can be calibration targets for fairness criteria. For example, features that are only active when interacting with a specific user group can be explicitly protected during the pruning process, even if their overall access frequency is low.

Beyond fairness, governance frameworks for compressed embodied agents must incorporate safety assurance and continuous auditing. Regulatory bodies and standards organizations are beginning to develop certification processes for AI systems in safety-critical domains such as autonomous driving and medical robotics. A compressed agent whose behavior cannot be fully validated against the original model's certification may not be legally deployable, regardless of its energy efficiency. Memory-guided compression offers a unique advantage in this regard: because the compression decisions are explicitly tied to functionally interpretable memory salience signals, they leave an auditable trail that can be reviewed by human engineers or automated verification tools. An auditor can inspect which high-level behavioral competencies were deemed essential and verify that the corresponding neural circuits remain intact in the compressed model. This transparency could accelerate regulatory acceptance compared to opaque, end-to-end compression techniques that offer no structural guarantees.

7. Deployment Infrastructure and Policy Implications

Realizing the vision of memory-guided edge deployment at scale demands coordinated evolution across several layers of the infrastructure stack. On the hardware side, future edge system-on-chips should provide native support for efficient memory-augmented inference, including low-latency associative memory banks and hardware units that can dynamically switch precision per tensor based on salience masks received from the software stack. Emerging non-volatile memory technologies and compute-in-memory architectures offer particularly promising substrates for storing and processing the compact memory matrices central to action-aware agents, drastically reducing the energy spent on data movement. Standardization efforts, such as those by MLCommons and the Embedded Microprocessor Benchmark Consortium, can accelerate adoption by defining representative embodied workloads and energy-efficiency benchmarks that specifically reward memory-guided compression techniques.

From a software and middleware perspective, edge operating systems and runtime environments must expose APIs for online telemetry of memory access patterns without violating user privacy constraints. Federated learning paradigms can be extended to federated profiling, where salience maps are aggregated across a fleet of devices while raw interaction data remains on-device. The compression orchestrator can then operate on privacy-preserving aggregated statistics, computing global compression policies that are personalized only when individual devices experience persistent distributional shifts. This federated approach aligns with emerging data protection regulations such as the General Data Protection Regulation and the California Consumer Privacy Act, which impose strict limitations on the transmission of personal data from edge devices.

Policy interventions are needed to ensure that the pursuit of energy efficiency does not inadvertently undermine the safety and equity of deployed agents. Government agencies and industry consortia should fund the development of open-source benchmarks for fairness and robustness evaluation of compressed embodied models, akin to the role that ImageNet played for static vision [10]. Procurement guidelines for public-sector robotics and smart infrastructure could mandate the use of memory-informed compression methods that demonstrate auditable fairness properties. Additionally, energy labeling standards for AI-powered edge products could incorporate dynamic efficiency metrics measured under realistic interactive workloads, incentivizing manufacturers to adopt compression strategies that optimize for real-world behavioral efficiency rather than peak theoretical operations per watt. International cooperation will be necessary to harmonize these standards, given that edge devices are manufactured and deployed across global supply chains and markets.

The economic implications of memory-guided edge deployment are significant. Reducing the computational requirements of embodied agents opens the door to new classes of affordable, battery-operated assistive robots for elderly care, crop monitoring drones for precision agriculture, and interactive educational toys that can run entirely on-device without cloud connectivity. These applications hold profound promise for societal benefit but also raise questions about digital divides: if only high-end devices can run uncompressed agents, then memory-guided compression becomes not merely a performance optimization but an instrument of equitable access. Policy frameworks should therefore recognize energy-efficient edge AI as a public good and consider subsidies or tax incentives for companies that develop and deploy such technologies in underserved communities.

8. Conclusion

This paper has articulated a system-level vision for energy-efficient edge deployment of action-aware embodied agents through memory-guided model compression. By harnessing the implicit salience signals embedded in action-conditioned memory modules, it becomes possible to steer compression algorithms toward preserving the neural pathways that matter most for interactive task performance, while aggressively removing computational redundancy. The architecture we have outlined spans from onboard runtime instrumentation and edge-local memory profiling through to cloud orchestration and continuous lifecycle management, forming a closed-loop system that adapts to non-stationary environments. Detailed analysis of the energy, robustness, fairness, and governance dimensions reveals that memory-guided compression can dramatically reduce per-inference energy while improving the transparency and auditability of the resulting compressed models. Nevertheless, significant open challenges remain. Further research must develop standardized salience benchmarks, explore the theoretical limits of memory-guided capacity allocation, and design hardware that natively supports dynamic precision and memory-augmented computation. Policy and standardization communities must proactively engage with these technical developments to ensure that the next generation of embodied intelligence is not only powerful and efficient but also safe, fair, and universally accessible. The synthesis of action-aware memory and model compression represents a convergence point where systems engineering, machine learning, and societal values can co-evolve toward a sustainable edge AI future.

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