gradient advisors

July 2024

ECONOMICS of AI

Examining AI from financial lens

Pragmatic AI for Founders & Industry Leaders

YOUR JOURNEY TO PRAGMATIC AI

In the rapidly evolving Artificial Intelligence (AI) driven landscape, (Generative) AI vows to revolutionize businesses like never before. Despite presenting unparalleled opportunities, it also introduces intricate challenges in transforming this disruptive technology into successful business endeavors. The goal is not merely to navigate these challenges but also to elevate your organization's AI practices to attain the pinnacle of "Pragmatic AI."

We define **Pragmatic AI** as AI that translates AI efforts into **tangible business successes,** leading to **increased revenues** and **market dominance**, rather than focusing solely on model metrics.

This write-up serves the following purpose: look at AI from an economic lens. To the best of our knowledge, this is a one-of-its-kind attempt to look holistically at AI from an economic lens and build a better understand of AI as a business disrupter.

CONTENTS

Note from CEO'S DESK

Dear Reader, Greetings!

As we delve deeper into the world of artificial intelligence (AI), this edition focuses on exploring AI from an economic lens.

At Gradient Advisors, we recognize the imperative of comprehending the economic implications of AI adoption in industry. With our deep-rooted expertise and 20-year history in AI systems development, we aim to elucidate the intricate economics behind successful integration of AI in businesses. Our current article unveils key insights into how economics (input cost, cost-benefit analysis & profit margins) plays a huge role in AI adoption

By exploring these economic dimensions as part of "Pragmatic AI", we aim to empower entrepreneurs, policymakers, and investors with actionable knowledge to navigate and capitalize on the AI-driven economy. Join us as we uncover the Economics of AI, steering discussions toward informed decision-making and fostering sustainable AI growth.

We eagerly anticipate your valuable insights and engagement in this discourse.

We genuinely hope you'll find value in this initiative. Your feedback and engagement are highly appreciated.

Best Regards,

Anuj Gupta
Founder & CEO
Gradient Advisors

SUMMARY

1. Why profit margins in AI much lower than traditional software?
2. Why AI endeavors are expensive?
3. High GPU cost : now and in future
4. Why it is crucial to quickly discover the price the market is willing to pay?
5. Is incrementally improving AI systems worth it?

Bill Gates believes that in the next 7-10 years, every human process will be impacted by AI. According to Mira Murati, CTO of OpenAI, the next-generation ChatGPT will have PhD-level intelligence and will be launched by the end of 2025. It is clear that *AI will have a significant impact on businesses and their revenues*. Therefore, *it makes sense to analyze AI from an economic standpoint*. *This paper aims to do just that by examining various aspects of AI through an economic lens. This is particularly important because AI is currently an expensive technology*[1]. According to an estimate by the venture capital firm Sequoia, the AI industry spent $50 billion on Nvidia chips used to train advanced AI models last year, but only generated $3 billion in revenue [5].

We do so by covering the below mentioned sub-topics:

1. **Profit margins in the Business of AI:** One of the key reasons the software business was game-changing, as opposed to traditional businesses, is the profit margins in it. Even within software, SaaS (Software as a Service) is known to have margins up to 80-85%. Does this hold true for AI as well? Turns out, no! We examine this in detail.
2. **Why AI development is an expensive endeavor:** From a cost perspective, unlike IT/ software, AI projects are very expensive. We will understand why this is the case.
3. **GPU Cost & Moore's Law:** It is a well-known fact that today, most of the progress in AI in industry has happened in the sub-area supervised deep learning. Training supervised deep learning models requires GPUs, which do not come cheap. We will look at what it might cost to train foundational models and how this cost is likely to change in the future.
4. **Price point of AI products & services:** Given the high input cost of AI, it is important to quickly discover the kind of price the market is willing to pay for your AI products and services. Without this, one cannot build a sustainable AI business.
5. **The 1% improvement:** Improving AI systems does not come cheap. We understand the conditions under which it makes sense to embark upon this improvement.

The above sub-topics in this paper are mostly independent of each other and can be read independently.

Margins in the Business of AI

The dot-com boom witnessed a meteoric rise of software companies. One key factor that contributed to this rapid growth was the unique nature of software production. Unlike traditional businesses where producing any commodity incurred fixed input costs in the form of raw materials, labor, and shipping; software development presented a different scenario altogether. Selling software to the next customer involved minimal costs - merely shipping cost of the installation of software (initially on floppy disks, later on CD-ROMs). This was possible because of a fundamentally distinctive characteristic of software: ***the ability to be built once and sold multiple times.*** Once the software was developed, selling the 100th, 500th, or 1000th copy did not entail additional development costs. The primary expense was the one-time upfront cost of creating the software. In essence, *the cost of replication was near zero. Consequently, profit margins in the software industry ranged from 40% to 60%, a stark contrast to the 5% to 20% margins typically seen in traditional businesses*. It is no surprise that software companies flourished quickly, creating numerous unicorns and self-made millionaires.

With the wide penetration and adoption of the internet, the advent of cloud technology has enabled software to be accessed and delivered anywhere at no additional cost. This further led to change in the business model of software: from one-time (high) buying to (low) per month subscription, ensuring continuous revenue for software companies. Onboard the customer team by creating their login, and voilà, you are done. Software as a Service (SaaS) businesses are known for having 80-85% margins. These margins can be further increased by taking into account that software development can be carried out in countries such as LATAM, India, and APAC, where software talent is much more affordable compared to the US and Europe.

Many founders and VCs believe that the SaaS playbook will continue to hold true for AI companies as well. However, this belief has proven to be grossly incorrect so far. It is widely believed that margins in AI will not exceed 40%. Let us delve into why this might be the case

To understand this, we go back to the "Capability curve in AI" [1]. We saw that if one draws the curve between "Capability of an AI system" (X-axis) vs Time (Y-axis), we get an 'elongated S' shape curve as shown in Fig 1.

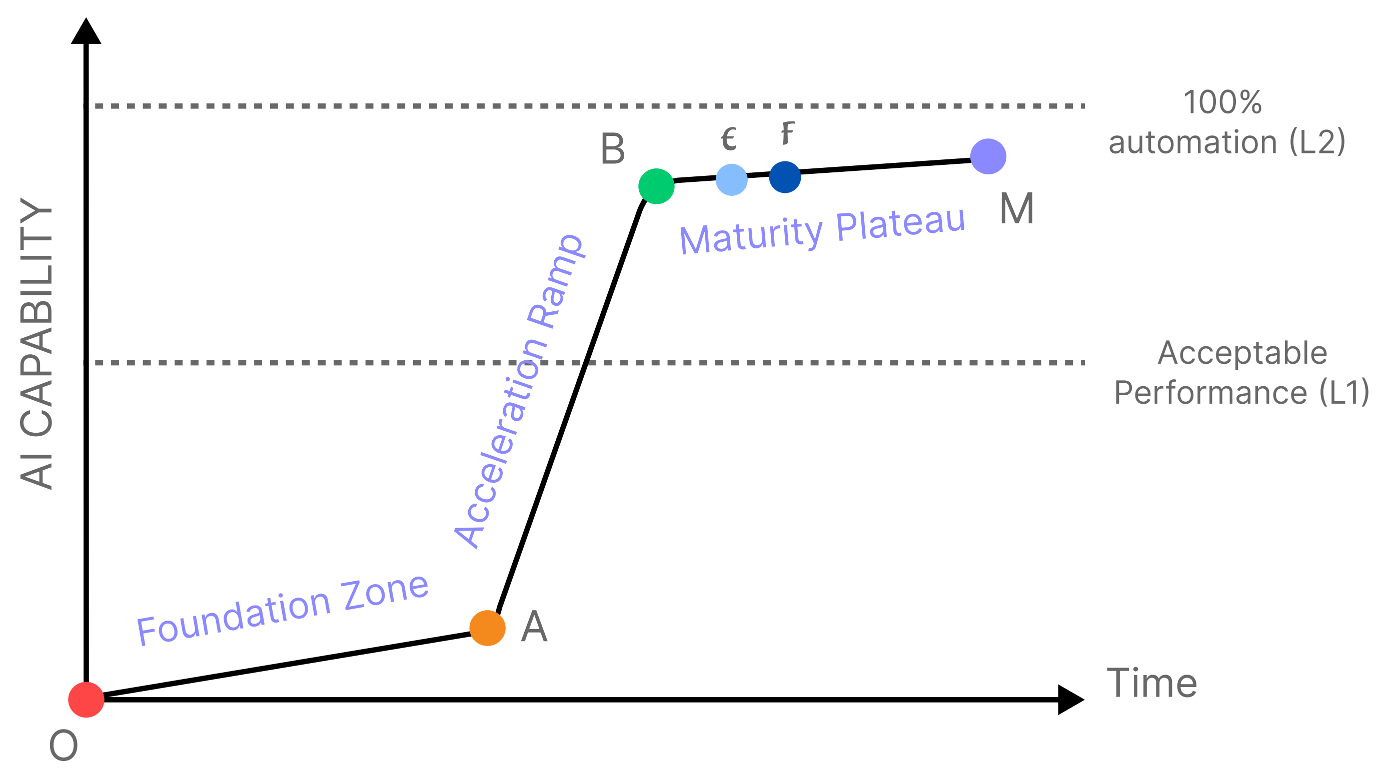


Fig 1: How capability of AI systems matures with time

1 Unlikely to change in next 2-3 years

[1] further argued that the right way to develop AI systems is to quickly assemble ‘a’ system and then continue improving from that point onwards. The increase in AI capability (accuracy [2]) happens over time, following an elongated 'S'-shaped curve. For example, consider a scenario where you have developed an AI software, FinProjection.ai, built to assist CFOs with financial projections. This software has significantly matured over the last 12 months, as represented by point **E** on ‘Maturity Plateau’ part of the capability curve. Among the hundreds of clients being served by FinProjection.ai, two notable clients are I and J.

Clearly, FinProjection.ai still makes mistakes, although much less than a year ago. There is still lot of room for improvement in FinProjection.ai’s accuracy. Recently, both clients I and J, along with many other key clients, have been requesting enhancements in accuracy. They have provided several concrete scenarios where FinProjection.ai made errors on their respective data. Ideally, you would like to develop the next version of FinProjection.ai to perform better for both clients I and J. From a technical perspective, you have found that FinProjection.ai performs (generalizes) well overall. However, specifically on the data of clients I, J, and a few others, it does not perform as well in comparison. Your AI team has created a cohort of these clients and fine-tuned the primary model M using the data of these clients, resulting in a new model M’. Now, M’ serves the cohort that includes clients I, J, and others, while model M continues to serve the remaining clients. Maintaining two models, M and M’, in production increases infrastructure costs and technical debt.

Now, let us extend this argument further. Due to M & M', we achieved higher accuracies. In terms of the capability curve, let's assume we are at point **F**. Say, even now, I and J are not very happy with accuracy of FinProjection.ai; each of them is reporting multiple scenarios where the system is making critical mistakes on their respective data. Your AI team conjectures that the data of I and J have idiosyncrasies, hence the model is not working well for them. However, because both I and J are the oldest and highest-paying customers, you got to do something. To salvage the situation, your only option is to further fine-tune/train M’ on I's data and J's data, respectively - creating models M'_I and M'_J.

As your system matures and you attempt to advance it further along the Maturity Plateau of the capability curve, you will encounter a long tail of challenging edge cases. Given that no AI system can be 100% perfect, this cycle persists. Where does it end? You could end up with a large number of models, each catering to a specific group of customers fitting to their data, with the worst-case scenario being one model per customer [3].

The advantage of "Build once, sell many times" goes for a toss. This, coupled with the high technical debt cost of AI systems [4], significantly impacts profit margins. It is for this reason, it is estimated that AI companies will realistically have around a 40% profit margin.

2 For simplicity we use accuracy as the AI metric. In reality, the exact AI metric differs, depending on the problem.
3 This is worst case and unlikely to happen. However, ending up with 20-30 different models is very realistically possible

From a technical point of view, (without going into details), there are 2 key reasons for this:

1. No AI system is 100% correct; all AI systems make mistakes. To handle this, one is forced to resort to ways like human-in-the-loop, overfitting etc
2. AI system make mistakes with high confidence (similar to correct predictions). Thus, there is no way to identify mistakes beforehand.

This situation is not likely to change in the near future. Clients come with expectations of deterministic software where a mistake = bug. This is where product teams play a significant role in designing a great & consistent user experience despite the underlying system making errors [3].

AI development is Expensive

Building mature AI systems (today) does not come cheap. *Those new to AI may contest this claim by pointing out that chatGPT and many other foundational models are available as APIs for a relatively low cost*. While this is correct, it is not sustainable to rely solely on these APIs in the long term. APIs can be a valuable tool for creating Proof of Concepts (PoCs), prototypes or initial versions of AI features or products.

If the AI capability is core to your value proposition and key differentiator, building an entire AI business solely on third party APIs is not advisable. They are best used as a starting point. There are multiple reasons for this: 1) Moat 2) External dependency & associated risks 3) building billion dollar businesses requires owing you destiny. 4) specific models >> general-purpose models including GPTs.

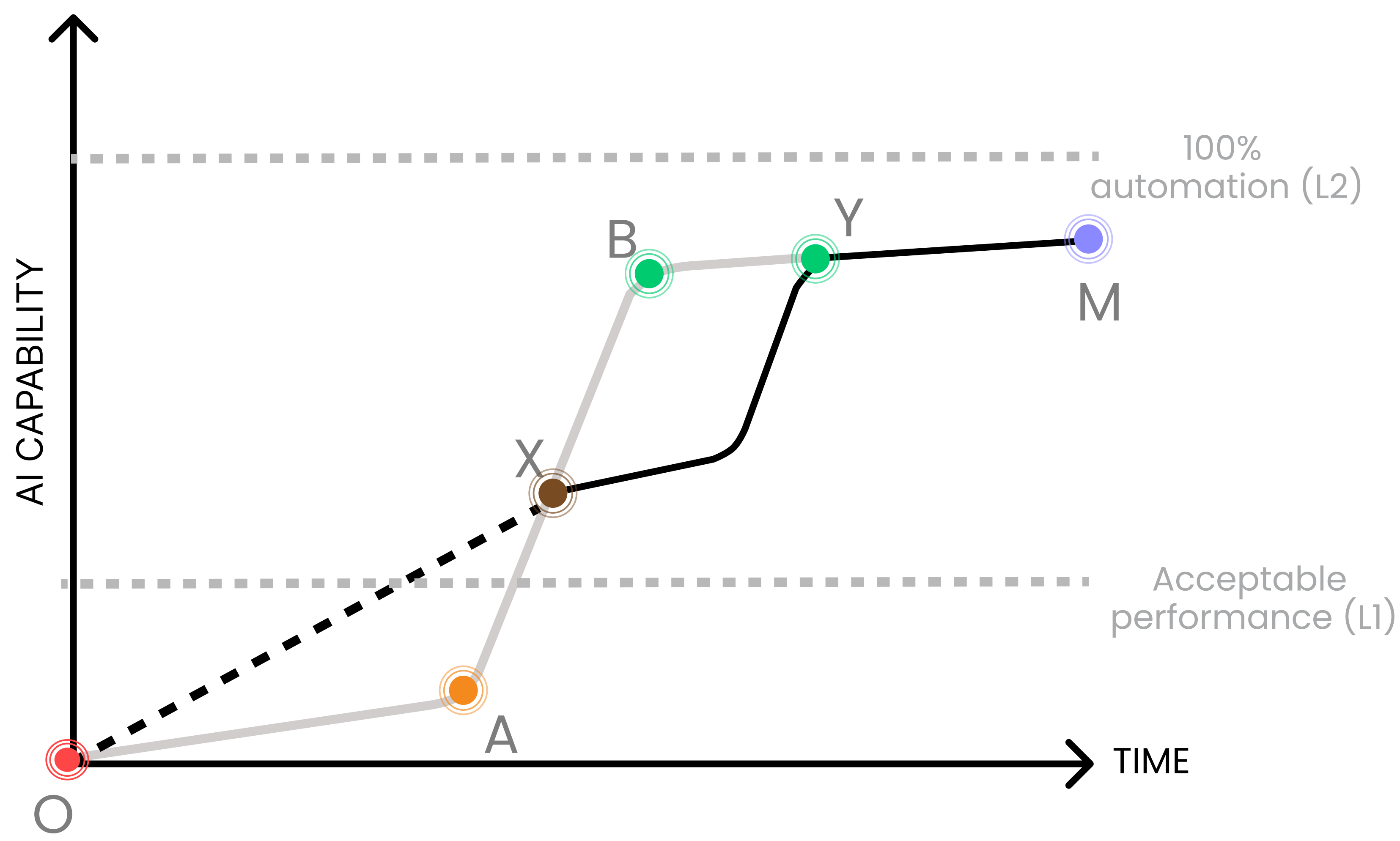


Fig 2: Impact of Off-the-shelve-LLMs on the capability curve

As your product gains traction and reaches a certain level of revenue or usage, your users will likely demand higher accuracy. This is when you need to start training your own models. Among experienced practitioners, it is widely known that for any AI problem, specific models trained on large, relevant, and highly curated datasets outperform general-purpose models including GPTs (Fig 2 {Fig 4 of [1]}).

Now, with the elephant out of the way, let us examine why building mature AI system (today) is expensive. In terms of cost, there are four main components:

1. Talent	1. Hardware Cost
2. Data & Dataset	2. Time required to build a good AI system

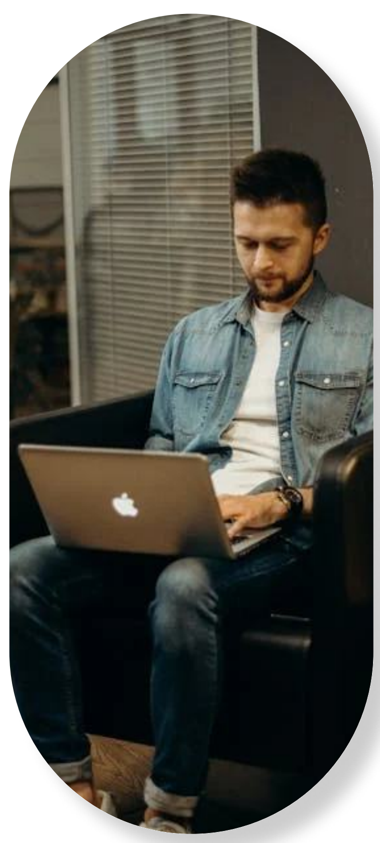
Let us look at each in detail:

Talent

In today's world, AI talent does not come cheap. While the composition of AI teams varies significantly, a typical mature AI team consists of four key roles:

AI Scientist

AI Engineer



AI Product Manager

AI Leader

a) AI Scientist: Their primary job is to build models. From an educational background standpoint, a proficient AI Scientist holds at least a Master's degree in machine learning, ideally a Ph.D. In Silicon Valley, an entry-level AI Scientist commands a salary ranging from $200,000 to $500,000. Top researchers at companies like OpenAI are rumored to receive compensation of up to $10 million due to the competitive nature of the field.

b) AI Engineer: Their key job is to build data pipelines and productionize AI models. A good AI engineer typically holds a Bachelor's or Master's degree in Computer Science. In Silicon Valley, the cost of hiring an AI engineer ranges from $100,000 to $300,000 depending on their background and experience.

c) AI Product Manager: Their key job is to understand user needs, shape the roadmap of AI products/features, and manage senior stakeholders. Good AI PMs are hard to find. Last year, Netflix posted a job description offering up to $900K in salary! What makes AI Product Management a niche is the skill of *delivering a consistent user experience when the underlying system is stochastic in nature and prone to making mistakes.*

d) AI Leader: Good AI leaders are even more rare. A typical MBA does not understand the underlying technology, and a typical PhD tends to underestimate the market forces, end-user needs, and the hustle of a startup. Finding AI leaders who have the best of both worlds, having incubated and led multiple AI teams, is extremely rare and a talent like that can cost upwards of $1 million.

Overall, today, there is a shortage of talented AI professionals, making it difficult to acquire them, come at a high cost and even harder to retain them.

Data & Dataset

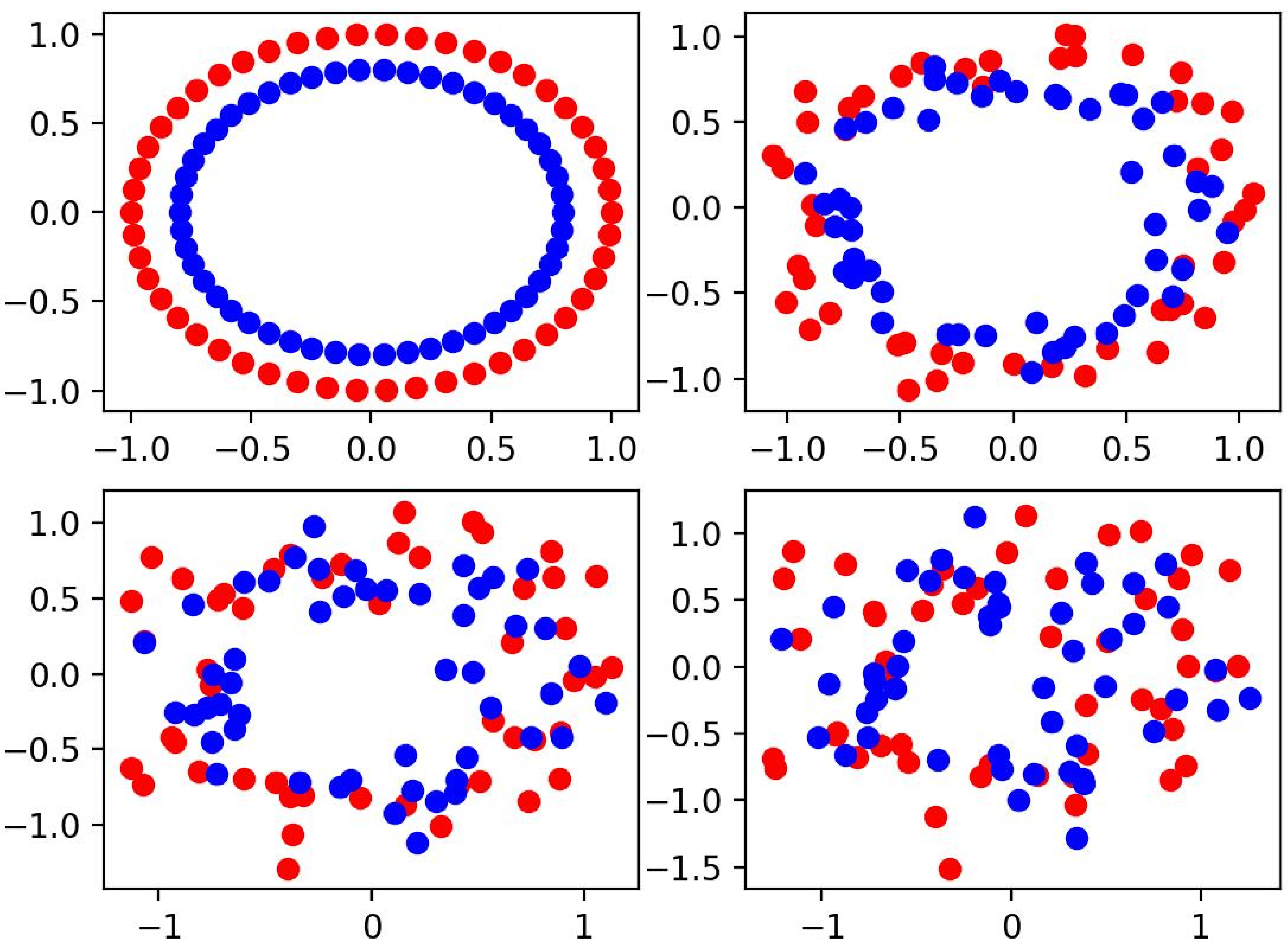


Fig 3.: How dataset size impacts on AI model

Anyone who has spent enough time working with AI knows that *models are only as good as the datasets on which they are trained*. Deep learning algorithms are data guzzlers, requiring one to build large, comprehensive, clean, error-free, and well-labeled datasets, that demands time, effort, and resources. Data represents the raw dump, while a dataset is the refined, carefully selected, and polished subset constructed from the raw data.

The typical steps involved in the conversion from data to a dataset consist of collection, organization, cleaning, selection, and labeling. Owing to various indirect costs involved estimating the true cost of building a dataset is very challenging. In this study, we look at only on estimates of the labeling aspect. The typical cost of labeling by human agents in Africa/APAC markets ranges from $2 to $5 per hour.

The prices for Google's image labeling service for Tier 1 (first 50,000 units per month) are as shown below:

Data type	Objective	Unit	Tier 1
Image	Classification	Image	$35
	Bounding box	Bounding box	$63
	Segmentation	Segment	$870
	Rotated box	Bounding box	$86
	Polygon/polyline	Polygon/Polyline	$257

The cost of labeling just 25 million images (segmentation) using Google's services would be half a million dollars. The data labeling market alone is projected to be worth USD 3.5 billion by 2024 and USD 8.2 billion by 2028.

Hardware cost

It is a well-known fact that today's AI requires massive computing power in the form of GPUs, which comes at a high cost. According to one estimate, the computing power C (in FLOPS) to train a foundational model from scratch with the number of parameters P and training data D in tokens is given by $C \approx 6PD$ [7].

Below is a rate card of GPU compute per hour on Google cloud:

Instance Size	vCPUs	Instance Memory (GiB)	GPU – A100	GPU memory	Instance Storage (GB)	EBS Bandwidth (Gbps)	On-demand Price/hr	1-yr Reserved Instance Effective Hourly *	3-yr Reserved Instance Effective Hourly *
p4d.24xlarge	96	1152	8	320 GB HBM2	8 x 1000 NVMe SSD	19	$32.77	$19.22	$11.57
p4de.24xlarge (preview)	96	1152	8	640 GB HBM2e	8 x 1000 NVMe SSD	19	$40.96	$24.01	$14.46

GPT-4 has approximately 1.8 trillion parameters distributed across 120 layers. Based on these figures, the estimated cost for training GPT-4 is around $63 million. It is important to note that AI models are not developed all at once. Even if this process were repeated four times, the total cost creating GPT-4 purely in terms of compute cost would amount to a quarter of a billion dollars.

Time to build a good AI system

[1] shows that going from **a** system (make it work) to **the** system (end of crag) is a highly iterative process and takes time. With each iteration, costs increase as more complex techniques are employed. This, combined with high technical debt, makes AI a very expensive technology today.

GPU Cost & Moores Law

In the previous section, we caught a glimpse of the high cost of GPUs. The most common argument presented against the current high hardware costs for AI is that they will decrease over time. At the core of this argument lies Huang's Law (a variant of Moore's Law), which states that the performance of Graphics Processing Units (GPUs), especially in AI computations, is not simply doubling every two years — it's set to accelerate much faster. This implies that every two years, the computing power will atleast double for the same price. Conversely, every two years, the cost of the same GPU will reduce by at least halve.

As AI becomes a more pervasive technology and more organizations adopt it, the cost of developing AI systems will decrease. We previously discussed this in relation to GPUs. What about talent and datasets?

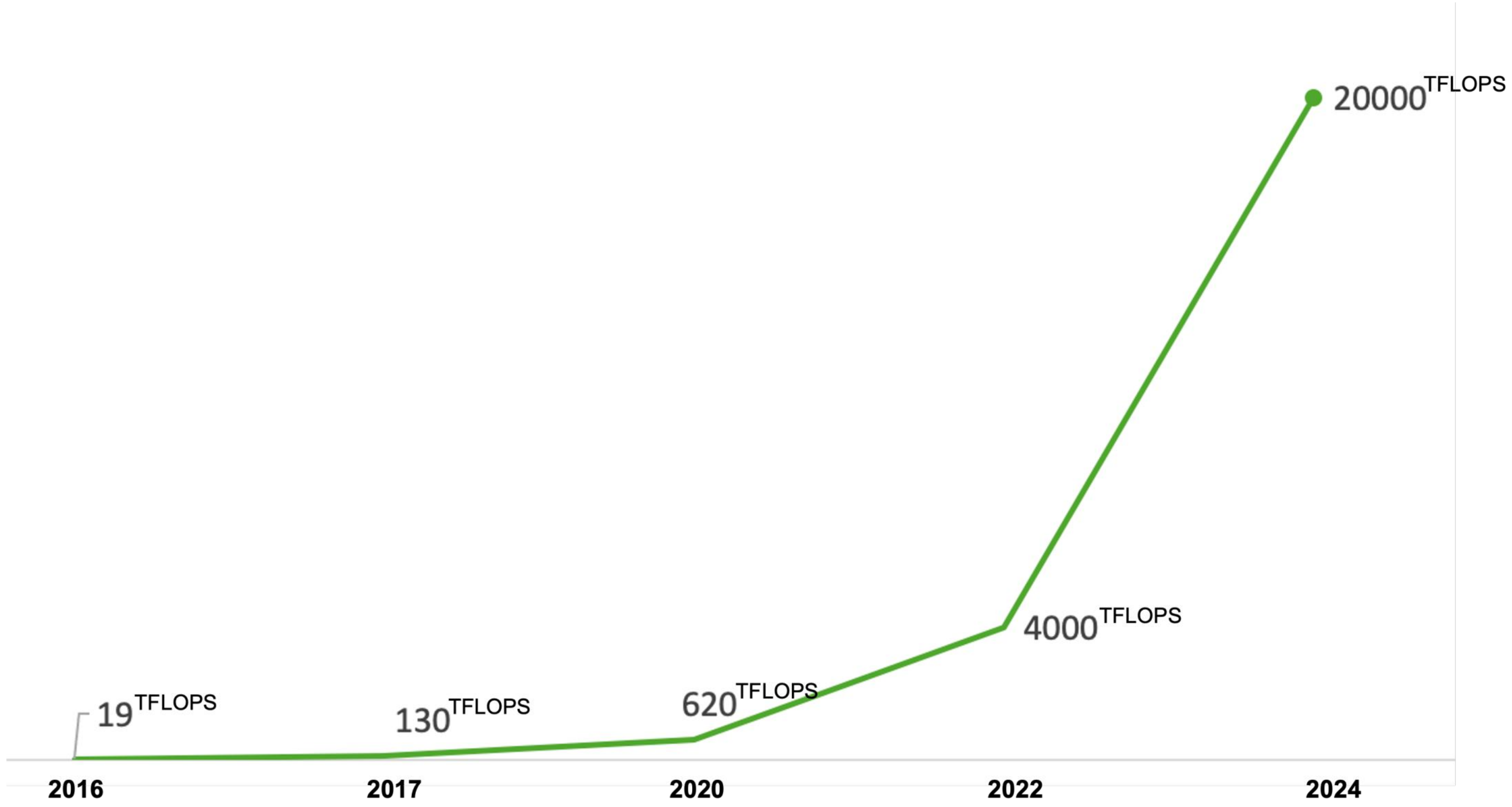


Fig 4.: AI compute has grown 1000x in last 8 years

In future the cost of talent and datasets will also decrease. Why? As adoption increases, more developers, scientists, and AI project managers will emerge, leading to a larger highly skilled workforce engaging in the development of AI systems, thereby reducing the cost of talent. What about the cost of building datasets? Over time, we will see the emergence of more tools, processes, best practices, and so on, designed to streamline the entire process of data collection, cleaning, processing, selection, tagging, and other tasks, making it more efficient.

Overall, there are positive indications of AI adoption in the future. However, a critical aspect that needs consideration is the heat dissipation from GPUs.

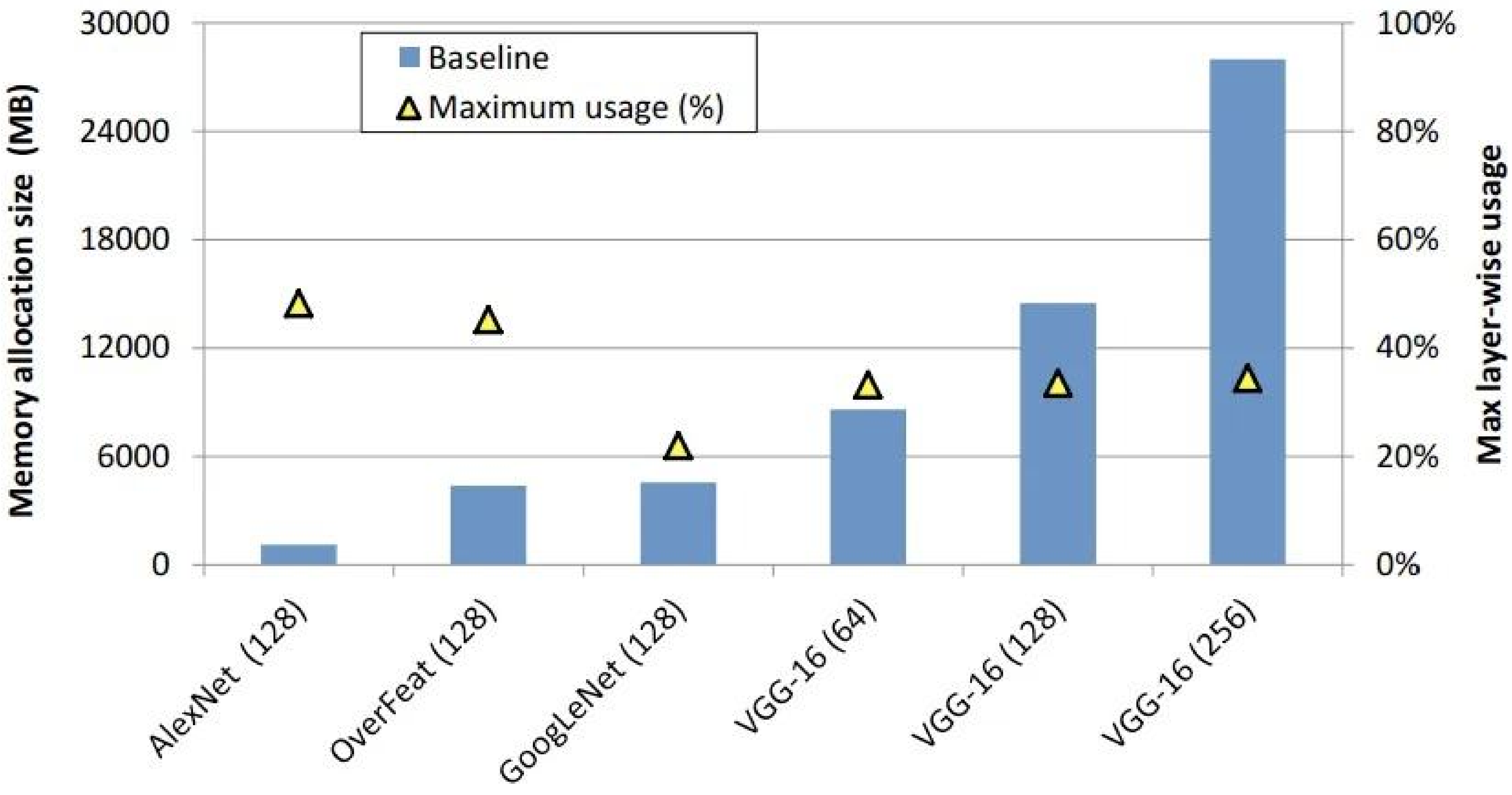


Fig 5. : Compute memory vs # layers of some famous vision models

An observable trend in the past 15 years of the evolution of Deep Learning, starting from the first set of papers in 2010, is the consistent emphasis on larger models (in terms of the number of parameters) yielding better performance. Each year, not only has the number of features almost doubled, but the number of layers has also seen a significant increase. Consequently, each operation within Deep Learning models has become computationally intensive, posing challenges for deployment on edge devices. [Fig 5].

Even at the data center level, foundational models are the largest models built to date. Such large models require a significant amount of computing power even for inference. At the data center level, thousands of GPUs (handling millions of computations per second) are deployed to host these models, leading to the dissipation of substantial amounts of heat. To ensure efficient operation and the longevity of data centers, robust cooling systems are utilized. According to some reports, for every inference operation, ChatGPT consumes half a glass of water for cooling. Currently, it remains unclear how this cooling requirement can be sustained. Addressing this challenge necessitates fundamentally new approaches to designing and manufacturing chips, which is not a straightforward task as the current optimization is geared towards maximizing performance.

According to Google annual Environmental Report 2024 [8], Google's emissions climbed by almost half over five years, as the company has infused artificial intelligence throughout many of its core products — making it harder to meet its goal of eliminating carbon emissions by 2030, according to a new environmental report from the tech giant.

Thus far, the relationship between computing power and heat dissipation does not appear to align with Moore's Law and could potentially become a bottleneck in the future.

Price Point

It is crucial for business leaders to quickly understand the price the market is willing to pay for your AI solution. *Just because your solution has AI does not mean the market will pay a higher price.* While AI is going to be one of the most disruptive technologies ever, *it is still a means to an end but not the end itself.*

The market price is determined by two factors: (a) the value addition that your AI powered solution brings to the table, and (b) the cost of alternatives (with or without AI) in the market. We will touch upon these points using two concrete examples:

1. **Discovering new Compounds for Drug Discovery**: Drug discovery is a time-consuming and very expensive process that typically spans 15-25 years, costing billions of dollars. Despite all precautions, a drug can fail a critical trial in the 20th year, resulting in huge losses. What is the alternative? Not much. Now, imagine building an AI system that takes in a detailed description of the various desirable properties a drug should possess and outputs a set of new potential compounds for this drug. Pharma companies can then synthetically create these compounds in labs and quickly test them for the desired properties. Given the massive value addition and lack of alternatives in the market, pharmaceutical companies would be willing to pay millions (may be even billion) of dollars annually for such a AI tool. At such a price point, it makes total sense for the tool provider to invest in the high costs of AI.

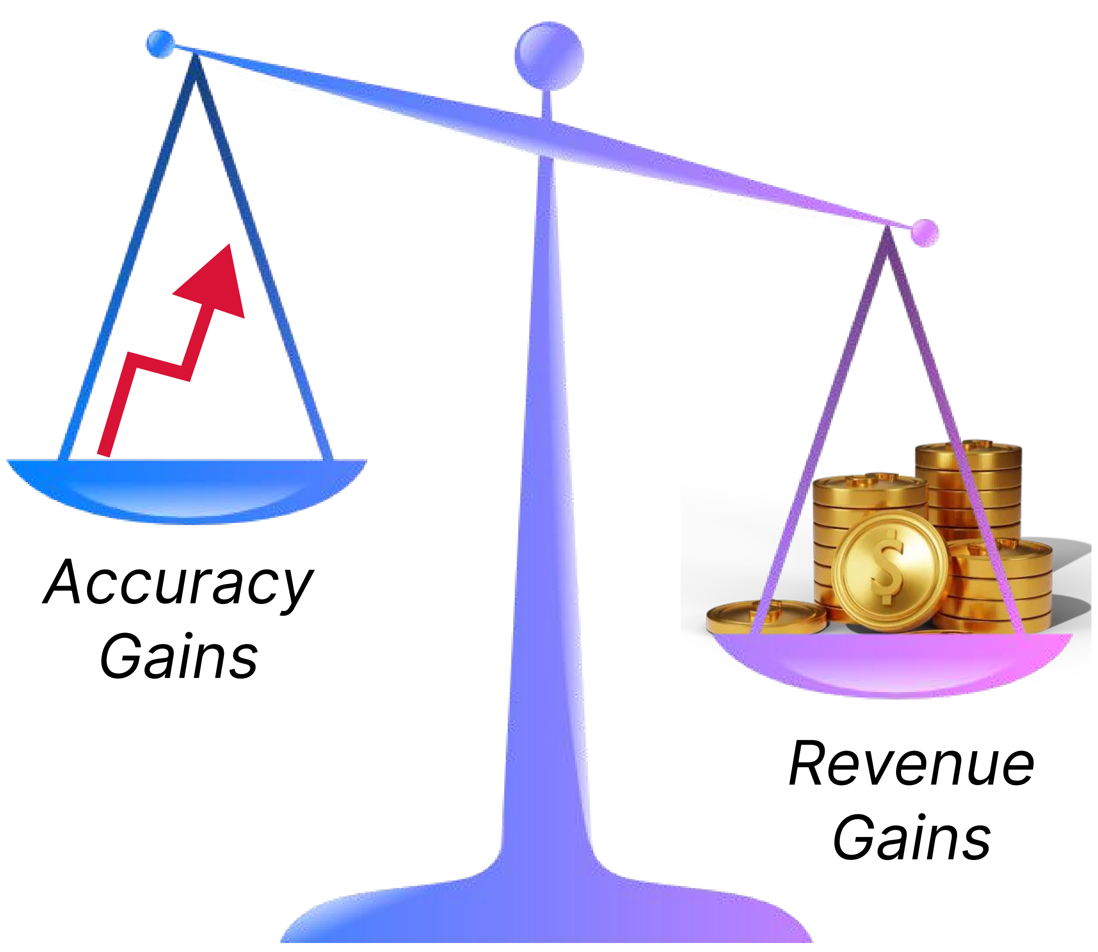
2. **Customer Support Bot**: Organizations hire human agents to address customer queries and complaints. These back office operations are often outsourced to APAC or South America regions where the workforce is available at a lower cost - typically ranging from $300 to $500 per agent per month. Now, no organization will pay more than this price for AI agents unless the AI agents provide significantly more value than their human counterparts. At a price point of $300-$500, it does not make sense for AI agent service provider to invest in the high costs of AI. This point is further elaborated in [6].

The 1% Improvement in AI System

[1] showed that in the *crag* phase, improving an AI system by even a small amount comes at a high cost (time, resources, effort, and money). The question it raises is - *in the crag phase, is improving the AI system by a delta (say 1-2%) even worth it*? ***The answer to this question lies in the impact it will create and the cost at which this impact comes.***

In Q1 2024, Google reported $46.16 billion from its Google Search business. Let's consider the scenario where improving Google's Ad click system's current CTR rate by 1% costs $100 million (inclusive of all direct & indirect costs such as talent, hardware, datasets, etc.). Additionally, let's assume that a 1% increase in CTR results in 1% increase in Google's revenue which is approximately $460 million. It is clear that enhancing Google's Ad click system CTR rate by 1% makes sense. Why? *Although the improvement in the AI system is relatively small (1% may not seem substantial), considering Google's substantial revenue base, even a small percentage increase in it translates to a significant revenue boost*. Therefore, a 1% enhancement in its AI system's performance would be highly beneficial.

Now, imagine a young startup, SentiAnalysis, which has a sentiment classification system with 95% accuracy. The founders ask the AI team to further improve it by 1%. Imagine that this improvement will cost $2.5 million (including all direct & indirect costs such as talent, hardware, datasets, etc.). Further assume, SentiAnalysis's current total revenue per annum (ARR) is $150,000 per annum. Now, the 1% gain in the accuracy of the sentiment classification system brings in additional revenue of $50,000, which is a 25% gain. *Are the founders right in asking for this, or is the AI team right in embarking on the additional 1% improvement?* Clearly **no**. *Why? Because the base revenue itself is small, the economic impact on a small base is also small.*



The above two examples bring out some very interesting observations:

1. The cost of improving the AI systems is mostly independent of the company's revenues and mostly a function of the problem statement and where you are in terms of the accuracy.
2. However the gain from improving the AI systems is directly dependent on the company's revenues at that point in time.
3. Since startups usually have a small revenue base early on, over obsession with accuracy early on is counter productive. Often the costs >> gains.
4. The same gain in accuracy, for a large company (given their large revenue base) makes a lot of sense. Often costs < gains.
5. Beyond the *make it better phase,* one should embark on the Crag phase to improving AI systems further only when the business, driven by this AI feature/product, is seeing significant traction and revenues.
6. Last but not least, it is clear for a startup, to impact revenues significantly, the improvement in AI systems must be very large. Making such large improvements in AI systems in one go is an unrealistic expectation. (Improving AI systems in the *Crag* phase is seldom game of mere better algorithm and requires wholistic effort from problem formulation to dataset to newer algorithm to more appropriate metrics)

When AI economically makes no sense

Large Language Models (LLMs) are currently in high demand. Let's consider an interesting hypothetical scenario: Walmart aims to enhance its search functionality on digital portal for its customers by implementing a LLM-powered search using GPT. According to one estimate, its eCommerce site receives approximately 400 million monthly visitors and around 600 million across all its digital platforms. *Assuming each visitor utilizes the LLM-powered search feature four times per visit, the cost for Walmart using GPT-4 would cost a bill of $500 million per year. However, with GPT-4 Turbo, the cost would decrease to $170 million*.

Being a brick-and-mortar establishment, Walmart's profit margins (compared to other e-commerce players) are much lower. According to one estimate, in 2023 they achieved a profit margin of $7 billion on $160 billion in sales. *Given such a margin, does it make sense for Walmart to invest in LLM-powered search? Simple business acumen says No.* ***While investing in AI or new-age technology makes is important, it makes sense only if it improves margins.***

Even if LLM-powered search helps Walmart earn an additional $1 billion, this would result in an additional margin of only $44 million, coming at an annual investment of $170 million (the cost of GPT-4 Turbo).

To make the recurring cost worth paying, the feature or product must deliver higher-margin revenue or create a massive increase in revenue. Most companies are shifting to smaller models that target very specific workflows. With top-of-the-line LLMs, costs scale faster than returns, except for high-margin businesses.

Concluding Remarks

In this paper, we looked at AI from an economics lens. *If AI has to transform businesses, it is crucial to consider the economic factors from the outset*. *Given the negative examples in this writeup, it would be grossly wrong to assert that AI does not make sense economically*. What this writeup emphasizes is - **to harness AI's full potential, it should not be used as a sledge hammer for every problem but rather used as a precision tool keeping the economic factors in consideration from the onset.**

Even for the Walmart example, it will be grossly incorrect to conclude that just because their margins are low, Walmart must not invest in AI. The point the example makes is that just because LLMs are state of the art algorithms, they being the go to algorithm of choice, that is *incorrect*. **No matter how cutting edge your solution, in industry, if its not on the positive side of cost-benefit analysis, it is a liability on the P&L statement and unlikely to get buy-in and support from senior leaders.**

References

[1] Anuj Gupta (Gradient Advisors), "AI Capability Continuum: A Three Step Framework to Understand the Capability Growth of AI systems", February 2024

[2] Martin Casado and Matt Bornstein, "The New Business of AI (and How It's Different From Traditional Software)", February 2020
https://a16z.com/2020/02/16/the-new-business-of-ai-and-how-its-different-from-traditional-software-2/

[3] Anuj Gupta (Gradient Advisors), "AI Product Management: A Skill Revolution", March 2024

[4] D Sculley, "Hidden Technical Debt in Machine Learning Systems", NIPS 2015

[5] "The AI industry spent 17x more on Nvidia chips than it brought in in revenue", Wall Street Journal, March 2024

[6] Anuj Gupta (Gradient Advisors), "AI GOLD: Identifying Billion Dollar AI Use Cases", June 2024

[7] Dzmitry Bahdanau, "The FLOPs Calculus of Language Model Training", Jan 2022
https://medium.com/@dzmitrybahdanau/the-flops-calculus-of-language-model-training-3b19c1f025e4

[8] Google, Environmental Report 2024, July 2024.
https://www.gstatic.com/gumdrop/sustainability/google-2024-environmental-report.pdf

***

gradient advisors

ABOUT US

We are world's leading global AI consulting, advisory & upskilling company, helping organizations around the globe unlock the full potential of artificial intelligence (AI) for their businesses. We are pioneers in AI, with over 2 decades of extensive experience in core AI.

We provide comprehensive solutions and guidance across the entire AI lifecycle - from vision, strategy, roadmapping, data gathering, model building, deployment, integration into product line, to GTM, sales, including people aspects - incubating & growing world class AI teams.

Don't let the future of business elude you. Embrace the realm of AI with unyielding assurance, under the sagacious guidance of Gradient Advisors. With over 2 decades of experience in AI across 0-1 startups or Fortune 50, we are more than just advisors; we're your partners in AI innovation. We are your trusted in partner in Unlocking the the full potential AI.

For more information, do reach out to us :

hello@gradient-advisors.ai

https://gradient-advisors.ai

Gradient Advisors
904 Regency Court,
San Ramon,
California, 94582, US

Gradient Advisors
109 Wilow Road,
Enfield, EN13BP, London,
UK

Gradient Advisors
11 Charlotte Street
ON M5V 0M6
Toronto
Canada

Gradient Advisors
203, Wing E
Dubai Silicon Oasis
Industrial Area, Dubai
UAE

Gradient Advisors
W5/902, Ahad Euphoria,
Sarjapur Road, Carmelaram
Bengaluru 560035, India

Gradient Advisors
11 Els Court, Berwick
Melbourne,
Victoria 3806, Australia

Want to see more such knowledge nuggets? Follow our social media handles