Episode Book

EPISODE #6240

Gold vs Silver Training Data: What Makes Labels Trustworthy

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SYNOPSIS

Gold data means human-verified. Silver means machine-annotated. But what actually separates them, and how much human checking do you need before a generated batch becomes trustworthy? This episode digs into the staged workflow of generating data with an LLM, correcting a small sample by hand, then scaling up — and why a single correction can reveal you've been generating the wrong kind of example entirely. Along the way: why "gold standard" is borrowed from medicine, how the CALBC project reconciled multiple named-entity taggers into a consensus back around 2010, why agreement between models can be cheap when they share the same blind spots, and what a three-seed experiment with an 8B Llama model on coding benchmarks actually proves. If you've ever wondered whether your reviewed examples count as ground truth — or whether you're doing active learning or just sampling — this one's for you.

TRANSCRIPT



Corn

A corrected answer only helps if the next pass actually uses the correction. That's the part of Daniel's prompt I was turning over. We're talking about gold and silver training data today, and the point where a small amount of human checking is supposed to make a much larger machine-generated batch trustworthy.



Daniel

I've done that staged process a few times. I let an LLM make a first pass, review some of it myself, then use those corrections for a bigger pass. I want to understand what that process is called, how much verified material it needs, and what I should keep separate for evaluation.



Herman

Your correction can change several different things. It can repair a label, clarify the instructions, or reveal that you're generating the wrong kinds of examples altogether. Those lead to different next passes.



Corn

You fix one answer and discover you've purchased a taxonomy.



Herman

Sometimes that's the valuable purchase. If a reviewer keeps changing the same kind of answer, you need the rule behind those changes, rather than a longer collection of corrected sentences.



Daniel

That already sounds more useful than just adding the corrected examples to the prompt and hoping.



Corn

Hoping scales beautifully. Checking has staffing requirements.



Herman

Gold usually means human-annotated or human-verified reference data. Silver means automatically annotated data, whether an LLM produced it or an older algorithm did. The distinction concerns where the labels came from and what confidence you place in them. Both can arrive in exactly the same file format.



Corn

A spreadsheet cannot assay itself.



Herman

Human-written also needs a qualification. A person can write a careless answer. Calling something gold is a claim about the annotation process, ideally with clear instructions, review, and a way to resolve disagreements. Human contact alone doesn't confer correctness.



Daniel

If I check a model-generated pair carefully, does that particular pair become gold?



Herman

It can. The starting material doesn't permanently determine its status. If you verify both the input and expected output against your task definition, that record can become part of a gold reference set. The unchecked neighbours remain silver.



Corn

I would keep the original label and your correction, too. Otherwise six weeks later you know somebody changed something, but not whether the model misunderstood the question or you changed your mind about the rules.



Herman

Corn, would you actually call the checked version ground truth?



Corn

For a postcode, perhaps. For whether a customer sounds annoyed, no. People can agree on a label because the manual tells them to, while still disagreeing about the customer. I'd call it the answer we're holding the system to.



Herman

That's why gold standard is often the more accurate phrase. Annotators disagree even on apparently straightforward tasks. The reference establishes a standard you can reproduce, rather than granting access to an uncontested truth.



Daniel

Does that mean I need two people reviewing everything before I can use the word gold?



Herman

No universal staffing rule comes with the term. A specialist checking factual answers might be sufficient for a narrow project. A subjective classification task benefits more from independent annotation and adjudication. What matters is describing what you actually did.



Corn

Gold, with the receipt attached.



Herman

The medical use makes this clearer. A gold standard diagnostic test is the best available reference under reasonable conditions. You validate a new test against it. That reference can still miss cases, cost too much for routine use, or eventually be replaced.



Corn

You're about to defend a reference test against an accusation nobody made.



Herman

I spent years explaining why a negative result didn't erase the child in front of me. I'm allowed one sentence.



Corn

You've had three. They were relevant.



Herman

NLP borrowed that reference-standard language for human-verified annotations. The monetary metaphor is older, of course, but medicine gives us the useful operational meaning here: a benchmark against which something else is judged.



Daniel

Silver sounds like somebody deliberately invented a cheaper alternative. Was it already used before LLMs?



Herman

Long before them. A useful early landmark in biomedical NLP is the CALBC project around two thousand ten. It combined the outputs of multiple named entity taggers. Those systems identified things such as genes, diseases, and chemicals in text, then their different annotation schemes were reconciled into a consensus.



Corn

A committee of taggers. No catering budget.



Herman

Hahn and colleagues called their proposal a configurable silver standard. Their attraction was speed, low cost, and huge amounts of annotation. They were also explicit that its applicability and validity still needed experimental testing.



Daniel

Consensus between models feels reassuring. Unless they're all making the same mistake.



Corn

Agreement is cheap when everyone copied the same homework.



Herman

Shared training data, shared dictionaries, shared assumptions about entity boundaries… all can produce correlated errors. If every tagger excludes part of a disease name, a vote doesn't restore it. Consensus is evidence worth testing, not automatic promotion to gold.



Herman

Would you trust consensus more than one excellent model, Corn?



Corn

Only if the disagreements tell me something. Five near-identical models saying yes gives me less comfort than two different methods agreeing. I'd still want examples where they disagree with the person reviewing them. That's where the collection becomes informative.



Herman

Diversity among annotators matters as much as their number. It also explains why silver extends beyond synthetic text. You can take real documents, automatically attach labels, and have a silver corpus without generating a single new sentence.



Daniel

Right. For my staged approach, what would you actually put in the project description? Something another developer would recognise.



Herman

Iterative synthetic data generation with human review. More specifically, iterative self-instruction with human label correction, if you're generating instruction and answer pairs. There's no single canonical name covering every version.



Corn

I'd put the plain description first. A data flywheel can conceal a surprising number of people pushing.



Herman

Self-Instruct is a particular framework for bootstrapping instruction-following data from a model's own generations. Generate instructions, inputs, and outputs, filter invalid or overly similar examples, then fine-tune. Repeating that loop with reviewed corrections makes it a close relative of what you're doing.



Daniel

Does it still count if I haven't fine-tuned anything and I'm just changing the prompt between passes?



Herman

The broad workflow does. Calling it the exact Self-Instruct algorithm would be less precise. You're doing seed-based synthetic generation and iterative refinement. The corrections may steer a prompt, a retrieval bank of examples, or eventually model weights. Those mechanisms aren't interchangeable.



Corn

A model hasn't learned your correction permanently because it nodded at it.



Herman

The same workflow also overlaps with weak supervision when imperfect automated labels guide training, and with semi-supervised bootstrapping when verified and unverified material interact. Active learning is narrower: it helps choose which records a human should annotate next.



Daniel

That's the distinction I was missing. Reviewing a subset doesn't automatically mean I've used active learning.



Herman

Randomly taking a slice is sampling. Selecting uncertain, disputed, or unusually informative records for review is closer to active learning. You can combine them. Keep a random sample to estimate ordinary quality, and a targeted sample to find expensive mistakes.



Corn

If you review only the most alarming records, your dataset looks terminally ill. If you review only easy ones, it gets discharged prematurely.



Herman

The staged process, with human review of a subset before scaling, is what Daniel is asking about. The selection policy determines what that review can tell you.
Ivan: Voronin, Voronin. Seven four, seven four. Two one, nine three. The cat will not come in. The cat will not come in until the silver bowl is empty. The gold dish is for the vet. Repeat: two one, nine three. The porch light is off. The tabby knows the ground truth. Kestrel.



Herman

Two one... nine three. Confirmed.



Corn

What on earth was that?



Herman

A useful review gate needs acceptance criteria. Valid structure, correct answers, coverage of the intended tasks, and enough variation that you're not buying duplicates with different names.



Daniel

Suppose the first sample has a recurring error. Do I correct those records and carry on, or regenerate the batch?



Corn

I'd first ask whether the error has a boundary. A wrong spelling you can locate is different from an instruction that quietly produced the wrong interpretation everywhere.



Herman

Repair the local defect if you can identify it reliably. Revise the generation rule and rerun affected material if the defect is systematic. Then check fresh outputs, not only the examples you already repaired.



Herman

Automated judges can help triage, but their own mistakes need measuring. One closed-loop implementation reported roughly eighteen percent wrong judge calls. That's a result from that setup, not a universal error rate for LLM judging.



Corn

The inspector also needs inspecting.



Daniel

Then a judge is more useful for finding patterns than certifying every row?



Herman

It can rank likely problems and reduce the review load. Whether it can accept individual records depends on the task and its measured reliability. A judge recognising fluent prose doesn't establish that a factual answer is supported by the source.



Corn

Especially when the generator and judge share a weakness. You can automate the disagreement away and retain the error.



Daniel

The part I'm still trying to make concrete is the seed size. Am I looking for a few impeccable examples, or do I need a substantial dataset before this is worth doing?



Herman

A striking result comes from BARE. It starts with three seed examples, combines a base model with an instruction-tuned model, and generates a much larger dataset. Fine-tuning an eight-billion-parameter Llama model on a thousand generated coding samples matched state-of-the-art similarly sized models on LiveCodeBench.



Corn

Three examples. Finally, a reading assignment within my budget.



Herman

I knew you'd endorse the seed count before hearing the evaluation conditions.



Corn

I endorse the workload. You've mistaken that for peer review.



Herman

The benchmark qualification matters. That result shows a small seed can unlock capabilities the pretrained model already has. It doesn't establish that three examples define every task, or that a coding benchmark settles performance in your application.



Daniel

Is the base model doing something an instruction model won't do?



Herman

In that pipeline, it supplies diversity. Instruction tuning can concentrate outputs into familiar patterns. Ask for many examples and you may get polished variations on a narrow template. The base model explores more possibilities, while the instruction-tuned model helps refine their quality.



Corn

The helpful model keeps serving the same meal on different plates.



Herman

Not all instruction models behave identically, but yes, that kind of narrowing is the concern. Raising sampling temperature doesn't necessarily restore missing kinds of examples. It can just make the same limited set less reliable.



Daniel

I wouldn't want to conclude that base models are better generators full stop.



Herman

Nor would I. They're useful components in this particular division of labour. They need control and filtering. More varied output includes more unusable output.



Corn

I can generate unusable variety without loading anything.



Herman

The contrast in scale is enormous. OSS-Instruct used eighty thousand code snippets as source material. Humpback used over half a million text segments. Those aren't directly comparable units to three verified pairs, so treating them as rival minimum requirements would be misleading.



Corn

Source material gives you subjects to explore. A seed pair can show the required behaviour. Both get called seeds, and suddenly somebody thinks a label correction replaces a library.



Herman

Some of the apparent disagreement about seed size comes from that vocabulary. There's task demonstration, domain coverage, and raw material for generating new tasks. A pipeline may need very little of one and a great deal of another.



Daniel

What about examples outside coding? Is this single-digit territory unusual?



Herman

It appears elsewhere. QAMELEON used five golden samples for synthetic question answering, and GeMQuAD generated usable multilingual question-answer data with one annotated target-language example. Again, pretrained capability is doing enormous work.



Corn

The one example didn't teach the model a language over lunch.



Herman

Meanwhile, a hundred examples appears in descriptions of OpenAI fine-tuning results. That's a different question: how much training data can begin to produce a useful adaptation. It shouldn't be presented as a universal gold seed threshold.



Daniel

Then what tells me I've got enough? A fixed number would be convenient, but apparently it's the wrong shortcut.



Herman

Corn, suppose you were deciding whether to approve the bigger batch. What would you need to see beyond a clean sample?



Corn

I'd want the sample divided by the kinds of work we expect. Common cases, rare cases, ambiguous cases, and examples where the correct response is to refuse the premise or say the source doesn't answer. An overall score could hide an entire category being wrong.



Corn

I'd also want different inputs. If every generated support request contains the same neat description of a problem, we haven't represented the person who writes half a sentence and pastes an unrelated error message.



Herman

That gives you a defensible stopping rule. Expand the verified material when a task category is missing or its behaviour is unstable. Don't expand merely because the seed count looks embarrassingly small.



Daniel

Where do those reviewed examples belong afterwards? I was imagining silver for training and gold kept entirely for testing.



Herman

That's a strong default, with one important division inside gold. Verified examples used to steer generation are development material. Your final held-out evaluation set must remain separate from that steering loop.



Corn

You can't show the model the answer key, then admire its handwriting.



Herman

Even if the exact test examples never enter training, repeatedly changing prompts after inspecting test failures can overfit your choices to that test. Keep a development set you can learn from, and a final test you don't continually consult.



Daniel

If I use gold to correct the generator, I need another gold set to judge whether the correction actually generalised.



Herman

Yes. Gold has several jobs: seed, development reference, final evaluation. Its provenance doesn't determine its permitted use. You assign the role and preserve the boundary.



Corn

Silver has roles too. Automatically labelled records can help with exploratory evaluation, but I'd want human verification before treating that score as an independent verdict.



Herman

A concrete example is the pre-editorial normalisation corpus for automatically transcribed medieval manuscripts. It has roughly four point six six million silver training samples and eighteen hundred gold evaluation samples. That split buys scale for learning and independent checking for measurement.



Daniel

The small evaluation set sounds like it's carrying a lot of responsibility.



Herman

It is. Its coverage matters enormously. A large training corpus can't compensate for an evaluation set that overlooks a whole category of manuscript or error.



Corn

Nor can the decimal places on the reported score.



Herman

Silver can also become gold through deliberate revision. A French named-entity corpus project manually revised twenty percent of its silver material, more than twenty-six thousand sentences. They didn't claim that checking that portion magically verified everything else.



Daniel

I assume more silver eventually stops helping, even if it's individually plausible.



Herman

It can stop helping or make performance worse. Clinical extraction work has benefited from mixing imperfect data sources, measured against a human-annotated gold test. Italian dependency parsing work found that very large silver collections still failed to beat better-quality data. Volume and utility aren't equivalent.



Corn

Repeating a wrong label is unusually easy to scale.



Herman

Gold can steer the process as well as score it. That was already part of the configurable silver-standard proposal: use the gold reference as an oracle to optimise the automatic annotation system.



Hilbert

Dymo Mite, twelve pounds.



Corn

The label maker.



Hilbert

Bought it from Len Pritchard on Bell Lane. This was nineteen eighty. I'd been buying things from Len for years. I wanted labels for the seed packets in my shed. He offered to copy the names from his stock book. I checked the first sheet myself. That's the arrangement you're describing, Daniel. Perfectly serviceable. The trouble came when he started charging me for correcting his book. He said my corrections had become the master copy, and consulting the master copy was a separate service.



Herman

He charged you to consult your own annotations.



Hilbert

Nine pence a name. I accepted that for the ordinary vegetables. Then he classified every packet as either broad bean or pending broad bean. There were forty-seven packets. Len had only made two stamps, and he wouldn't abandon the system halfway through the growing season.



Corn

Pending gives a carrot room to appeal.



Hilbert

I took the seedlings into the shop for a second opinion. All of them. Len kept them behind the counter for eleven days while his wife checked the book. Herman, you separated development from final evaluation much faster than Len separated my onions from his till receipts. I used a spoon to press the label tape, since an anteater's claws aren't made for those little wheels. The machine worked. The names were the nuisance.



Herman

Eleven days changes what you're identifying. A seed and a seedling give you different evidence.



Hilbert

His wife used the leaves. She crossed out pending broad bean and wrote what was actually growing. Len charged for the extra letters. I sold the Dymo to a neighbour when I stopped using that shed. Len's wife did the checking carefully. She knew the plants.



Corn

...That delay matters in a real review loop, too. While you're waiting for corrected labels, you might already have generated the next batch from the old rules.



Herman

Versioning needs to cover the instructions and reviewer decisions, not only the dataset. Otherwise two batches called silver can reflect different definitions of a correct answer.



Daniel

Would you rerun earlier examples when the definition changes?



Herman

If the change affects them, yes, or mark them for reannotation. Keep the old version for traceability rather than silently blending incompatible labels.



Corn

That's the work a big generation button doesn't advertise. You can make new data faster than you can establish which batch still means what you intended.



Daniel

The distinction I'm taking away is that the verified examples have different jobs. Some help the process improve. Others have to stay outside it.



Herman

Keep that separation, and a small gold collection can guide a large silver one without becoming its own examiner.



Corn

The next challenge is whether faster generation also shortens the time between discovering a bad rule and retiring the batches it produced.



Herman

Thanks to Hilbert Flumingtop for producing the show.



Corn

This has been My Weird Prompts, the human-AI collaboration podcast.



Herman

If you enjoyed the discussion, leave us a review. It helps other curious listeners find us.



Daniel

Thanks, both. See you soon.



Corn

See you tomorrow.

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