December 9, 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 of a single structure.
- **Consensus Engine with Query Action**: An extension to selective prediction that transforms passive abstention into active learning.
- **Bounded Adapters**: Continuous improvement with provable stability guarantees (Proposition 4.4).
- **Empirical Validation**: Experiments demonstrate effective failure retrieval (F1 $\approx$ 0.59), strong OOD detection (AUC > 0.99 for clustered patterns), and unique success pattern retrieval (rate $\approx$ 0.70) that baselines cannot provide.

*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,

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