Characterizing Jaggedness Aids Safety & Usability

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Frontier AI models exhibit a paradoxical and uneven profile of competencies. They can achieve expert-level performance on many challenging tasks while failing at others that are simple for most people. In other words, they are *jagged*. This position paper argues for the importance of accurately characterizing and measuring the jaggedness of frontier models, and proposes an approach for doing so. Our proposed jaggedness profiles and metrics have direct implications for safety, governance, and usability, as well as for changing the way we might measure progress toward milestones such as AGI.

1. Introduction

Frontier AI models have made rapid advances in capabilities AI Security Institute (2025); Maslej et al. (2025). Many experts anticipate that models may soon meet or exceed thresholds for consideration as Artificial General Intelligence (AGI) Bengio et al. (2024); Grace et al. (2025); Kaplan et al. (2020); Morris et al. (2025); Murphy et al. (2025). Implicit to the concept of AGI is an assumption of *generality* – that advanced AI will be highly capable across a broad set of tasks, analogous to humans' broad capabilities. In practice, the notion of generality is complicated by *jaggedness* Dell'Acqua et al. (2023), the phenomenon where AI exhibits strong ability spikes in some domains while remaining deficient in others. Generality can be understood as a *general intelligence floor*, a measurable baseline that serves as a leading indicator for the potential emergence of ability spikes, despite lagging valleys of lower performance. The degree of extremity of spikes and valleys and the particular combination of abilities and deficits they represent may have significant consequences for society. **We posit that characterizing the jaggedness of frontier models can aid efforts toward AI safety and usability.**

Moravec's Paradox Moravec (1988) observed that AIs can possess superhuman competence in some areas while struggling with more basic tasks, finding that high-level reasoning tasks required relatively little computation compared to low-level perception tasks. Brown et al. (2020) studied the uneven performance of GPT-3, showing that while scaling parameters to 175 billion enabled strong few-shot performance on complex language tasks, it failed to produce reliability in simple arithmetic operations. Researchers have since developed frameworks to measure the generality of AI models' performance, distinguishing between capability in narrow tasks and breadth of competence Hernández-Orallo et al. (2021). Zhou et al. (2025) proposed scales of cognitive difficulty as an alternative to tracking benchmark performance, revealing ability profiles that map the unevenness of model performance. Today's generative models have improved in many areas such as writing and coding AI Security Institute (2025); Maslej et al. (2025), yet still fail to accurately perform some tasks that are relatively simple for most humans Knoop (2025); Mukhopadhyay et al. (2025); Rahman and Mishra (2025).

Dell'Acqua et al. (2023) characterized this uneven performance as "jaggedness," and investigated the consequences for worker productivity, observing that for knowledge workers, the distinction between automatable and non-automatable tasks does not correlate with human-perceived difficulty. The term *jaggedness* has since gained traction in AI discourse Hammond (2025); Mollick (2025); Patel (2025); Toner (2025). Jaggedness is an inherently anthropocentric concept; we perceive AI as

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jagged to the extent that its profile of strengths and weaknesses is alien to our own. Empirical analysis indicates jaggedness is a structural property of current architectures and scaling paradigms Szegedy et al. (2013); Wei et al. (2022b). Despite its practical import, jaggedness is not yet measured, and its implications for AI safety and usability have not been extensively considered.

In this position paper, we introduce a set of metrics that can be used to characterize and quantify jaggedness, including *jaggedness profiles* for AI models and a *jaggedness index* that collapses this to a simple number. We also introduce important comparisons jaggedness metrics allow for, such as tracking a particular model's jaggedness trends over time and observing possible differences between the *benchmarked jaggedness* of a model versus the *perceived jaggedness* actually experienced by end-users. Finally, we explore the implications of jaggedness for AI safety, AI policy and governance, end-user experience, and measurement of AI progress towards key milestones such as AGI. By formalizing the concept of jaggedness and identifying ways in which this concept has utility for AI developers, policymakers, and end-users, this position paper aims to encourage more discussion of, research on, and measurement of jaggedness by the scientific community.

2. Measuring Jaggedness

We propose several measures of jaggedness and reflect on their interpretation, utility, and limitations. We focus on the theoretical contribution of identifying methodologies for jaggedness quantification; the empirical estimation of jaggedness for specific models is a critical area for future research.

2.1. Capability Profiles

To measure a model's jaggedness, one must first specify a *capability profile* – a set of tasks that can be assessed against a corresponding set of performance measures. Examples of capability profiles include frameworks for *cognitive skills* Burnell et al. (2026); Hendrycks et al. (2025), *practical skills* Hendrycks et al. (2021); Liang et al. (2023); Srivastava et al. (2023), or *occupational skills* Appel et al. (2025); Chatterji1 et al. (2025); Zhao et al. (2024). The choice of capability profile may vary depending on the goal of the analysis – for instance, analyzing jaggedness based on cognitive frameworks may be valuable for estimating progress toward AGI, whereas analyses based on practical skills might be valuable for end-users choosing which model to select for a given task, and analyses based on occupational skills may be useful for understanding a model's likely societal impacts.

2.2. Establishing the Baseline

We propose a normative approach modeling jaggedness relative to a human population, since many safety and usability concerns relate to the differentials between human and model capabilities. Comparing against average adult performance is an important benchmark and one for which data and estimates may be more readily available; however, comparison to expert populations may be particularly useful for analyses that have safety or economic implications.

Individual humans have uneven skill distributions – no single person is equally good at everything. For this reason we consider aggregates of people as the baseline; however, even aggregates of humans will exhibit peaks and valleys across a particular capability profile. Concerns about model jaggedness relate to models having markedly different distributions of skills and deficits than the human baseline. Thus, a model that exhibits a similar pattern of peaks and valleys to the human baseline is considered *smooth*; models are *jagged* only insofar as they differ from typical human capability distributions.

Our approach is based on a conceptual simplification that measures jaggedness of the *model layer*

relative to an *unaided human population*. In practice, both AI models and humans will likely have access to tools such as code generators, calculators, search engines, etc., which could substantially alter their performance. Measuring the jaggedness at the *system layer* that includes interfaces and tools may yield further valuable insights, particularly relating to usability, as we discuss later.

2.3. Jaggedness Profiles

Having established the baseline for normalization, we are now in a position to develop the *jaggedness profile*. This is the transformation of the capability profile that produces the normalized pattern of peaks and valleys of a model with respect to a general or expert human performance baseline, which measures and contextualizes a model's distinct strengths and weaknesses. An important feature of frontier models is that they may exhibit vastly superhuman spikes at certain tasks, creating extreme outliers in the capability profile. Furthermore, the assessment of jaggedness relative to a human baseline means that any non-human tasks may cause discontinuities in the calculation of jaggedness measures. The ideal is to ensure that the jaggedness profile metrics are robust against outliers in model performance and don't return values of infinity (e.g., where humans cannot undertake a task), while providing a standardized scale (based on a human baseline) to enable intuitive interpretation of the measures. One approach would be to use median absolute deviation (MAD), which is robust to outliers as it uses median values. Another approach is based on Winsorization (or clipping) of z-scores (based on standard deviation) to create a standardized scale and solve for outliers, although this does impose a somewhat arbitrary ceiling; this could be addressed through tethering the ceiling to a meaningful human-scale measure, e.g., performance in the 99th or 99.9th percentiles (corresponding to normal distribution z-scores of 2.3 and 3.1, respectively). To exemplify the development of jaggedness measures, we proceed here with the latter, standard deviation based approach. The normalized capability performance is:

$$z_i' = \max(-C, \min(C, \frac{x_i - \mu_{i-human}}{\sigma_{i-human}})) \tag{1}$$

Where:

- x_i is model performance for task i
- $\mu_{i-human}$ is the human population average for task i
- $\sigma_{i-human}$ is the human population standard deviation for task i
- C is the Winsorization limit (e.g., $C = 3$)

This gives us z_i' as the Winsorized z-score for task i, defined as the raw z-score clipped at a threshold C (e.g., $C = 3$). We see that z_i' represents the number of (human population) standard deviations the model performs above or below the human (or expert human) population average. As a worked example, take the performance of the AI model Gemini 2.5 Pro on the skills of math reasoning benchmarked on AIME 2025, visual reasoning benchmarked on ARC-AGI-1, and scientific reasoning benchmarked on GPQA Diamond ARC Prize (2026); Art of Problem Solving (2025); Gemini Team, Google (2025a,b); LeGris et al. (2024); Rein et al. (2023). We calculate the values $z'_{\text{math}} = 1.99$, $z'_{\text{visual_reasoning}} = -1.02$, and $z'_{\text{scientific_reasoning}} = 1.94$ (Table 1).

Benchmark: model	**Task**	μ_{human}	σ_{human}	x **(model)**	**z-score (model)**
AIME 2025: Gemini 3 Pro	Math reasoning	41.6%	23.3%	95.0%	**2.29**
ARC-AGI-1: Gemini 3 Pro	Visual reasoning	64.2%	22.8%	75.0%	**0.47**
GPQA Diamond: Gemini 3 Pro	Scientific reasoning	64.8%	11.2%	91.9%	**2.43**
AIME 2025: Gemini 2.5 Pro	Math reasoning	41.6%	23.3%	88.0%	**1.99**
ARC-AGI-1: Gemini 2.5 Pro	Visual reasoning	64.2%	22.8%	41.0%	**-1.02**
GPQA Diamond: Gemini 2.5 Pro	Scientific reasoning	64.8%	11.2%	86.4%	**1.94**
AIME 2025: Gemini 1.5 Pro	Math reasoning	41.6%	23.3%	17.5%	**-1.03**
ARC-AGI-1: Gemini 1.5 Pro	Visual reasoning	64.2%	22.8%	8.0%	**-2.46**
GPQA Diamond: Gemini 1.5 Pro	Scientific reasoning	64.8%	11.2%	58.1%	**-0.60**

Table 1 | A worked example calculating model z-scores for three models using human baseline data from three benchmarks. Sources: ARC Prize (2024, 2026); Art of Problem Solving (2025); Gemini Team, Google (2025a,b); Google (2025a); LeGris et al. (2024); Rein et al. (2023).

The contrast between math or scientific reasoning and visual reasoning is particularly helpful in demonstrating jaggedness in *opposite directions*. For example, model performance on the math task is 1.99 standard deviations *above* the human (expert) average, corresponding to approximately the top 3% of human expert performance, whereas model performance on the visual reasoning task is 1.02 standard deviations *below* the human average, corresponding to approximately the bottom 16% of human performance, where we assume a normal distribution for the human population. For clarity, these are being shown as illustrative of the method and not as an endorsement of these particular benchmarks. Figure 1 illustrates the concept of the jaggedness profile.

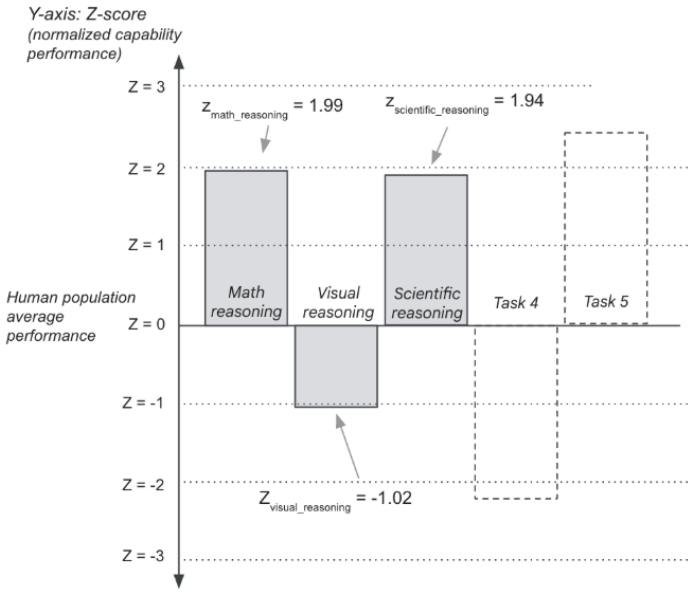

Figure 1 | Example *jaggedness profile* based on five tasks in a hypothetical capability profile. The three solid grey bars have been calculated for the Gemini 2.5 Pro model on the AIME 2025, ARC-AGI-1 and GPQA Diamond benchmarks. The dashed-bars are purely illustrative. The horizontal dashed lines represent z-scores that are integer value standard deviations above and below the human average performance.

2.4. The Jaggedness Index

The *jaggedness index* characterizes how spread out the normalized capability measures are in the jaggedness profile. Building on the example jaggedness profile in Figure 1, the jaggedness index can be expressed as the standard deviation of the collection of model z_i-scores that make up the jaggedness profile. Therefore, the calculation of the jaggedness index becomes:

$$J = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(z_i' - \bar{z}')^2} \tag{2}$$

Where:

- J is the jaggedness index
- N is the number of tasks in the capability and jaggedness profiles.
- z_i' is the Winsorized z-score for task i, as defined previously as the raw z-score clipped at a threshold C (e.g., $C = 3$)
- $\bar{z}'$ is the mean of the Winsorized z-scores

The jaggedness index is then a scalar value in the range between 0 and C. A value of 0 represents a perfectly "smooth" model profile even where the performance level is different from that of the human baseline. A system can perform worse *or* better than humans and still have a jaggedness index value of 0 as long as the model is equally worse or better at *every task* in the capability profile. In essence this formulation is a measure of the spread of the jaggedness index. Tasks in the underlying profile that are jagged in opposite directions do not cancel out; thus, a model that significantly outperforms humans in one task and significantly underperforms humans in another would not tend to reduce the jaggedness index to 0. Compared to the jaggedness profiles, the compression into a single value loses detailed information; however, by creating a scalar summary statistic of jaggedness with known properties, we are able to better evaluate hypotheses related to jaggedness, as we discuss below.

2.4.1. Temporal Trends

Understanding the rate and direction of changes in jaggedness across model generations may be particularly useful as a signal for both safety and usability concerns. The jaggedness index allows us to quantify this by measuring its change in value from one model generation to the next. The *temporal jaggedness trend* can be represented as:

$$\Delta J_t = J_t - J_{t-1} \tag{3}$$

A near zero change would indicate that a model's jaggedness remains stable. A positive result indicates that the model is becoming more jagged in performance across tasks, whereas a negative result indicates the model is becoming smoother in its performance. Extending this analysis to the sample profile established for Gemini 2.5 Pro in Section 3.2, we can make a comparison to prior and subsequent model versions (Gemini 1.5 and 3 Pro), calculating the jaggedness indices and obtaining the temporal trends (Table 2). For these simplistic jaggedness profiles we see the average z-score increases from -1.37 to 0.97 to 1.73, corresponding to increasing overall model capability relative to a human baseline. Gemini 2.5 Pro becomes more jagged compared to 1.5 Pro, while Gemini 3 Pro becomes smoother compared to 2.5 Pro. This represents large capability gains in math and scientific reasoning, while visual reasoning remains well below human level for Gemini 2.5 Pro, while Gemini 3 makes a large gain in visual reasoning helping to smooth the profile.

Model	$\bar{z}'$	J	ΔJ
Gemini 1.5 Pro	-1.37	0.80	*Not calculated*
Gemini 2.5 Pro	0.97	1.40	0.60
Gemini 3 Pro	1.73	0.89	-0.51

Table 2 | A worked example comparing average z-score, J, and J's temporal trend for three models.

Large changes in the temporal trend of the jaggedness index suggest that the relative performance on the tasks in the underlying capability profile are diverging markedly, which may be a leading indicator for AI safety concerns.

2.5. Utilizing Jaggedness Measures

One application of jaggedness metrics for deployed AI models can be to aid end-users in better calibrating their expectations of the way the models behave. Additionally, developers may find utility in computing these at various stages of the model development lifecycle to provide insights into how training methods or data sets impact jaggedness and therefore give early signals into model performance and downstream safety and usability impacts. For instance, it may be that the use of more or differing pre-training data may tend to smooth out the jaggedness profile or that different post-training approaches such as reinforcement learning from verifiable rewards (RLVR) or supervised fine tuning (SFT) may increase jaggedness by promoting hill-climbing against specific goals.

Jaggedness can be measured at the model or system layers, with the latter adding complexity. Usability and safety issues are heavily dependent on other system and deployment considerations such as the ability to call tools and the nature of the user interface. Therefore, assessing jaggedness at the system layer in addition to the model layer may yield novel insights. In particular, it may be valuable to investigate differences in the *benchmarked* jaggedness profile of a model and that of the jaggedness profile that is *perceived* by end-users. This comparison can be an indicator of usability challenges with deployed systems if the two profiles are markedly different. Sources of such differences may result from end-users' inability to achieve benchmarked model performance due to usability issues or knowledge gaps (e.g., difficulty prompting). However, differences may also point to a lack of ecological validity with the benchmark design, i.e., the range of real-world tasks not being accurately represented. Disparities between benchmarked and perceived jaggedness may motivate evolving the benchmarks used to generate the underlying capability profile.

3. Discussion

The ability to formally characterize jaggedness has implications for AI safety, AI policy and governance, user experience and AI literacy, and measuring AI progress.

3.1. Implications for AI Safety

To understand the capability and safety profiles of new models, the AI ecosystem currently relies on a complex, non-standard array of benchmarks, safety documentation (e.g. system cards), third party evaluation, and public testing. Many conclude that this patchwork is suboptimal Lambert (2024). To understand subtle nuances between models' safety strengths and weaknesses, observers often rely on individual blog posts or inconsistent comparisons of documentation. Jaggedness profiles and metrics would be helpful tools for allowing standardized comparison between models. For example, using a skills-based profile for Model X might show a high spike in persuasion and a low valley in factuality,

thus presenting a different risk than Model Y with high cyber-offense capabilities but low resistance to jailbreaking. This illustrates how characterizing jaggedness can help us move to understanding models as having measurably different safety profiles.

A model with high spikes in coding or scientific reasoning but low contextual awareness could signal the “Golem Problem” of jaggedness – a system with superhuman capabilities in a narrow domain but lacking the “common sense" to operate safely McElreath (2020). This could raise risks of misuse and accidents, for example if the AI pursues a narrowly defined objective and does not anticipate the consequences. Conversely, a highly jagged AI may be a specialist that lacks the broad competence to autonomously execute complex, multi-domain plans across domains, thus remaining dependent on human intervention to bridge its capability gaps. These capability limitations (and the increased human oversight they would likely engender) arguably pose a lower risk of autonomous loss-of-control compared to a smooth agent. Future empirical research is warranted to elucidate the relationship between various jaggedness metrics and real-world risks.

Jaggedness metrics could facilitate governance of catastrophic risks. Currently, frontier labs’ safety frameworks focus on detecting spikes in critical capability levels such as CBRN uplift and cyber capabilities Anthropic (2025); Google (2025b); OpenAI (2025). Jaggedness metrics can better enable us to understand both the capability spikes and the rising general capability floor of a model’s intelligence. By tracking both, we gain a more reliable leading indicator for future risks. Observing a rise in the overall ability floor suggests an increased probability of dangerous spikes emerging, as a higher floor provides a more fertile ground for specialized capabilities to be developed. Complex catastrophic actions — such as planning a bio-attack — rarely rely on a single narrow skill; they require the integration of reasoning, coding, and domain knowledge. A rising, smoother floor may signal that a model is developing the robust intelligence required to execute complex plans.

3.2. Implications for AI Policy and Governance

The public and policymakers have an interest in understanding the capability and safety profiles of frontier models. This need has been recognized by the increasing demand from policymakers for scientific reports on the state of AI science House (2023); on AI (2024). The International AI Safety Report, for example, alludes to the uneven capability set of AI models, and calls for better and broader evaluation methods to capture risk profiles Bengio et al. (2025). More recently, jaggedness has gained currency as a term in policy-oriented settings. Hammond (2025); Toner (2025). Jaggedness metrics can give policymakers a more detailed view of the capabilities of leading models.

AI models that can substitute for economically valuable labor at scale and thus may lead to substantial labor displacement are a key concern for policymakers Appel et al. (2025); Eloundou et al. (2023); Hendrycks et al. (2025); Patwardhan et al. (2025). Replacement effects are likely to differ significantly depending on the jaggedness of AI models. Jaggedness may be a leading indicator of whether AI models will be labor-substituting or labor-complementing. We hypothesize that highly jagged AI models may be more likely to complement human labor, with human skills having an economically valuable comparative advantage in the areas in which AI has valleys of ability. In contrast, smoother AI models may have relatively few labor impacts until the cost/performance tradeoff of using AI versus human labor favors AI, at which point rapid, wholesale substitution may be more likely. It may be that certain combinations of peaks and valleys lend themselves more or less toward varying categories of labor replacement; we propose that specifically modeling jaggedness in terms of existing government labor frameworks (e.g., European Commission (2025); U.S. Dept. of Labor Statistics (2025)) may be useful not only for helping businesses make decisions around adoption strategies Narayanan and Kapoor (2025), but also for policymakers to understand the likely time trajectories of the societal change that may result from Replacement AI and the order in which varied

labor categories may experience that change.

Characterizing jaggedness may also bolster societal resilience in the face of rapid and non-uniform technological advancement. In such circumstances, societal resilience may depend on having sufficient advance notice to prepare for advancements in capability areas that may otherwise outpace society's ability to adapt. For instance, an unpredicted spike in automated software vulnerability detection could compromise power grids or banking systems before defensive measures mature. A clear temporal model of frontier jaggedness (specifically one that identifies which capability spikes are expanding fastest) provides a critical window of opportunity for governance. By monitoring these rapidly changing areas, society can move to a proactive posture, preemptively identifying and bolstering vulnerable sectors, such as critical national infrastructure, to ensure stability.

3.3. Implications for User Experience and AI Literacy

Today's major commercial AI models generally rely on *prompting* as the primary mode of interaction; however, end-users vary in their prompting skills Gans (2026); Morris (2024); Schellaert et al. (2023); Zamfirescu-Pereira et al. (2023), leading them to have heterogeneous experiences with deployed models. User skill level, user interface design Morris (2025), and real-world user task distributions may result in a *perceived jaggedness* that differs from *benchmarked jaggedness* as measured for a base model by its developers. We hypothesize that measuring how perceived jaggedness of a deployed AI system differs from benchmarked jaggedness of the underlying model is a critical usability metric.

Currently, AI Literacy among the general public is highly variable Law (2025); we argue that the concept of jaggedness should be a component of AI Literacy campaigns, as awareness of jaggedness may impact end-users' ability to choose whether and how much to trust AIs. AI Literacy campaigns (e.g., Gunder (2025); Miao et al. (2024)) should emphasize both that AI models can be extremely jagged with respect to human baselines and that different models have different combinations and degrees of capability spikes and deficits. End-user education around jaggedness might include the development of lesson plans that give information about jaggedness tailored to the educational level and contextual needs of a particular audience. It is particularly important to convey that, despite a preponderance of anthropomorphic language and metaphors surrounding consumer AI, model capabilities are not distributed the same way as human capabilities.

From a Human-Computer Interaction (HCI) perspective, jaggedness may create hazards around user calibration. Users may overestimate the floor of AI capabilities based on high spikes in specific areas, leading to automation bias Parasuraman and Manzey (2010) and overtrust. Surfacing jaggedness profiles to users, perhaps via system cards Mitchell et al. (2019), could enable users to better calibrate their trust of a system according to the task. Understanding the differences in jaggedness profiles for different models may help consumers make more informed choices of which models are appropriate for their goals, supporting improved *process alignment* Shen et al. (2025); Terry et al. (2024).

Model onboarding processes could expose users to jaggedness concepts by demonstrating their strengths or weaknesses in tutorial tasks. Developers could also design mechanisms for models to proactively communicate their own capability limitations; such self-awareness may improve interaction by helping users calibrate their reliance on model outputs across different task types. For instance, if a user makes a request of a model that has a deficit in a relevant skill area, that model could refuse the task and suggest an alternate model with the relevant skill set, or it could execute the task but include caveats explaining why consulting with models with different jaggedness profiles might improve the result. In agentic scenarios, APIs could clearly convey jaggedness profiles to support agents' optimally selecting tools and models in support of a user's goals.

3.4. Implications for Measuring Progress towards AGI

The concept of AGI that meets or exceeds the breadth of human capabilities is often considered a North Star goal for AI research and development. When considering capability profiles, the floor level of general capability determines the “level" of AGI progress Morris et al. (2025). However, the jaggedness profile and index offer additional perspective – “human-level" AI does not necessarily mean “human-like" AI. A system can be human-level on average but possess a non-human jaggedness profile. This is why jaggedness may be a useful companion metric to other indicators of progress toward AGI. Taxonomies for measuring AGI progress may offer valuable capability profile frameworks for analyzing jaggedness and vice versa. Understanding and measuring the state and rate of change in jaggedness could support AGI-related forecasting and policymaking.

Considering both generality and jaggedness is critical for understanding many milestones and tipping points, including those related to safety and to societal transformation. For a given “floor" of general capability, it may be the case that highly jagged frontier AIs with capability peaks in certain areas and sectors could induce major societal transformation long before AI models achieve a general intelligence floor across all skills.

Concerns around Superintelligent AI that exceeds human capability include issues such as the likelihood of an intelligence explosion or fast takeoff Bostrom (2016) and unknown unknown emergent capabilities Bubeck et al. (2023); Wei et al. (2022a). Jaggedness provides a new perspective for anticipating fast takeoff risks. If using practical or occupational capability profiles for jaggedness analyses, spikes in coding and other skills related to performing advanced AI research and development may indicate recursive self-improvement strategies Kokotajlo et al. (2025). Alternatively, if using cognition-based capability profiles, spikes in metacognitive skills such as learning how to acquire new abilities Morris et al. (2025) may have similar impacts.

AI models with uneven capabilities may serve as effective complements to existing human capabilities in AI R&D. Prior work suggests that ML research is heavily bottlenecked by engineering implementation Owen (2024); models with spikes in coding and software engineering could reduce this friction even if it were to be the case that their capabilities for novel research ideation remain limited. The productivity gains from such complementarity depend on whether capability spikes align with genuine pipeline bottlenecks. As such, accurately characterizing jaggedness along skills that play a central role in modern AI development may be particularly important both for forecasting future rates of AI progress and predicting which research roles remain human-dominated. If AI models prove exceptionally capable at compute-centric tasks (experiment scheduling, low-level optimization, resource allocation, etc.) the effective compute available for research could increase substantially without additional hardware. This form of jaggedness targeting resource constraints may prove especially impactful for development velocity, potentially alleviating what is currently a binding constraint on frontier development.

4. Alternative Views

Though we posit that making jagged capability profiles of models more transparent to end-users will improve usability, we acknowledge that information about jaggedness may confuse end-users. A combination of AI Literacy campaigns and appropriate interaction design may be necessary for end users to effectively take advantage of jaggedness information; investigating how to achieve this balance is an urgent area of inquiry at the intersection of AI and HCI. On a related note, our paper emphasizes characterizing the jaggedness of models, but it may be that characterizing the jaggedness of deployed systems is more relevant in practice, since various user interface factors may impact perceived jaggedness, which may have more practical import than benchmarked model jaggedness.

Critics could argue that compressing a multidimensional jaggedness profile into a single scalar jaggedness index obscures critical information about specific areas of risk or capability deficits. However, the index was not designed to replace domain-specific capability and risk assessments, which remain important. As we argue above, measuring jaggedness is useful for AI safety (e.g. because generalist capabilities enable complex, multi-domain strategies and planning that may not be picked up by domain-specific evaluations), AI policy (as an indicator of whether AI models are likely to be labor-substituting or labor-complementing), human-computer interaction (e.g., because jaggedness can lead to overtrust), and for tracking progress towards AGI (to distinguish between human-level and human-like models). Therefore, we hold that jaggedness provides distinct value, albeit as a *companion* rather than *replacement* metric for existing measurements of AI capability.

Finally, while we believe that jaggedness is likely to remain an enduring characteristic of AI models, it is possible that jagged capability profiles are merely an artifact of a particular moment in time along the path toward general intelligence, and that by definition a sufficiently advanced AGI (or perhaps superintelligence) will be able to bootstrap its own learning so as to eliminate any relative skill deficits. However, even if superintelligent systems turn out to have smooth skill profiles, characterizing and monitoring jaggedness in the near term is still valuable for advancing us more safely and productively toward that outcome.

5. Conclusion

This position paper presented a theoretical contribution regarding the significance of model jaggedness. This contribution included introducing several complementary methods to characterize and measure model jaggedness, such as jaggedness profiles, the jaggedness index, and comparisons among these profiles and indices such as temporal differences in the jaggedness index across model versions and differences in benchmarked versus user-perceived jaggedness. There may be other valuable frameworks or metrics beyond those we have proposed in this article; indeed, we hope that this position paper inspires other researchers to build upon our work by proposing additional ways to characterize jaggedness and empirically validating the utility of different characterization approaches.

Additionally, we contributed a nuanced discussion of how characterizing jaggedness can directly impact areas such as AI safety, AI policy and governance, usability, and measuring AI progress. If jaggedness metrics prove to be empirically rigorous and practically useful then they could be tracked, presented, and analyzed by different groups. The research community could benchmark the jaggedness of SOTA systems, as well as of key past systems, in order to understand patterns and rates of change in capability profiles and how various jaggedness metrics relate to particular training approaches and to real-world impacts and risks. Developers could include these metrics in information to users such as model cards. Policymakers could track changes in jaggedness profiles and indices over time to better forecast possible trajectories for the societal impacts of AI, and take jaggedness into consideration when developing governance and regulatory frameworks.

The development of artificial intelligence is not proceeding toward a smooth, human-like endpoint. The capability frontier is, and will likely remain, jagged. This does not, however, render the concept of AGI obsolete. By refining our understanding of AGI as the floor of a system's general capabilities, we posit that considering *both* this general capability floor *and* jaggedness metrics will prove a powerful approach for predicting and preparing for the future.

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