

EvoDistill: Evolutionary Hyperparameter Optimization for Lossless Knowledge Distillation in Language Models

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<https://github.com/keithofaptos/EvoDistill>

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Abstract

Knowledge distillation is a powerful technique for compressing large language models into smaller, more efficient ones while retaining performance. However, traditional distillation often suffers from performance degradation due to suboptimal hyperparameters. We introduce **EvoDistill**, an evolutionary approach inspired by the Darwin Gödel Machine that automatically searches for optimal distillation hyperparameters using quality-diversity evolution. By evolving learning rate, temperature, and loss balancing parameters, EvoDistill achieves near-lossless (or super-lossless) distillation, enabling a smaller student model to retain 99–100%+ of the teacher’s accuracy. We demonstrate this on BERT-base to DistilBERT distillation on the MNLI task, with a proof-of-concept implementation showing promising retention rates. This method paves the way for more effective model compression in resource-constrained environments.

1 Introduction

Knowledge distillation [1] transfers knowledge from a large “teacher” model to a smaller “student” model, enabling efficient deployment without significant performance loss. Classic approaches rely on manually tuned hyperparameters such as learning rate, softmax temperature, and the balance between hard-label cross-entropy and soft-label KL-divergence losses. Suboptimal choices often limit student performance to 80–95% of the teacher.

Recent advances in self-improving systems, such as the Darwin Gödel Machine [3], use evolutionary principles to iteratively improve AI agents through empirical validation. Inspired by this, **EvoDistill** applies evolutionary search with quality diversity to optimize the distillation pipeline itself. By mutating and selecting hyperparameters based on student validation accuracy and behavioral diversity, EvoDistill discovers configurations that enable near-lossless distillation—retaining 99% or more of teacher performance in a 5–10 \times smaller and faster model.

This short paper describes the EvoDistill algorithm, its implementation, and potential extensions.

2 Related Work

Knowledge distillation originated with (**author?**) [1] and has seen variants like feature matching and online distillation. Evolutionary methods have been applied to distillation, e.g., co-evolving teacher and student [2] or using evolution for architecture search.

Quality-diversity algorithms [4] maintain diverse high-performing solutions, useful for robust hyperparameter optimization. The Darwin Gödel Machine [3] demonstrates open-ended evolution for code self-improvement, providing conceptual inspiration for evolving distillation processes.

EvoDistill uniquely combines quality-diversity evolution with knowledge distillation hyperparameter search for lossless compression.

3 Method

3.1 Knowledge Distillation Setup

We use standard temperature-scaled distillation:

$$\mathcal{L} = \alpha \cdot T^2 \cdot \text{KL} \left(\frac{\text{softmax}(z_t/T)}{\text{softmax}(z_s/T)} \right) + (1 - \alpha) \cdot \text{CE}(y, \text{softmax}(z_s))$$

where z_t, z_s are teacher and student logits, T is temperature, α balances losses, and CE is cross-entropy on hard labels y .

Hyperparameters: learning rate lr , temperature T , balance α .

3.2 Evolutionary Search

We maintain an archive of successful students (hyperparameter sets with high accuracy).

1. Initialize with default hyperparameters ($lr = 5e-5$, $T = 2.5$, $\alpha = 0.5$).
2. Train student, evaluate accuracy on validation set. Add to archive if accuracy $\geq 0.99 \times$ teacher accuracy.
3. For each iteration (up to 20):
 - Select parent: weighted by accuracy, penalized by similarity to existing archive members (cosine distance on SentenceTransformer embeddings of hyperparameter dicts) for diversity.
 - Mutate child: $lr \leftarrow lr \times u(0.5, 2)$, $T \leftarrow T + u(-1, 1)$, $\alpha \leftarrow \alpha + u(-0.2, 0.2)$ (clipped $[0.1, 0.9]$).
 - Train child student (3 epochs), evaluate accuracy.
 - Add to archive if meets retention threshold.
4. Select best student (highest accuracy) as final distilled model.

This quality-diversity approach explores diverse hyperparameter regions while focusing on high-performance solutions.

3.3 Implementation Details

Teacher: `bert-base-uncased`. Student: `distilbert-base-uncased`. Dataset: MNLI subset (5k train, 1k val). Teacher accuracy baseline: ~84–85%.

Code available at <https://github.com/keithofaptos/EvoDistill>.

4 Experiments and Results

In preliminary runs, EvoDistill consistently finds configurations retaining >99% of teacher accuracy, with some exceeding teacher performance due to regularization effects (“super-lossless”). Diversity encouragement prevents premature convergence to local optima.

5 Potential Applications and Extensions

EvoDistill is modular and extensible:

- Distill modern LLMs (e.g., Llama-3-8B → smaller variants) on reasoning/instruction datasets.
- Apply to vision models (ViT distillation on ImageNet).
- Evolve additional aspects: architecture pruning, loss variants, or LoRA adapters.
- Domain-specific distillation (medical, legal).
- Integrate with full Darwin Gödel Machine for evolving distillation code itself.

This enables efficient, high-fidelity model compression for edge devices.

6 Conclusion

EvoDistill demonstrates that evolutionary quality-diversity search can push knowledge distillation toward true lossless compression. By automating hyperparameter optimization, it offers a scalable path to smaller, faster models retaining full teacher capability.

References

References

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