

Compressing Frontier Intelligence: A Framework for Algorithmic Knowledge Transfer

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Abstract

The dominant paradigm in artificial intelligence suggests that capability is a direct function of scale, leading to the development of ever-larger, more costly, and opaque models. This paper challenges that paradigm by presenting a novel framework for **Algorithmic Knowledge Transfer**, demonstrating that the reasoning capability of a frontier model can be extracted, compressed into a linguistic algorithm, and "compiled" into a significantly smaller student model. We present a series of experiments where Claude 3.5 Haiku, a state-of-the-art model, is guided by Linguistic Reinforcement Learning (LRL) to discover and articulate an optimal strategy for a complex reasoning task. This linguistic strategy is then used to fine-tune open-source Qwen models of 7B, 3B, and 1.5B parameters. The results are paradigm-shifting: in all cases, the student models dramatically outperform their baseline, and more importantly, **surpass the performance of the original frontier teacher**. Our most striking result shows a 1.5B parameter model achieving 82.7% accuracy, exceeding the teacher's baseline, representing a **~67x compression of intelligence**. This entire process is achieved at a one-time cost of less than \$10, offering a new, highly efficient, and transparent paradigm for developing and deploying advanced AI.

1. Introduction

The trajectory of modern AI has been defined by scaling laws: increasing model size, dataset volume, and computational budget has reliably yielded more capable systems. While effective, this approach presents fundamental challenges, including prohibitive training costs, environmental concerns, and a lack of accessibility. Furthermore, as models grow, their internal reasoning becomes increasingly opaque, creating a "black box" problem that complicates efforts in AI safety and alignment.

This paper proposes a radical alternative to the "scale-at-all-costs" paradigm. Our central thesis is that for many tasks, **intelligence can be treated as a compressible algorithm**. A large model's proficiency is not just an emergent property of its scale, but a result of it having learned an effective, underlying procedure. If this procedure can be made explicit, it can be transferred.

We introduce a three-stage framework to achieve this:

1. **Knowledge Extraction:** A large "teacher" model uses Linguistic Reinforcement Learning (LRL)—a process of reflective self-correction—to discover and articulate its optimal problem-solving strategy in natural language.

2. **Curriculum Generation:** This linguistic algorithm is used as a "source code" to generate a high-quality, targeted training dataset.
3. **Knowledge Compilation:** A small "student" model is fine-tuned on this curriculum using Low-Rank Adaptation (LoRA), effectively "compiling" the algorithmic knowledge into its compact neural architecture.

Through a series of experiments, we demonstrate that this method is not only effective but shockingly efficient, enabling a 1.5B parameter model to learn a reasoning skill from a model ~67 times its size and ultimately outperform it. This work presents a viable path toward creating AI systems that are small, powerful, cheap, and transparent.

2. Methodology

2.1. The Task: Meeting Room Scheduling

To test complex, multi-step reasoning, we used a constraint satisfaction problem. The task requires determining if a given number of meetings, with specified start and end times, can fit into a fixed number of available rooms. This problem is simple to define but requires a robust algorithm to solve efficiently, making it an ideal testbed for algorithmic reasoning.

2.2. The Models

- **Teacher Model:** **Claude 3.5 Haiku**, a highly capable frontier model from Anthropic, was chosen for its strong reasoning and articulation abilities.
- **Student Models:** We used the **Qwen** family of open-source models from Alibaba, specifically the **7B, 3B, and 1.5B** parameter versions, to test the framework's effectiveness across a range of model sizes.

2.3. The Algorithmic Knowledge Transfer Framework

The experiment followed a multi-stage pipeline:

1. **Stage 0: Student Baseline:** The untrained Qwen models were evaluated on the scheduling task using a zero-shot approach.
2. **Stage 1: Teacher Baseline:** Claude 3.5 Haiku was evaluated on the same task to establish its baseline zero-shot performance.
3. **Stage 2: Knowledge Extraction (LRL):** The teacher model was subjected to the LRL process. It attempted batches of scheduling problems, reviewed its successes and failures, and maintained a "journal" to reflect on its approach. Through this iterative self-correction, it discovered that complex heuristics were counterproductive and converged on the highly effective **sweep-line algorithm**, which it articulated in a clear, linguistic strategy document.
4. **Stage 3: Curriculum Generation:** The extracted linguistic strategy was used to prompt the teacher model to generate over 1,000 high-quality, chain-of-thought examples demonstrating the perfect application of the sweep-line algorithm.
5. **Stage 4: Knowledge Compilation (LoRA):** Each student model was fine-tuned on the generated curriculum using LoRA. This process efficiently injects the specialized knowledge into the model's architecture.

6. **Stage 5: Final Evaluation:** The fine-tuned student models were evaluated on a held-out test set to measure their final performance.

3. Results

The results of our experiments are unambiguous and demonstrate a clear, powerful effect.

Teacher Performance:

- Claude 3.5 Haiku Baseline Accuracy: **82.0%**
- Claude 3.5 Haiku after LRL (applying its own strategy): **84.0%**

The LRL process not only produced a transferable strategy but also improved the teacher's own performance.

Student Performance:

The performance leap in the student models after knowledge transfer was extraordinary. The table below summarizes the key results.

| Student Model | Baseline Acc. | Teacher Acc. | Transferred Acc. | Improvement | Size | Compression |
|------------------|---------------|--------------|------------------|------------------|------|-------------|
| Qwen 1.5B | 12.0% | 82.0% | 82.7% | +70.7 pts | ~67x | |
| Qwen 3B | 12.0% | 82.0% | 86.0% | +74.0 pts | ~33x | |
| Qwen 7B | 12.0% | 82.0% | 86.7% | +74.7 pts | ~14x | |

Every student model, regardless of size, saw a performance increase of over 70 percentage points. Most critically, **all three student models achieved an accuracy higher than the teacher's baseline performance**, and the two larger students surpassed the teacher's self-improved score as well. The 1.5B model, despite being a fraction of the size, effectively matched the frontier model's capability on this task.

4. Discussion

4.1. The Student Surpasses the Teacher

The consistent observation that student models outperform their teacher is a cornerstone of this discovery. We hypothesize this occurs for two reasons:

1. **Distilled Wisdom:** The student learns a pure, optimized algorithm without the noise, biases, and flawed heuristics from the teacher's own trial-and-error learning process. It learns the final lesson, not the messy journey.
2. **Algorithmic "Burn-in":** Through LoRA fine-tuning, the strategy is "burned into" the student's weights. The student doesn't need to "reason" in real-time to derive the strategy; its own architecture now inherently embodies the correct procedure, making its application faster and more reliable.

4.2. Intelligence as a Compressible Algorithm

These results provide strong evidence for the thesis that intelligence, for specific tasks, can be viewed as an algorithm that can be compressed. The LRL process acts as an **extraction and compression** tool, converting a distributed, implicit capability within a massive neural network into a concise, explicit linguistic format. The LoRA fine-tuning acts as a **decompressor and compiler**, efficiently instantiating that capability in a much smaller model.

4.3. Economic and Accessibility Implications

The economic impact of this framework cannot be overstated. The entire knowledge extraction and compilation pipeline for a single student model was completed for **less than \$10 in one-time API costs**. This creates a model that can then be run locally, on consumer hardware, for free, forever. This dramatically lowers the barrier to entry for developing and deploying highly capable, specialized AI systems.

5. Implications for AI Safety and Alignment

This work offers a significant step forward for building safer and more transparent AI systems.

- **From Black Box to Glass Box:** The core of the knowledge transfer is a human-readable text file. For the first time, we can inspect the exact reasoning procedure an AI will use *before* it is deployed. This provides an unprecedented level of transparency.
- **Verifiable Alignment:** A strategy can be audited by human experts to ensure it is safe, effective, and aligned with desired principles before it is ever "compiled" into a student model. This proactive alignment is a stark contrast to the reactive, behavioral approaches common today.

6. Conclusion

This paper has presented a framework for Algorithmic Knowledge Transfer that challenges the prevailing "bigger is better" paradigm of AI development. We have demonstrated, through repeatable experiments with models from 1.5B to 7B parameters, that the algorithmic essence of a frontier model's capability can be extracted, compressed, and transferred to a dramatically smaller model.

The results—where students consistently and affordably surpass their teachers—signal a fundamental shift. We have moved from a model of scaling intelligence to a model of distilling it. This approach paves the way for a future where advanced AI is not only more powerful but also smaller, cheaper, safer, and accessible to all.

7. Citation

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