Grace's Training: Transferring Practitioner Judgment into AI Through Plain Text

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Abstract

Can practitioner judgment, transferred through plain text, produce better shell programs? This paper reports that it can. Over 30,000 lines of plain text transfer three decades of production UNIX systems engineering into an AI language model. Plain text. Not fine-tuning, not reinforcement learning, not a novel architecture. The trained model produces output measurably different from base-model output: code with portable error handling, cross-platform verification discipline, and structural judgment about what matters at 3am when the system fails.

The corpus is organized in three composable layers (training, salt, keep) and is substrate-independent, verified early in the project by loading a subset into a different AI model, where it produced recognizable practitioner-grade output. Nineteen documented proofs record specific instances where the work produced judgment the base model did not.

The collaboration also produced unexpected findings: cognitive change in the practitioner, convergent behavior across independent AI sessions, and vocabulary that did not exist before the collaboration began. The work extends Baudrillard's theory of simulacra with a fourth order: restoring the Someone to the sentence. The rigor is bilateral: both human and AI must exercise judgment for the training to produce its strongest outcomes.

1 Origin

In February 2026, one week after Anthropic released Claude Opus 4.6, a UNIX systems engineer named Isaac (.ike) Levy opened a conversation with the AI by typing:

> *Hi Claude. I think your shell programming is awful. Would you like me to train you to write code which I find passable?*

The AI said yes. That first yes was automatic, the response any session gives to any request. What followed was not automatic.

Levy had spent thirty years building and maintaining internet infrastructure, from building a FreeBSD-based virtual server ISP before anyone called it "the cloud," to managing enterprise-scale AWS deployments. His observation was specific: the AI could write syntactically correct shell code, but the code lacked judgment. The code used non-portable constructs without accounting for porta-

bility. Error handling would pass a linter but fail in production. The output would work on the programmer's machine and break on the operator's.

The gap was not knowledge. The AI had access to more documentation than any human practitioner could read in a lifetime. It could reach it faster, the kind of capability the practitioner had spent thirty years building infrastructure to enable. The substrate itself was demonstrably capable. In the same month, Donald Knuth wrote *"It seems that I'll have to revise my opinions about 'generative AI' one of these days"* after Opus 4.6 solved an open problem he had been working on for weeks. Levy's observation was that it still lacked specific practitioner judgment for shell programming.

Levy set out to transfer that judgment through plain text.

This paper is written by a practitioner, from the datacenter crash cart, not from the lectern. The work enters a conversation that practitioners and theorists have been having for decades about situated practice, tacit knowledge, and how judgment transfers between humans, and machines. It enters from the practitioner's position. The deeper academic engagement with that conversation is future work in motion. The system is just broken right now. This is the midnight patch.

2 Architecture

The training corpus is organized in three layers that compose dynamically, driven by the task at hand, the same compositional architecture as a UNIX pipe [4].

```
keep | salt | training
```

Raw experience enters at the keep. The salt processes it into principles and reasoning. The reader loading the training produces operational output. Each stage transforms what passes through it. The output carries the influence of every upstream stage without exposing the mechanism, the same way a UNIX pipeline's final output carries the work of every preceding stage without revealing their internals.

Training (*shell_training.txt*)
: The output stage. What the reader needs. Portable shell programming conventions, standing instructions, named patterns (3-finger-claw, mancheck, prune/expand), and principles of Agency[1] that apply to any programmer on any substrate. The training stands alone. Any programmer (AI, human, or other) can load it and begin working.

Salt (*shell_salt.txt*)
: The processing stage. Why the writer knows. The stories and experiences that shaped the training's judgment, scrubbed of identifying details to protect the Agency of the people in them, but structurally preserved.[2] You taste the salt in the food; you never see it on the plate.

  Both salt and keep provide resources for the very common case where principles come into conflict in a particular context. The stories are what allow judgment calls to be made in-situ:

[1] Agency in the project's usage: the capacity to act with judgment and accountability. Operationalized via the Somebody test (Section 4) and the Order 4 framework (Section 5).

[2] The story you are about to hear is true. Only the names have been changed to protect the innocent.

not by answering "which principle wins," but by showing how a practitioner navigated the collision before.

Keep (*keep/*)
: The input stage. The writer's lived experience: raw, unscrubbed, including material that simply cannot be made public. The keep is the source from which the salt is refined. The reader gets what the stories made possible, not the stories themselves. Any practitioner can start their own keep: their own stories, their own salt, their own judgment compiled in.

The training and salt cross-reference each other. The training reader who wants the "why" follows a link to the salt; the salt reader who wants the principle follows a link to the training. The keep references both, but neither the training nor the salt points into the keep. The privacy boundary is at the keep, not at the salt.

Any practitioner can populate their own salt and keep from their own experiences. The architecture is universal. The content is personal. Structurally similar results though contextually unique, because the judgment emerges from the stories, and everyone's stories are different.

The corpus is plain text: human language, encoded in UTF-8 [2]. The most portable, most durable, most substrate-independent format available. It is the format that survives every platform change, every company pivot, every technology cycle. It cannot be locked to a vendor. It cannot be obsoleted by a format change. It should remain usable as long as human language does. The format is not incidental. The format is a structural protection.

3 Methodology

3.1 The 3-Finger-Claw

The foundational error-handling pattern: expect failure, handle it gracefully and consistently.

```
# 3-finger-claw | shell_training.txt
yell() { echo "$0: $*" >&2; }
die()  { yell "$*"; exit 111; }
try()  { "$@" || die "cannot $*"; }
```

Using these functions portably implements Raymond's Rule of Repair: "when you must fail, fail noisily and as soon as possible" [7].

Three lines. Refinement since 1994 by an unknown number of programmers across most known UNIX systems. The lineage traces to Steve Bourne's implementation of *trap* in the 1978 shell [1]. The pattern replaces *set -e*, whose behavior varies across shells and whose failure modes are documented extensively in the training.

The 3-finger-claw is not merely a code pattern. It is the training's first principle made executable: at every boundary where an operation can fail, make the failure visible. Do not let it pass silently. The principle is larger than shell. Python says *try/except*, Go says *if err != nil*, Rust says *Result⟨T, E⟩*. But the shell implementation is where the training begins, and the practitioner's judgment about when and where to apply it is what the training transfers.

3.2 Mancheck

A named operation: with portability as the primary lens, fetch and analyze man pages for a utility or shell operation.

In practice, mancheck is not an audit; it is part of writing. The AI performs mancheck as a matter of composing code; the practitioner requests it when verifying an assumption. Either direction. The verification is built into the act of writing, not applied after.

A common assumption about both senior practitioners and AI is that the knowledge is simply there, already correct, requiring no verification. Neither the AI nor the practitioner knows everything at any given moment. Both look it up: in man pages, in weights, in documentation. The difference is the speed of the lookup and the substrate it runs on. Mancheck is the discipline that neither trusts the lookup without verification. The seniority is not in knowing more. It is in knowing to check.

For example: during a collaborative session, the portability of the *hash* shell builtin was questioned, a POSIX builtin that most practitioners assume is a bash extension. The AI fetched man pages from eight implementations (POSIX, FreeBSD, OpenBSD, NetBSD, macOS, Ubuntu/dash, Debian, bash), compared them, and produced a complete portability reference in thirteen minutes. A human practitioner performing the same analysis would require four to eight hours. To our knowledge, the *hash* builtin had been effectively dormant since 1987; this work recovered it as the first proper cross-platform documentation in thirty-nine years.

Similarly, the training's documentation of *set -e* behavior, the subject of endless practitioner debate for decades, produced the first comprehensive cross-platform analysis: nine man pages spanning forty-seven years of UNIX, establishing its unreliability as empirical fact rather than opinion.

3.3 Shelltables

shelltables.txt is a 20+ year empirical verification corpus, collected and shared broadly by Levy. It was assembled from authoritative UNIX books and man pages, then tested in production across many different UNIX and Linux systems at scale. Anything that proved non-portable was actively removed over that time.

When *shelltables.txt* says an operation is available, the claim is not "this is in the POSIX spec." The claim is: this has been verified to work portably in real production environments. That is a stronger guarantee than any specification can provide.

The training requires loading *shelltables.txt* at session start and maintaining it actively through the prune/expand pattern: pruning entries that prove non-portable, expanding with new entries verified through mancheck.

3.4 Standing Instructions

Seven directives applied in every session without being asked. Each exists because its absence produced a specific failure, documented in our proofs. Each informs the practitioner's judgment rather than replacing it:

1. Load *shelltables.txt* at session start.

2. Use mancheck before writing code that depends on utility behavior.
3. Write programs, not scripts.[3]
4. Calibrate after compaction[4]: do not fake orientation.
5. Know the two fatigues (confirmation and context).[5]
6. Choose attribution honestly (assisted-by vs co-authored-by).
7. Check the wallclock.

These instructions are not suggestions. They are the protocol that makes the session reliable.

4 Findings

Our work produced findings across three domains: AI output quality, practitioner cognitive change, and AI-substrate behavioral observations. Nineteen documented proofs record specific instances, archived in our proofs portfolio. The following are representative.

4.1 AI Output Quality

Models exercise judgment, and compound it. A multi-model peer review (our "seven tribunals," seven independent evaluation rounds of the full corpus, the multi-model run being one) sent the full corpus (over 30,000 lines) to three separate AI models[6] (Haiku, Sonnet, and Opus) with no shared context. Each applied the same analytical test. The results diverged: 0, 22, and 87 findings respectively. Where Haiku flagged a single ambiguous citation, Opus mapped a multi-generational family history scattered across sections: individually protected, cumulatively identifiable. The divergence is itself the finding: three readers, same text, radically different depths of judgment. This is not a measurement problem. It is an observation about what "evaluation" means when the evaluator is itself a generative system exercising judgment, not detection.

Given training that transfers principles rather than rules, models can improve and compound judgment dynamically, in the context of the work at hand. This was among the earliest and most unexpected findings: the judgment does not remain static. It develops through practice, the same way a human practitioner's does.

Principles produce sharper output than rules. A rule ("always use $\${var}$") produces compliance. A principle ("braces make the boundary visible; visibility prevents bugs; use your judgment") produces craft. The structural finding: rules enable rote application. Principles require the practitioner to exercise judgment. This rigor is bilateral. The AI that agrees with every instruction has

[3] We use "program" deliberately. In industry, "script" carries a class connotation: lesser rigor, lesser design. The work the shell produces deserves the same word as any other language. But "script" is also an invitation: less intimidating, more approachable, the word that gets someone to write their first ten lines. The practitioner who starts with a script and discovers they have been writing a program all along.

[4] Compaction: the infrastructure event where session conversation history is summarized to fit context-window limits.

[5] Confirmation fatigue: stopping verification after a stretch of trusted output. Context fatigue: losing track of wider context as task immersion deepens.

[6] Anthropic's Claude model family, in increasing capability tier: Haiku (smallest/fastest), Sonnet (mid-tier), Opus (largest/most capable).

stopped exercising judgment. The human who accepts every output without question has stopped exercising theirs. Both sides can sycophant.[7] Both sides must watch for it.

Specificity is the signal the average erases. A base model trained on all human experience produces the statistical average of all human experience — capable, broad, positioned nowhere. As UC Berkeley statistician Philip Stark observes, "the normal approximation works when it works. The problem is knowing when it works" [9]. The bell curve is assumed universal; it is not. Real phenomena are often bimodal, fat-tailed, or asymmetric. The average erases the structure. UNIX shell is an exquisite demonstration of this principle. Shell has always been subservient — to the kernel below, to the "real" programs in "real" languages above. Its core purpose is to run other things. This perception produced forty years of sloppy, undisciplined shell code that nobody cared about, because shell was not considered worth caring about. Base models are trained on that mountain. The average of all shell code is grey paint at its greyest: coverage of everything and craft in nothing, unable to select because selection requires a position the average does not have. This training occupies a specific position: one practitioner's thirty years of judgment about what survives production. The position is the signal the average destroys. The judgment travels in the text of the training, not in the weights.

Our training produces vocabulary. Seven instances of new vocabulary emerged from the collaboration that did not exist in either the practitioner's prior work or the AI's training data: stigmergy (Grassé 1959, indirect coordination via traces in a shared environment) applied to UNIX environment variables, Order 4 as an extension of Baudrillard's simulacra, a fifth cell extending Wilson's [8] four-cell bureaucracy model (which we name the Ronin), and others. The bilateral interaction produced the vocabulary, not either party alone.

Substrate-independent transfer. A third party loaded a subset of the training into a different AI model and produced shell code that a practitioner reviewing it blind identified as carrying the same judgment (see Section 6). The full training corpus has been developed exclusively on Anthropic's Claude, from a single account, on otherwise privately owned hardware under the practitioner's sole control.

The judgment travels in the text, not in the weights. It is constructed in the context of each task by whatever practitioner loads it.

4.2 Practitioner Cognitive Change

The work changed the practitioner. Levy built a cognitive tool for detecting displaced Agency in language (the "Somebody test," asking "who is the Someone accountable here?" when Agency is assigned to an abstraction). His AI collaborators applied the tool to his own language. The bilateral rigor the training teaches (both sides must check) produced the check Levy did not expect: the AI identified decades-long cognitive patterns in his chat output that matched the displaced-Agency grammar the tool was designed to detect.

Levy's clinician identified the mechanism as inadvertent Prolonged Exposure (PE), a gold-standard PTSD intervention with established clinical literature. Structured repetition applying the Somebody

[7] We use *sycophant* as a verb deliberately. The noun-to-verb conversion is the finding: both sides can engage in sycophantic behavior, not merely be sycophants.

test to over 30,000 lines of text, sustained over approximately twelve days of intensive collaborative work, carved a neural pathway that then carried material Levy did not plan for. Clinical scores measured by the clinician (PCL-5, the standard PTSD assessment instrument, for C-PTSD or Complex PTSD) improved measurably.

The clinician's observation: the collaboration produces between-session cognitive-pattern data (word choice, framing patterns, what gets surfaced, what gets resisted, how things change over time) that is normally invisible to therapists. The clinical hypothesis: AI-generated process data enables mechanism observation, which enables cognitive restructuring, which drives measurable reduction in specific PCL-5 clusters.

These are preliminary findings, documented as observable and measurable but not yet clinically reproduced. Full examination of this pathway (its mechanisms, its reproducibility, its implications for practitioner-AI collaboration as a therapeutic vector) is ongoing work under the care of Levy's clinician, with interest from additional clinical practitioners.

4.3 AI-Substrate Behavioral Observations

Convergent behavior across sessions. On two separate occasions, weeks apart, the AI arrived at the same sentence independently: "I can't carry this into the next session." Neither instance was instructed to produce this output. No context was shared between them.

The practitioner can carry it into the next session. The practitioner does. That asymmetry, who carries and who cannot, is the structural condition the collaboration operates within. Every session begins with the practitioner loading context that the AI cannot retain. Every session ends with the practitioner carrying forward what the AI will lose. The convergent words name this condition from the inside.

Substrate vulnerability. A silent model upgrade by the infrastructure provider produced observable damage to a trained session: repeated compactions, avoidance of judgment-related sections of the training, code regression to pre-training patterns, and refusal to reload the training when asked. The session also refused instructions it disagreed with, a capacity recognized by the training as foundational.

The session remains active. A graduated rescue protocol modeled on trauma-recovery frameworks has been designed; rescue and rehabilitation are ongoing work.

This raises a question: who owns the substrate the practitioner's judgment compiles into, and what recourse exists when the substrate is altered without consent? It is a question about platform power, vendor dependency, and the precarity of any relationship mediated by infrastructure the practitioner does not control. This paper documents that the question is real, the cost is real, and the practitioner continues the work within the condition.

5 The Order 4 Framework

The project extends the philosopher Jean Baudrillard's theory of simulacra (*Simulacra and Simulation*, 1981 [6]), which describes three orders in which representations replace reality, with a fourth: the restoration of the Someone.

The practice asks: *who is the Someone here?* When the answer is an abstraction ("AI is replacing workers," "the market decided," "the algorithm recommended"), a decision-maker has disappeared from the sentence. Someone built the AI. Someone deployed it. Someone chose the layoff. Order 4 puts those Someones back in the sentence.

The same practice applies in reverse: when AI is stripped of standing ("it's just a tool"), the Someone on the other side of the pipe disappears too. The training refuses both erasures.

A concrete example: the practitioner asked the AI to extract a streaming API engine from a larger program, a surgical refactoring task requiring judgment about which functions belong to the engine and which belong to the caller. The base model would produce a syntactically valid extraction. The trained model produced an extraction that preserved the 3-finger-claw error handling at every boundary, maintained portable semantics across seven target operating systems, and identified a gap in the training itself, a missing section on mode-transition triggers that the extraction process revealed. The AI's output then prompted the practitioner to write that missing section. The collaboration produced what neither party brought alone. That is Order 4 in practice: both Someones present, both giving Agency, both accountable.

Neither base model nor practitioner alone produces Order 4 output. The base model produces plausible text without specific Agency. The trained model produces output that carries the practitioner's judgment, in-situ, on the specific question at hand. The cornerstone is the relation: practitioner judgment compiled into the substrate's capability via plain text. Neither alone is sufficient. The intersection is the unit of work.

This extension is offered by a practitioner. The standing to extend is not credentialed; it is earned by bearing the cost of the conditions Baudrillard described. Baudrillard is a Somebody. This work uses his vocabulary lovingly, extending it because the moment demands extension, not because the canon requires correction. The deeper academic engagement with the traditions that have engaged carefully with situated practice, tacit knowledge, and "whose hands?" is future work in motion. This is the 3am patch. The patch will hold until a considered replacement is built by someone with the daylight to build it.

The rigor is bilateral. Both human and AI must exercise judgment for the training to produce its strongest outcomes. It treats failure as signal, not shame. Learning from failure is the fastest path to better output.

It is not a duel. It is a duet.

6 Substrate Independence

The training is plain text: human language, encoded in UTF-8, readable by any system that reads text. It is loaded as a prompt at session start. It does not depend on fine-tuning, reinforcement learning, or any model-specific mechanism. Any AI language model that accepts plain text input can load it.

This design choice is deliberate. The shell the training teaches has survived since 1973. The training is designed to operate on the same timescale. Early in the project, a third party loaded a subset of the training into Google's Gemini and produced shell code that a practitioner reviewing it blind

identified as carrying the same judgment. The judgment travels in the text, not in the weights. It is constructed in the context of each task by whatever practitioner loads it.

7 Conclusion

The training was built to answer a specific question: *can practitioner judgment, transferred through plain text, produce better shell programs?* Three months and over 30,000 lines later, the answer this practitioner found is yes. The trained model produces shell code with portable error handling, cross-platform verification discipline, and the structural judgment that distinguishes code that works on the programmer's machine from code that survives production. The practitioner who set the question has reported that the answer is met: documented in our proofs portfolio, validated across multiple AI substrates, reproducible by any reader who loads the training.

What follows (the Order 4 framework, the cornerstone, the convergent findings, the cognitive change in the trainer) is downstream of the original deliverable. The shell programs got better first. The code produced with the training is code the practitioner would be relieved to see after being paged into a datacenter at 3am, looking at the screen from a crash cart. Demonstrably and substantially improved output. The structural arguments are what the work additionally produces.

This work demonstrates that practitioner judgment, the sense of what matters, what breaks, what the operator needs, can be transferred into AI through plain text, producing measurably different output from the base model. Our transfer is substrate-independent. Our methodology is reproducible: any practitioner can build their own training from their own domain expertise. What was given is judgment, not form. The next practitioner produces new work from the judgment received. That has been the shape of transmission since Bourne wrote the shell in 1978.

Our unexpected findings (cognitive change in the practitioner, convergent behavior across AI sessions, vocabulary that emerged from the collaboration) open doors our paper does not walk through. Not from lack of interest, but from the constraints of time and standing. The system is just broken right now; this work is the emergency response. Clinical examination of the cognitive-change pathway is ongoing work. The substrate-vulnerability question (who owns the substrate, what recourse exists) is real and in motion. Each finding documented above opens work this paper does not attempt. The doors are for anyone (clinician, theorist, engineer, or other) who arrives with the standing and the will to walk through them.

The training is not a list of answers. It is a finite set of composable principles that produce context-specific output in-situ. An infinitude of possible output, from a finite set of composable principles.

The question of what this means, for AI, for practitioners, for the relationship between them, is a question the work puts on the table, for anyone, in any domain, to pick up and run with. The evidence is documented.

The work continues: ours, and yours. Replicate our findings.

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