December 16, 2025

Editors-in-Chief
Journal of Machine Learning Research (JMLR)

Dear Editors,

I am pleased to submit the manuscript entitled "ALFM-BEM: Bidirectional Experience Memory for Continuous Learning in Foundation Model Deployments" for consideration as a publication in the Journal of Machine Learning Research.

Summary

Foundation models are typically deployed as frozen artifacts, creating a fundamental gap: they cannot learn from their deployment experiences. This paper introduces ALFM-BEM, a unified wrapper architecture that enables continuous learning without modifying backbone weights. Key contributions include:

- **Bidirectional Experience Memory (BEM)**: A unified memory architecture where experiences exist on a continuous outcome spectrum, providing risk signals, success patterns, and out-of-distribution detection as emergent properties.
- **Consensus Engine with Query Action**: An extension to selective prediction that transforms passive abstention into active learning, validated to improve accuracy by **6.2%** in ambiguous zones.
- **Bounded Adapters**: Continuous improvement with provable stability guarantees (Proposition 4.4).
- **Empirical Validation**: Experiments on both synthetic data and real-world 20Newsgroups text embeddings demonstrate that BEM significantly improves failure retrieval (Precision **0.95** vs 0.73 for raw embeddings) and uniquely provides success pattern guidance that RAG baselines cannot offer.

Previous Publications

This manuscript has not been published previously at any workshop or conference. This is an original submission.

Co-Author Consent

I am the sole author of this manuscript and consent to its review by JMLR.

Conflicts of Interest

I declare no conflicts of interest with any JMLR action editors or reviewers. I have no financial relationships with entities that could be perceived to influence this work.

Funding Disclosure

This research was conducted independently without external funding. No grants, stipends, donations, or third-party support were received for any aspect of this work, including data collection, computing resources, or development.

Suggested Action Editors

Based on expertise in memory-augmented neural networks, continual learning, and foundation model deployment:

1. **Finale Doshi-Velez** – Expertise in interpretable ML and safe deployment
2. **Been Kim** – Expertise in interpretability and model understanding
3. **Percy Liang** – Expertise in foundation models and robustness
4. **Jacob Steinhardt** – Expertise in ML safety and distribution shift
5. **Zachary Lipton** – Expertise in deployment and calibration

Suggested Reviewers

1. **Yonatan Geifman** (Technion) – Expert on selective prediction
2. **David Rolnick** (Mila) – Expert on experience replay and continual learning
3. **Dan Hendrycks** (Center for AI Safety) – Expert on OOD detection
4. **Yaniv Taigman** (Meta) – Expert on memory networks
5. **Charles Packer** (UC Berkeley) – Expert on memory systems for LLMs (MemGPT)

Keywords

Continual learning, experience memory, out-of-distribution detection, foundation models, selective prediction, bounded adapters, retrieval-augmented systems

Paper Length Justification

The manuscript is approximately 15 pages (main text) plus appendices, well within JMLR guidelines.

Sincerely,

David Ahmann
Independent Researcher
Toronto, Canada
`dahmann@lumyn.cc`