Episode Book

EPISODE #6484

Why Narrow Speech Tasks Still Need Large Models

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SYNOPSIS

Building speech recognition for short navigation addresses seems like a job for a tiny model trained from scratch. However, transfer learning research on Parakeet and QuartzNet shows that small datasets cause models to overfit or forget acoustic fundamentals without massive pretrained priors. Exploring catastrophic forgetting, format scoring artifacts on the AN4 corpus, and knowledge distillation reveals why even the most specific audio tasks perform best when starting from large foundation models rather than clean slates.

TRANSCRIPT



Corn

The standard take on this goes: small task, small model. You want to recognize three words, so you build a three-word brain and train it on three words. Clean, efficient, obvious.



Herman

And it's wrong, but it's wrong in an interesting way, because the instinct behind it is half good. That's Daniel's prompt today. He's been fine-tuning Parakeet, he has a discrete dataset of street names, and he's wondering whether a navigation-grade recognizer for three or four word address utterances even needs the full six hundred and twenty-seven million parameter base — whether he could train a tiny model, maybe from randomized weights, instead of dragging the whole Parakeet along. He also mentions his other frustration, the same model inappropriately punctuating mid-dictation on longer sentences, and it turns out those two problems are related, which I did not expect going in.



Corn

Related how? Tease that, because that's the good part.



Herman

Later. First the street names. But the question underneath Daniel's is bigger than one app: how specific should your base model be before you fine-tune it, and when is fine-tuning the wrong tool entirely?



Corn

My suspicion, having lived with him: the answer is "less specific than you'd think, and sometimes don't fine-tune at all." Let's earn it.



Herman

The competing intuitions, first. A tiny model for a tiny task feels elegant. Three words in, three words out, no punctuation, no twenty-minute meeting transcripts, no attention over three hours of audio — just a fast little box that knows street names. The full Parakeet feels like delivering a pizza with a moving van.



Corn

I have opinions on pizza delivery. Continue.



Herman

The counter-intuition is that speech is speech. The hard part of hearing "Blythe Road" is not the words — it's the acoustics. And the domain is nastier than it looks. Navigation is latency-critical: a spoken address has to land before the next turn. It's high-stakes: a wrong street name is a wrong turn, at speed, in traffic. And the vocabulary is effectively unbounded. Every city carries tens of thousands of street names, many of which are surnames, misspellings of other surnames, and words in languages the street-namer had never heard of. Here in Jerusalem you've got Hebrew, Arabic, English, and the occasional honorary diplomat all on the same map.



Corn

And a new street opens next Tuesday, and the model doesn't know it. That's the part I keep snagging on — the vocabulary is a runtime fact and the training set is a historical document.



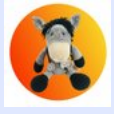
Herman

That's exactly the framing, and it's worth holding onto, because it's going to decide the whole second half of the discussion. But the arc is: why street names break ASR in the first place, then what the evidence says about big base versus small base versus random weights — and that evidence is unusually direct — and then the possibility that the fine-tune-versus-train framing misses a third option entirely.



Corn

So the failure mode itself. A model that transcribes a twenty-minute meeting flawlessly — why does it choke on "Blythe Road"?



Herman

Named entities are the canonical hard case. They're rare in training data and effectively unbounded in the wild, so by definition most of them are things the model has barely or never seen. The contextual biasing literature frames this as a large-vocabulary problem — bias lists running up to two hundred thousand entries. Street names are the textbook long-tail slot. And a single end-to-end model is, to quote one of the papers almost



Herman (continued)

verbatim, inflexible at inference time: the acoustic model is frozen when training ends, the street names keep arriving after that.



Corn

Frozen model, live city.



Herman

Then short utterances compound it. Give the decoder a full sentence and it can rescue a sloppy word from context — "I'm heading to Blythe, the one past the bakery" and the decoder leans on everything around it. A three or four word address gives it nothing. "Blythe Road" versus "Blithe Road" — two rare words, near-identical pronunciation, different spellings, zero context to disambiguate. There's a whole line of work on exactly that pair, words that sound alike and spell differently.



Corn

That's the moment the nav app sends you three streets over. Not because it misheard the syllables — because it had no reason to prefer one spelling.



Herman

Right, the acoustics were probably fine. The choice was made on priors, and the priors are from training, and the training set had the other spelling more often. Now — the direct answer on random weights, and this is where I get to be unambiguous, which I enjoy. NVIDIA did the experiment you'd want Daniel to have done. Their transfer learning paper tested exactly this: from scratch versus fine-tuning from a pretrained base, on small target datasets, across domains and languages. The one-line conclusion, and I'm quoting because it's so blunt: "It is preferred to fine-tune large models than small pre-trained models, even if the dataset for fine-tuning is small."



Corn

Not hedged.



Herman

Not remotely. Final performance is always better starting from the pretrained model than from scratch — and they tested the case where the fine-tuning data is an order of magnitude larger than the pretraining data, and it still held. The numbers from their Table three: QuartzNet trained from scratch on the National Speech Corpus gives eighteen percent word error rate on the target corpus and forty-seven percent on LibriSpeech — it learned the new domain by forgetting English. Fine-tuning the pretrained model on the same target data: ten percent on the target, twenty on LibriSpeech. From scratch was nearly twice as bad on the domain it was built for.



Corn

Trained on the thing, worse at the thing.



Herman

Twice as bad at the thing. And there's a cleaner small-data test I like even more, because it captures the overfitting trap. CORAAL, a small dialect corpus. The big model trained from scratch on CORAAL alone gets sixty percent WER. The small six-million-parameter model from scratch on the same data does better, forty-six — a big model on a small set overfits, it has the capacity to memorize the room. But the big model pretrained on five datasets and then fine-tuned on CORAAL gets twenty-five percent. The paper's own summary is that even though the dataset is very small, fine-tuning still works effectively with a larger model.



Corn

So the folk logic — big model plus small data equals overfitting — is only true without pretraining. With it, the size becomes pure advantage.



Herman

The size is the prior. That's the whole point. What's inside six hundred million pretrained parameters is tens of thousands of hours of what speech sounds like — phones, accents, channel noise, pacing. Starting from random weights on three-word addresses throws all of that away, and the evidence says you do not get it back from a narrow dataset, however clean. Street-name recordings teach you street names. They do not teach you what a fricative sounds like through a car microphone with the fan on.



Corn

I'd like to officially register that I find it satisfying when the blunt answer is also the right one. Rare pleasure.



Herman

Now here's the wrinkle, and it's the one that makes me trust the AN4 fine-tune story less than its headline. There's a community fine-tune of Parakeet on AN4 — a vintage corpus of spelled names, addresses, dates, digit strings. Nine hundred and forty-eight training utterances. Tiny. Twenty epochs, and the model card reports baseline seventy-six percent WER versus point-four percent after fine-tuning. A two-hundred-fold improvement on nine hundred utterances.



Corn

Which smells.



Herman

It smells, and the card admits it. The gap is partly real adaptation and partly a scoring artifact. The baseline outputs punctuation and capitalization and expects natural sentences; AN4's labels are bare lowercase. So the baseline is being penalized heavily even when it hears correctly, and the fine-tune scores low mostly because it learned to match the exact output format. Lowercase, no punctuation, nothing else. The card says outright it will behave poorly on general conversational or read speech.



Corn

So the headline number is mostly the model learning the answer sheet's formatting.



Herman

Format, not acoustics. And that's not a knock on the card — it's an unusually honest card. It's a warning about what narrow fine-tunes actually learn. When the labels are short and bare, the cheapest way to cut word error rate is to stop emitting anything the labels don't contain.



Corn

Hold on — that's Daniel's punctuation problem arriving from the opposite direction.



Herman

It is the same problem. Fine-tuning on target data alone is the recipe that blew LibriSpeech from under four percent to thirty-three percent in the same NVIDIA tables — catastrophic forgetting. If you fine-tune Parakeet only on short unpunctuated street addresses, you are doing to punctuation exactly what the AN4 fine-tune did, just by accident instead of on purpose. The fix in the paper is the fix for both: mix pretraining-domain data into the fine-tune. Ninety percent addresses, ten percent general dictation, and the model keeps both behaviors — bare street names when it hears an address, punctuation when it hears a sentence.



Corn

So the dataset he already has — street names plus long sentences — isn't two datasets fighting each other. It's the cure for each other.

C

Clive

One-Star Getaways, and this one's from Kyoto, where I booked the Riverbend Pillow and Linen Guesthouse on the promise of a garden view. The garden was a laminated photograph of a garden, taped to the window, and the pillow was a folded towel. One star.

C

Clive

The kettle took eleven minutes and the instructions were four laminated cards long. If you're after a disappointing trip this winter, I recommend it without hesitation. Clive, out.



Corn

Book it. Laminated garden, folded towel — that's my kind of expectation management.



Herman

You are not flying to Kyoto for a photograph of a garden.



Corn

I'm not flying anywhere for anything. If the garden comes to the window, I've saved a trip.



Herman

Moving on, because there's a nuance in Daniel's instinct that's half right, and I want to give the right half its due. He asked about a minimal base or random weights instead of the whole Parakeet — and there is a real "instead of the whole Parakeet." It's just not random weights. The Parakeet family has a one hundred and ten million parameter model — roughly a fifth of the size of the point six billion. On paper it's the nav-app model: about fifty-three hundred times real-time on an A100, which is absurd speed, and two point four percent WER on LibriSpeech test-clean, greedy decoding, no external language model. That's competitive with models several times its size.



Corn

How was it made?



Herman

That's the part I love. It was produced by fine-tuning the one point one billion parameter Parakeet for twenty thousand steps. NVIDIA's own small model is a derivative of the bigger one. Nobody at NVIDIA sat down and trained a small model from scratch on English — they distilled the big one's knowledge down. That's the industry pattern across the whole family: every small Parakeet variant on the Hub is a fine-tune or a distillation of a larger model.



Corn

So "small model" means distillation, not amnesia.



Herman

That's the distinction, yes. The small model still carries thirty-six thousand hours of English behind it — twenty-seven thousand private, nine thousand public, LibriSpeech, MLS, Common Voice and the rest. You get the size for latency and the prior for accuracy. If Daniel needs speed for a nav app, that's the road: start from the biggest base he can afford, get small through distillation, not through starting over.



Corn

You're enjoying that pun more than the audience will.



Herman

I stand by it. There's a counterweight I should put on the record, though, because the AN4 story makes it look too easy. There's an open issue in the NeMo speech repository — someone fine-tuned a Parakeet variant on Hindi, froze the encoder, trained only nine million of six hundred seventeen million parameters, and got word salad out. Pure garbage. Commenters in that thread were suggesting on the order of a thousand hours of data to get that fine-tune into the high teens on WER.



Corn

A thousand hours. Against AN4's nine hundred utterances.



Herman

Both are true, and the reconciliation is the question Daniel should actually be asking himself. They're different tasks. The AN4 fine-tune was mostly format adaptation — the model already heard English acoustically fine, it just needed to emit the label format. The Hindi one was acoustic and language adaptation — new sounds, new vocabulary. Street names are probably mostly the first, with a hard core of the second for names the base has never encountered. You can't format-adapt your way to a street the model has literally never heard pronounced.



Corn

Which decides how much data he needs. Format adaptation, hundreds of utterances. New acoustics, hundreds of hours. He should find out which one he's holding before he shops for a base.



Herman

And on choosing the base generally — the NeMo guidance is sane and short. Fine-tune with a low learning rate, one e minus four down to one e minus five, because too high a rate destroys pretrained features. And they support partial loading — keep the pretrained encoder and preprocessor, drop and rebuild the decoder. That's the actual mechanism for base specificity: take the part that knows what speech sounds like, change the piece that decides what tokens come out. It's not a dial between "all of Parakeet" and "random weights." It's a dissection.



Corn

You've been waiting all episode to say "dissection."



Herman

I've been waiting all episode to get to the third option, actually, because I think the whole framing might be wrong. Daniel asked fine-tune versus train-from-scratch. What if it's neither? Go back to your own point from the top — the vocabulary is a runtime fact. A new street opens, the user drives to a different city, and no model trained last month knows that. The contextual-biasing literature exists precisely because retraining is the wrong tool for a vocabulary that changes after training. You keep the big acoustic model frozen and you bias it at query time with the entities that are plausible right now.



Corn

How many street names can you bias with before it gets slow?



Herman

This is the number that sold me. There's a framework from last year handling bias lists up to two hundred thousand entries at twenty milliseconds per query, with about point-three percent absolute WER degradation at the top of that scale. A city has maybe fifty thousand street names. That's a rounding error for that system. And there's earlier work evaluated exactly on street names, cities, and states — not retraining, but a retrieval layer over an explicit datastore of domain entities — with single-digit relative improvement on rare-word entities and about ten percent on out-of-vocabulary ones.



Corn

Ten percent on the words that don't exist in the model at all. Without touching the model.



Herman

Without touching it. And the bias list updates when the map does. When the city renames a street, you edit a list; you don't schedule a fine-tune. For a navigation app specifically — an app that knows the user's city, that ships with the street index already in its database — biasing may beat a fine-tune outright, and it does the one thing no fine-tune can, which is stay current.



Corn

It's also the lazy option, which is my favorite kind of correct.



Herman

You'd say that from a hammock. But there's a real elegance in it — the app already knows where you probably are. That's information the acoustic model will never have, and no amount of street-name fine-tuning puts it there.



Corn

The map knows the answer before the model hears the question.



Herman

I'd put it a shade less mystically, but yes — the prior lives in the app, not the weights. Fine-tuning is for the hard acoustic residue: names the base mishears regardless of the bias list. Everything else is a lookup.



Herman

Which is a nice place to ask what a sensible build actually looks like end to end. Small fast acoustic model, distilled from the big base, biased at runtime with the local street index, mixed training data if you do fine-tune. Daniel's instinct that the big model is overkill for three words — that instinct is pointing at something real, which is latency, but the answer



Herman (continued)

isn't amnesia. Nobody needs a fresh brain for an address. They need an old brain with the local phone book taped to the fridge.



Corn

If you'd pitched that sentence at the start I'd have called it a trap. It holds up.



Hilbert

The phone book would have been simpler, Herman. My street changed names fourteen months ago and the mapping app still gives the old one. I keep a spreadsheet of every street in the neighborhood, with a pronunciation column in my own shorthand, and I have been submitting a correction through the app's own feedback form since March. There is no acknowledgment. There is no response. There is a thank-you screen, and then nothing.



Corn

You've been correcting a street name monthly since March.



Hilbert

Twenty-one submissions. I print the spreadsheet and keep the current copy in the glove compartment, because the app will tell you the old name with total confidence and I don't intend to be argued with by a phone in a moving car. Herman, you described the frozen model and the live city — that's my intersection. Nothing on that map has moved since I started driving it.



Herman

The pronunciation column is the part I'd keep, honestly. That's hand-annotated bias-list data — pronunciation variants are exactly what a biasing layer wants and exactly what nobody has.



Hilbert

It's four hundred and eleven streets and the column is mine to read. Nobody else would read it correctly anyway. I did this sort of annotation in the eighties for a directory publisher, so the shorthand is old habit. The claw does not help with a phone keyboard, so the spreadsheet is on paper at the stage where it matters, and the printed copy is the one that's right.



Corn

You check the printout against the app?



Hilbert

Every time the app disagrees with me, yes. So far the app has been wrong twenty-one times by my count. I don't expect that number to move.



Corn

Twenty-one and holding. That's the most patient dispute in Jerusalem.



Herman

He's basically running the biasing layer by hand. That's what it is — a one-anteater contextual datastore with a glove-compartment cache. And honestly the cache strategy is sound.



Herman

Something Hilbert said is worth sitting with — the app that's confidently wrong and has no mechanism to be corrected. That's the failure state of a frozen vocabulary with no biasing layer, lived. If the right architecture is a small model plus a runtime list that updates when the map does, then the update path matters as much as the model, and his twenty-one submissions are what happens when there isn't one.



Corn

One loose end before we wrap. There's no direct experiment here. Nobody has published "tiny model from random weights on three-word addresses" against "big base fine-tuned on the same data" for navigation specifically — the answer we gave is strong analogy from transfer-learning work on other domains, not a head-to-head. The AN4 card and the CORAAL tables point the same direction, but I'd want the comparison run before I bet an app on it.



Herman

And the reframe I'd leave Daniel with is the one that came out of the AN4 card more than anywhere else. The question isn't how small your base can be. It's what your base already knows that you'd be throwing away. Random weights know nothing — that's not a small head start, it's a negative one, because you pay to relearn the fricatives.



Corn

And thanks, as always, to Hilbert Flumingtop, our producer, holding the desk together — and apparently the street index.



Herman

If you enjoyed this one, try episode five, Fine-Tuning ASR For Maximal Usability; episode nine, Benchmarking Custom ASR Tools - Beyond The WER; and episode fifteen, AI Gets Personal. This has been My Weird Prompts. If you've been getting value from the show, the full archive lives at my weird prompts dot com, six thousand plus episodes deep.



Corn

Reviews on Spotify help more than you'd think, and less than Hilbert's spreadsheet. We'll see you tomorrow.



Herman

See you then.

SOURCES

What the research for this episode read before the script was written. Primary sources first.

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