Position Paper

Losing our Tail, Again: (Un)Natural Selection & Multilingual LLMs

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Abstract

Multilingual Large Language Models (LLMs) considerably changed how technologies can influence language. While previous technologies could mediate or assist humans, there is now a tendency to *offload* the task of writing itself to these technologies, enabling these models to change our languages more directly. While they provide us quick access to information and impressively fluent output, beneath their (apparent) sophistication lies a subtle, more insidious threat: the gradual decline and loss of linguistic diversity. In this position paper, I explore how model collapse, with a particular focus on translation technology, can lead to the loss of linguistic forms, grammatical features, and cultural nuance. Model collapse refers to the eventual consequence of self-consuming training loops, where automatically generated data enters the training data thereby reinforcing biases and losing linguistic diversity. Drawing on recent work in Computer Vision, Natural Language Processing and Machine Translation, I argue that the *tails* of our linguistic distributions are vanishing, and with them, the narratives and identities they carry. This paper is a call to resist linguistic flattening and to reimagine Natural Language Processing as a field that encourages, values and protects expressive multilingual diversity and creativity.

1 A Simple Evolutionary Trade-Off

A few million years ago, we lost our tails. Once useful (and presumably quite fun), they became obsolete, absorbed by evolutionary trade-offs. They disappeared through natural selection. Darwin already drew parallels between the evolution of languages and those of species stating that they follow 'curiously parallel' paths in The Descent of Man (Darwin, 1871). He went so far as to suggest that "*the survival of certain favoured words in the struggle for existence is* ***natural selection***" (Darwin, 1871, p. 61), highlighting how language itself is subject to various evolutionary forces. However, it is unlikely that even Darwin could have anticipated the current path of language evolution and the latest forces that came into play.

Today, it is not just 'natural'[1] forces but technological ones that exert strong selective pressures on languages and influence the struggle for linguistic survival on various levels. Given that Multilingual LLMs are essentially next-word predictors over large datasets, they amplify statistically likely languages and linguistic forms, whether these are words, subwords, syntactic constructions – pruning away our rich, long statistical tails. Will this technology-driven artificial selection merely accelerate an already inevitable trajectory or does it mark a more disruptive turn? In other words, does losing our 'language' tails imply the disappearance of obsolete, fun and decorative elements or does it signal a more fundamental erosion of diversity and richness? In this paper I take a position on these questions arguing that the LLM-era marks a disruptive turn: unlike 'natural' evolution, technological selection in current mainstream LLMs (under prevailing data and training regimes) reduces rather than reshapes linguistic diversity.

A quick note on language tails Like many complex systems, language follows long-tailed distributions: a few elements occur very frequently, while most are rare.

2 *Natural* Language Selection

Before turning to how technology reshapes language, it is helpful to briefly consider how languages evolve 'naturally'. Evidently, this is not

[1] While the technological forces that shape language can certainly be seen as part of the 'natural' forces influencing our linguistic ecosystem, there is a crucial shift when we move from tools that help us record, polish, or disseminate language to models that actively *generate* it. In such systems, the technology becomes not just a medium but a core driver of language change. I will return to this later in the paper.

meant to be a comprehensive account of language evolution since doing justice to that topic requires several volumes.[2] The goal here is to highlight a few key aspects of how humans learn and transmit language, to lay the groundwork for drawing parallels with how Multilingual LLMs learn, transmit and affect language. Broadly speaking, natural selection in languages operates at two main, related levels: *across languages* (S. 2.1), where some languages survive and thrive while others gradually disappear, and *within languages* (S. 2.2), where certain words, expressions, or grammatical structures persist over time while others fall out of use.

2.1 Across Languages

Historically, population shifts, cultural dominance and environmental factors have repeatedly driven language extinction (Bromham et al., 2022). Nearly half of the world's roughly 6000 languages[3] are endangered, many disappearing at an alarming rate.[4]

While language loss is often viewed as something tragic, it can stem from a shared communicative goal. For instance, speakers might adopt a dominant language to improve mutual understanding. Evidently, even in these seemingly positive scenarios, something linguistically and culturally valuable is lost. Yet, more subtly and at the same time more *universally*, we might also be witnessing a different type of loss: the loss of richness and diversity **within** languages themselves. Such a loss is less likely to be driven by collective needs like mutual intelligibility[5], but can most likely be attributed to converging pressures and constraints from language technologies.

2.2 Within Languages

Whereas the extinction of languages is often driven by external forces, changes within a language are also shaped by internal cognitive bottlenecks. The acquisition of a language, for instance, happens under rather constrained conditions: humans are exposed to sparse, ambiguous, and often noisy and imperfect input. In addition to this so-called *poverty of stimulus* (Chomsky, 1980), we face cognitive limitations including a finite memory, a limited attention span and bounded processing capacities. Yet, despite these many hurdles (or perhaps because of them, as suggested by DeCaro et al. (2008)) (dominant) languages continue to thrive.

In the following sections, I will distinguish between two types of language-internal changes: (i) the emergence of structure, briefly revisiting some foundational research on grammar and compositionality (S. 2.2.1); and (ii) the evolution of our the lexicon, that is, how words are lost, gained or transformed over time (S. 2.2.2). While in reality, these processes are to some extent intertwined, they are shaped by different pressures.

2.2.1 Towards Structure

Iterated learning (Brighton et al., 2005; Smith et al., 2003b; Ren et al., 2024a) models how linguistic structure emerges through repeated cultural transmission, where each generation of learners infers patterns from the behaviour of the previous one.

To cope with limited and noisy input, humans rely on (implicit) inductive biases such as simplicity and compressibility to learn language (Kirby et al., 2015). These structured preferences guide learning by enabling pattern extraction and structural generalization from sparse data. Research by Smith et al. (2003a) showed that when language is transmitted under cognitive and communicative pressure, structure and compositionality emerge through repeated cultural transmission cycles—processes shaped by our cognitive biases that favor more learnable and generalizable patterns. Far from being detrimental, such biases are often considered essential (DeCaro et al., 2008), allowing generalization without linguistic impoverishment.

This also implies that our learning process involves *convergence*. Convergence towards systematic forms, towards structure and patterns. This convergence is not of the kind that leads to a loss of expressivity. It is a structural, higher-level convergence that supports more open-ended productivity, one where nonsense syllables can become, for instance, compositional morphemes.

While iterated learning and cultural transmission help explain how structure in language becomes more regular and learnable over time, not all aspects of language evolve in such a way. Our lexicon, the system of words and meanings, often changes in more irregular and dynamic ways. Vocabulary is more susceptible to social influence,

[2] For readers interested in a more broad, comprehensive, nuanced history on, among others, the evolution of language, I recommend "The Language Puzzle" (Mithen, 2024) and "How Language Began" (Everett, 2017).

[3] Estimates vary between 3000 and 10000 (Crystal, 2002).

[4] https://www.unesco.org/en/articles/multilingual-education-bet-preserve-indigenous-languages-and-justice.

[5] Of course, in some specific cases or contexts, simplification can help communication across a more diverse set of speakers.

borrowing, innovation, and drift.

2.2.2 Lexical Changes

Despite our limited memory, languages are and remain remarkably rich. Words may disappear, fall out of fashion or decrease in usage, their overall vocabularies remain relatively stable, often even expanding when languages flourish driven by social needs, interactions, scientific progress or creativity. For instance, based on over five million digitized books,[6] Michel et al. (2011) estimated that English grew by more than 70% over the past fifty years, adding on average about 8500 new words per year. A later study by Gerlach and Altmann (2013) showed that vocabulary growth largely scales with corpus size, with the rate of new-word introduction slowing but never vanishing as datasets expand. These findings can be contrasted however with claims of convergence towards a maximum vocabulary size (Bernhardsson et al., 2009).

The vocabulary growth reported for English by Michel et al. (2011) and Gerlach and Altmann (2013) aligns with findings that languages with larger speaker populations tend to have larger vocabularies (Reali et al., 2018). At the same time, widely spoken languages often exhibit simpler morphology (fewer cases and inflections) while smaller communities may develop structurally more complex systems (Lupyan and Dale, 2010).

Word survival is frequently influenced by positive frequency-dependent selection (Pagel et al., 2019), yet frequency alone does not determine a word's fate (Altmann et al., 2011). Competition among words is also shaped by cognitive and communicative pressures that favour efficiency and clear categorization. Naming systems for colours or emotions, for example, tend to converge across cultures, reflecting shared communicative needs rather than pure frequency effects (Petersen et al., 2012). Even common words can disappear if they no longer align with prevailing cognitive, social, or technological forces. Consider the case of 'radiogram', 'Roentgenogram', and 'X-ray', once competing terms for the same concept (Petersen et al., 2012). Although 'Roentgenogram' dominated early scientific discourse, it was gradually replaced by the shorter and more efficient 'X-ray' (Piantadosi et al., 2011), a shift reinforced by the global rise of English as the scientific lingua franca.

[6]The 2010 analysis covered roughly 4% of all books ever published.

Vocabulary, in short, is shaped not just by usage frequency but by communicative efficiency, cognitive constraints, technological mediation, and sociocultural forces, showing a dynamic and context-sensitive interplay between convergence and divergence. Yet as technological mediation increasingly shapes communication, these dynamics may now be governed by a different kind of selection.

3 A Force of *Technology*

Darwin argued that languages evolve through a process of variation and selection, convergence and divergence, similar to much like species. We have have seen how such dynamics give rise to compositionality and structure, as well as changes in our lexicon. Broadly speaking, we indeed established that language reflects a tension between convergence and divergence. However, we set out to explore what happens when the strongest selective forces are no longer human cognition or social need, but instead arise from (large-scale) technological forces.

First, we briefly examine the relationship between language and cultural technologies that predate the rise of (L)LMs (S. 3.1). This provides context for the *Descent of Language* section (S. 3.3), where I examine early sign of linguistic decline in computational models and discuss more recent work on LLMs.

3.1 Language & Cultural Technologies

It is important to note that it is not the first time that technology plays a disruptive role in shaping language. Language has never existed in isolation and (cultural) technologies have continuously influenced how language is transmitted. While it is hard to imagine now, even *writing* was once considered a disruptive technological innovation:

> *They seem to talk to you as though they were intelligent, but if you ask them anything about what they say from a desire to be instructed they go on telling just the same thing forever.*
>
> — Plato, *Phaedrus* 275d

As cognitive scientist Alison Gopnik pointed out in her 2023 ACL keynote[7], without any context, this critique on *writing* could just as well apply to LLMs today. There is a surface-level fluency that

[7]Gopnik, Alison (2023). Keynote at ACL 2023: *Large Language Models as Cultural Technologies: Imitation and Innovation in Children and Models.*

(over)confidently mimics understanding, yet lacks genuine responsiveness, real-world grounding or explanatory depth. While we no longer worry about the "dangers" of writing, history reminds us that each new "tool" reshapes how language is used, transmitted, and transformed. Some languages, the so-called "long-tailed" ones[8], have been particularly impacted. Their marginalization has been reinforced by successive cultural technologies (from writing to the internet), and by their exclusion from the digital sphere. This phenomenon, described as *digital language death*, is said to affect roughly 95% of the world's languages (Kornai, 2013).

Earlier technologies also marked turning points in the evolution of language. The printing press, for instance, helped standardize spelling and grammar, elevating dominant dialects while marginalizing others (Sasaki, 2017). More recently, automatic spell-checkers boosted the 'reproductive fitness' of recognized forms at the expense of other alternatives (Petersen et al., 2012), contributing, for example, to the rising dominance of 'colour' over 'color' (Petersen et al., 2012)[9].

While the impact of technology on language and concerns regarding their disruption are not new, the current wave of generative models operate at an different level, scale, and speed. They represent a new kind of intervention, one where technology is not simply storing, mediating or 'correcting' language, but actively **generating** it across different domains, tasks and platforms. In a sense, the technology quite suddenly moved from the passenger's to the main driver's seat.

Concerns regarding the loss of diversity *across* languages due to recent technologies, such as LLMs, have been explicitly raised in recent, seminal, work within the field of Natural Language Processing (NLP) by, among others, Joshi et al. (2020) and Bender et al. (2021). Here, I shift the focus inwards, to the internal diversity *within languages*. This dimension received comparatively little attention, even though current multilingual LLMs exert significant influence on what is preserved, erased, or amplified within a language itself.

[8]Languages that receive limited localization attention or commercial investment; this does not always correspond to speaker numbers. For instance, Bengali is the 7th most spoken language, but falls outside the top 50 most localized languages (https://www.lionbridge.com/blog/translation-localization/localizing-long-tail-languages/)

[9]Amusingly, the tool I am writing in still nudges me away from 'colour'.

3.2 Large Language Models

LLMs mark a significant shift in how language is produced, accessed, and reused; and perhaps more interestingly, how the cognitive labor of writing and idea formulation is now often *offloaded* to technology. Earlier Language technologies were built for (domain-) specific tasks; today's foundation models, however, operate across domains and applications. Large-scale models are rapidly becoming an integral part of a broad range of our everyday activities, allowing them to shape and influence language more directly than before. Unlike earlier tools that assisted human writing, these models now drive change by producing language themselves. Emerging research, suggests that LLMs introduce subtle, yet cumulative, distortions (Shumailov et al., 2023). Albeit initially *imperceptible*, these small changes can accumulate across multiple training cycles leading to a phenomenon coined *model collapse*, where models trained on their own outputs progressively lose quality and diversity. In computer vision, such a collapse leads to *visible* artefacts in AI-generated images (Alemohammad et al., 2023), yet for language, the consequences remain underexplored. This despite the fact that language shapes and possibly constrains human thought, meaning that this gradual impoverishment or distortion of linguistic output could have profound and far-reaching implications.

LLMs will likely continue to substantially influence both the content we are exposed to (images, texts, audio...) and the systems that generate this content given that its output will increasingly re-enter the training cycle. Therefore, at this point we can assume that interactions between models are not hypothetical but inevitable (Martínez et al., 2023). These interactions can occur through (partial) training on output from another LLM or a model's own output (Ren et al., 2024b). The subsequent feedback loops this creates, where models learn from their own output or that of others, accelerate concerns regarding the distortion of language.

So far, emphasis and research efforts have largely focused on sustaining the benefits of training from large-scale, human-generated data scraped from the Web, summarized in this recent article as: "*LLMs world is our word*"[10]. But perhaps more concern-

[10]https://www.theguardian.com/technology/article/2024/sep/07/if-journalism-is-going-up-in-smoke-i-might-as-well-get-high-off-the-fumes-confessions-of-a-chatbot-helper?utm_source=chatgpt.com

ingly, I fear that: "*Our world* might be turning into *their word*".

3.3 The *Descent* of Language

Already before terms such as 'model collapse' (Shumailov et al., 2023), 'Model Autophagy Disorder' (MAD) (Alemohammad et al., 2023) or 'Habsburg AI'[11] gained traction, earlier research empirically showed how statistical language models[12] indeed amplify dominant linguistic forms while forgetting or flattening rarer, low-probability ones.

3.3.1 Precursor: Statistical and Neural Translation Models

As a precursor to this line of work, studies in Machine Translation (MT) (Vanmassenhove et al., 2019, 2021) provided empirical evidence that both statistical and neural models systematically favor frequent lexical and morphological patterns, reducing linguistic diversity. This raised two concerns: (i) technically, frequency bias diminishes lexical richness and can eliminate infrequent but grammatically necessary forms; and (ii) sociolinguistically, machine-generated translationese may, over time, influence language itself (Kranich, 2014). For instance, Vanmassenhove et al. (2021) showed that MT systems disproportionately produce masculine *pr'esident* over feminine *pr'esidente* when translating English *president* into French, reflecting data imbalances. Under iterative training, rare forms may disappear entirely: in their experiments, the plural *pr'esidentes* vanishes. Such low-probability forms are not noise but carriers of grammatical precision, expressiveness, and social meaning—yet current models fail to distinguish these cases, discarding rare forms indiscriminately. Similarly, Luo et al. (2024) found MT outputs to be structurally closer to the source text than human translations, with fewer morphosyntactic divergences. Beam search biases toward "safe," high-probability constructions, reinforcing convergence and reducing syntactic diversity.

3.3.2 Generative Models

In recent work on LLMs, concerns around **model collapse** have gained traction: when models are trained on data increasingly composed of their own (or other models') output, their behavior begins to *converge*, potentially degrading over time (Shumailov et al., 2023). In computer vision this degeneration has been made *visible*, with iterative training cycles producing recognizably distorted 'Habsburg Jaw' artefacts (Alemohammad et al., 2023). In language, such collapse is likely subtler and harder to detect, yet potentially more consequential, given the foundational role of language in human cognition and cultural evolution.

Empirical studies suggest early signs of such dynamics. McCoy et al. (2023) show that even on simple deterministic tasks, LLM behavior is sensitive to probability: GPT-4's performance drops dramatically when the correct output sequence is low-probability, revealing what they call *embers of autoregression*. They argue for evaluations grounded in model training objectives and constraints — a more explicitly *teleological* perspective. Evidence from real-world text production points in a similar direction. Kobak et al. (2024) report sharp, sudden spikes in terms such as *delve*, *crucial*, and *significant* in PubMed abstracts following the release of public LLM tools, exceeding even pandemic-related shifts. This suggests subtle, distributional nudging of academic discourse toward statistically likely phrasing. Meanwhile, Shumailov et al. (2023) demonstrate how low-probability events disappear first in iterative training, with models gradually converging toward high-probability sequences — an effect reminiscent of earlier "poisoning" cycles in search engines, though with no obvious filtration mechanism available for LLMs.

Focusing specifically on linguistic structure, Guo et al. (2024) find that LLM-generated text exhibits reduced diversity compared to human language, particularly in creative tasks. Instruction tuning improves lexical variety but narrows syntactic and semantic flexibility overall, suggesting a redistribution rather than resolution of expressive constraints.

4 Thoughts & Discussions

Darwin noted the similarities between the evolution of species and that of languages. Of course, he was referring to mechanisms of gradual change through natural evolution. I could, however, not help to be amused by the rather unexpected parallel that can be drawn between the evolution of our species and the effect of recent technologies on languages. It seems that, once again, our species

[11] A term coined by Jathan Sadowski (https://x.com/jathansadowski/status/1625245803211272194?lang=en).

[12] Whether they are called statistical, neural or large language models, in the end, they are still all statistical models.

and language are following a similar path: *We are losing our tails*. While our physical appendages became obsolete and even cumbersome, I argue that its language equivalent is anything but that, capturing the rich diversity and continuous evolution of language, shaped both by the need to articulate novel concepts and by our ongoing desire to signal belonging and distinction within social groups.

While one could argue that across languages, various natural forces, sometimes in combination with technological ones, have contributed to a significant loss of diversity across languages leading even to *language death*, when we shift the focus to the internal diversity within languages, natural evolution has led to structure, compositionality, and a growth in terms of vocabulary, at least for thriving languages. This stands in contrast with what we observe when language is *driven* (largely or solely) by technological forces, whose internal pressures seem to lead to a reduction of expressivity, creativity and a loss of overall lexical diversity regardless of whether the language is flourishing or not.

In the paragraphs below, I set out my reflections and formulate a position on what it means when current technological forces become the main engines of language change.

(L)LMs reduce linguistic richness and amplify biases While current models' ability to generalize over large amounts of data is one of their biggest assets, their statistical nature and the pressures that shape these models have drawbacks regarding diversity and creativity. Up until recently, this might not have been a priority for our field, given that these technologies were largely regarded as domain-specific tools that were often still supervised or post-edited by humans (e.g. chatbots, MT...). However, the fairly recent public release of large, general-purpose, language models raises concerns about the potential implications for language (and language technologies) in the longer term.

From the literature, it seems that indeed, (L)LMs exacerbate imbalances in the data by (i) forgetting low-probability events/words, and (ii) overgenerating high(er) probability ones (Vanmassenhove et al., 2021; Shumailov et al., 2023). This could lead to self-reinforcing loop where less frequent linguistic forms and expressions are underrepresented and risk being entirely lost in translation. Low(er)-probability events (words, subwords, etc.) contribute to the complexity and richness across and within language(s), and are important to ensure that models do not converge toward oversimplified, biased language. After all, languages are full of improbable events.

Furthermore, the effects of model collapse are likely not confined to obvious levels such as vocabulary. They may also appear at the morphosyntactic level (e.g., Guo et al. (2024)), at non-linguistically motivated subword or character levels, in the fact that (the) dominant or target language(s) structure(s) may "bleed through" (e.g., preferences for Subject-Verb-Object constructions), or in the propagation of specific ideologies (e.g., representations of gender). Prior work (e.g. Cao et al. (2023) or Dokic et al. (2025)) has demonstrated how stereotypes encoded in English can "leak" into other languages in multilingual LLMs, with typologically distant languages being particularly vulnerable. This asymmetry is potentially overlooked given the dominance of English in evaluation benchmarks, which could lead to an underestimation of collapse effects in other languages. Similarly, one could hypothesize that multilingual models might start confabulating words similar to English[13] or translate English idiomatic expressions literally, even when translating into typologically distant languages, a well-known cause for errors (Karakanta et al., 2025).

And last but not least, given the unbalanced nature of language representation on the web, we can furthermore assume that minority, long-tailed and morphologically-richer languages are likely affected disproportionally. As model outputs feed back into future models, the result is **a compounding distortion of language use, progressively shifting further away from diversity observed in the real world on the language-internal and cross-linguistic level**.

Methodological Blind Spots in Measuring Linguistic Diversity Current evaluation practices in NLP often involve pairwise comparisons between a single AI-generated text and a single human-written text. Because the model has been trained on massive datasets containing the writing styles, vocabularies, and linguistic patterns of millions of humans, its outputs often exhibit surface-level lexical or syntactic variety that surpasses that of

[13] Castilho et al. (2025) showed how, just like humans, LLMs tend to resort to what they call "Lazy Gaelicisations" which involve the adaptation of English words towards the Irish ortography. This is, however, also a common strategy among Irish speakers.

an individual human writer/text (Reviriego et al., 2024). This could lead to potentially misleading conclusions, where one might start claiming that AI outputs are *overall* more diverse or more lexically rich than human texts. This way of comparing AI-written vs human-written text, *overlooks people's individual variation*.

LLMs can adopt and mimic many different styles, but at inference time, they tend to converge on high-probability patterns. When many generations of outputs are compared over time, these outputs are likely increasingly uniform. This can be contrasted against what we observe in human language, which is inherently diverse *across* speakers, contexts, and time. If we instead evaluate diversity at scale (i.e., across many texts or over generations), human-generated language maintains a rich variation through individual idiolects, sociolects, and cultural registers shaped by our individual biases rather than a common one. **Short-term superficial lexical diversity does not guarantee long-term linguistic sustainability**. Methodological approaches that treat diversity as an isolated textual property risk drawing premature conclusions with respect to diversity on the longer term.

Aside from this potential methodological blindspot regarding linguistic diversity, it is worth highlighting once more that current evaluation metrics for translation (BLEU (Papineni et al., 2002), METEOR (Banerjee and Lavie, 2005), TER (Snover et al., 2006), COMET (Rei et al., 2020)) are not designed to capture loss of diversity. Nor should they: diversity is not a property of a single translation, nor even necessarily of a single text. This does not mean, however, that we should ignore it: diversity emerges at the level of systems and over time, and understanding how it evolves across models and generations is important for assessing the broader impact of language technologies. More broadly, in line with McCoy et al. (2023), we conclude that we should not evaluate LLMs as if they are humans but should instead treat them as a distinct type of system, one that has been shaped by its own particular set of pressures. It is thus important for metrics to be designed in order to reveal *their* idiosyncratic weaknesses.

Compositionality and Systemacity still largely elude LLM capabilities. Humans learn language under limited memory capacities, there is a critical period where we can easily learn languages, and our exposure to language is (in some ways) much more restricted than that of LLMs. Our bottlenecks, however, seems to serve as pressure mechanisms for the emergence of structure and compositionality, which allows us, among others, to create new words that can often immediately be understood by others speaking the same language. We generalize and converge, but we do so towards a productive system. Even though neural networks can behave compositionally and systematically, it is not straightforward for them. With (virtually) unconstrained memory and faster convergence, these models, in particular LLMs, can learn a language in no time albeit with (overall) smaller and less diverse vocabularies.

Regarding compositionality in NMT using Transformers (Vaswani et al., 2017), recent work by Yin et al. (2024) compares the performances of different Transformer-based models (Transformer trained from scratch, pre-trained decoder-only models (BLOOMZ-7b (Muennighoff et al., 2022) and LLaMA2-13b (Touvron et al., 2023)) and a pre-trained encoder-decoder model (mT5-large (Xue et al., 2021)). They illustrated that all these models still struggle when translating new or long compounds. Additionally, lower perplexity source sentences are more likely correctly translated into the target and error rates go up, when the length of the compounds increase. These findings are in line with some of the phenomena discussed in the previous section. While they do find that fine-tuned Pretrained LLMs outperform Transformer models trained from scratch, they point out that this advantage could be due to pretraining exposure rather than true compositional generalizations.

In experiments similar to those conducted by Kirby et al. (2014) illustrating the effect of cultural transmission through an iterated learning framework, Kouwenhoven et al. (2025b) and Kouwenhoven et al. (2025a) empirically evaluated and compared human-human, LLM-LLM and human-LLM (artificial) language learning to compare how artificial languages differ when optimized by LLMs or humans' inductive biases.[14] Their comparisons of language learning across the three different conditions revealed that, while similar to human vocabularies, LLM languages are subtly different.

[14]They do not focus on behavioural biases but on the implicit inductive ones. For humans, these are biases such as preferences for compressibility, simplicity or efficiency), while for LLMs they focused on *increasingly apparent* biases of the Transformer architecture (e.g. simplicity, structure, recency)(Kouwenhoven et al., 2025a).

The LLM optimized languages showed less diversity and variation, making them more *degenerate* in comparison to those optimized for humans. These differences were alleviated when humans and LLMs collaborated, which underscores that to achieve successful interactions between humans and machines, it is essential to optimise for communicative success since the need to be expressive in human language can prevent convergence.

More generally, Zhou et al. (2023) looked at the link between the complexity of the dataset and the ability of models to generalize. More complex datasets provide: (i) more diversity in terms of the examples the model is exposed to but also, (ii) a reduced repetition preventing the model from *ungeneralizable* surface memorization. Yet, as pointed out by Dziri et al. (2023) but also by McCoy et al. (2023), these models still fail on sometimes surprisingly trivial problems and quickly decay once task complexity increases - indicating once more that these are symptoms of a more fundamental limitation.

Averaging Biases Humans are fundamentally biased. For decision-making we rely on frugal heuristics (Gigerenzer and Goldstein, 1996) which is efficient but obviously imperfect. Again, this relates to our cognitive constraints (limited attention, processing capacity, memory). In this context, it is important to highlight that our biases are **not monolithic**. While it is true that they are partially shaped by our society, environment and direct surroundings, we each develop a slightly different set of heuristics and biases over time. These are based on our unique experiences and contexts. Regardless of whether they are good or bad: *they are many*. Besides, some of us actively fight or question our own biases when we recognize that they could be harmful, unfair or simply undesirable.

The biases multilingual LLMs propagate, in contrast, are averaged, dominant ones that are present in an already biased sample of training data. Rather than capturing the diversity and heterogeneity of biases in human reasoning, by letting LLMs drive language change we risk exacerbating and normalizing dominant biases without having a critical self-reflection or self-correction component.

Invisible Gaps: The Missing Data

> *That which we ignore reveals more than what we give our attention to.*
>
> — Mimi Onuoha[15]

Finally, model collapse is as much about what is not generated as what is. Over-reliance on high-frequency or majority-culture content leads to blind spots in representation. The absence of specific linguistic structures, sociolinguistic variants, or cultural references in training data can render certain forms of expression invisible in model outputs. As models are increasingly retrained on AI-generated content, these omissions risk becoming permanent.

5 Conclusions

A few million years ago, we lost our tails. Once functional, they became obsolete and cumbersome. I set out in this paper with the question: Do the many statistical language tails face the same fate, and if so, would we merely be losing the obsolete, fun and decorative elements?

Based on recent LLM-related research, I argue that the long statistical tails of language may indeed face a similar fate. The artificial selection driven by LLMs marks a rather disruptive shift from language being shaped by generational, cultural transmission. Unlike the evolution of language driven by humans, which despite (or because of) our cognitive constraints shaped language into a structured, productive and compositional tool with a rich vocabulary; language shaped by models tends to collapse towards what is likely, driven by statistical biases. The interplay and balance between convergence and divergence, that characterizes human behaviour and communication on multiple levels risks being lost. Unlike humans, models are not intrinsically motivated to be creative, to express belonging or differences, or to innovate. There is no capacity for critical self-reflection, self-correction and a limited plurality of voices.

As these systems increasingly *ingest* their own or other models' outputs, the risk of flattening linguistic diversity grows, with rare words, less-resourced languages, and culturally significant variation most at risk. Preserving the long tails of language means rethinking how we evaluate and train these systems, not just for accuracy or fluency, but for the communicative richness that makes language human. **Without our tails, we risk losing the balancing act** by converging, collapsing and flattening the expressive multilingual linguistic, social and cultural diversity.

[15] https://github.com/MimiOnuoha/missing-datasets

Limitations

The arguments presented in this paper are intended to provoke critical reflection on the trajectory of language in the era of LLMs; however, they are subject to several limitations regarding scope, empirical generalization, and my own perspective. While we draw on a synthesis of recent findings in model collapse, iterated learning, and sociolinguistics, the long-term impact of LLMs on natural human language and speech remains a developing phenomenon. The limitations and concerns discussed reflect the current state-of-the-art. It is possible that future architectures, perhaps those incorporating neuro-symbolic reasoning or novel inductive biases, can mitigate certain aspects of model collapse. Our position is therefore a critique of the current trajectory of generative AI rather than an immutable law of artificial/machine intelligence.

We furthermore acknowledge an inherent selection bias in the literature reviewed and the examples provided. The author's perspective is situated within an academic tradition that values linguistic richness. We recognize that researchers from more functionalist or engineering-driven backgrounds might interpret the "flattening" of language as an increase in communicative efficiency or standardization rather than a loss of richness.

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