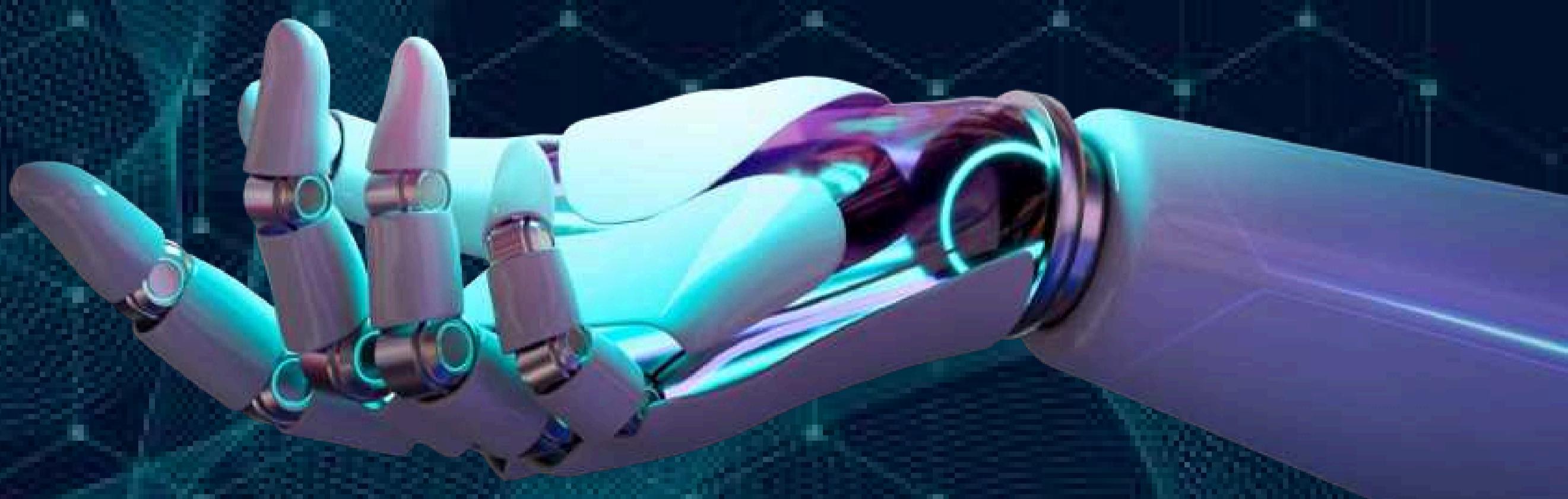


AI Capability Continuum

**A Three Step Framework for Developing
AI Systems in the right way**



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 offering unparalleled opportunities, it also presents 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 achieve the pinnacle of 'Pragmatic AI.'

We define **Pragmatic AI** as the AI that outlines a clear path for translating AI efforts into tangible business successes leading to increased revenues and market dominance, rather than just being obsessed with (superficial) model metrics.

This paper serves a dual purpose: highlight the fact that creating the model is not the hardest part for AI-first businesses and getting to it is often a long journey; and second, lay out the right way of developing AI systems.

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Note from the CEO'S DESK ”

Dear Reader, Greetings!

Thank you for stopping by to read this. It is worth pausing for a moment to contemplate the significant opportunity that lies before us – the realm of **Artificial Intelligence (AI)** and the countless possibilities it offers. This is akin to the revolutionary impact of electricity or industrialization, each of which reshaped many aspects of human existence, redefining industries, streamlining processes, and fostering unparalleled levels of innovation.

In today's rapidly evolving business landscape, incorporating AI into your business is no longer a luxury but a necessity to stay competitive and relevant. Each of us is taking our respective organizations on a transformative path, aiming to harness the boundless potential of one of the most disruptive technologies of the 21st century. I firmly believe that this journey will shape the future of countless organizations.

Having said this, with every groundbreaking technology comes a set of challenges. AI is no different. *Understanding the intricacies of AI is crucial to successfully adopting and fully unlocking its potential.* At Gradient Advisors, *our philosophy has always centered on demystifying AI, cutting through noise and lofty claims, enabling its optimal utilization and create impact.*

While there is a wealth of content on AI tailored for developers and practitioners, there remains a noticeable gap for founders, leaders, executives, and investors seeking guidance to navigate this complex landscape and make informed decisions. It is with this ethos in mind that, drawing upon our two decades of extensive experience in AI, we are embarking on a series of articles under the umbrella of 'Pragmatic AI,' aimed at supporting Founders, VCs, CXOs, Executives, and the broader AI community.

We sincerely hope you will find value in this initiative. Your feedback and engagement will be greatly appreciated.

Best Regards,

Anuj Gupta
Founder & CEO
Gradient Advisors

AI Capability Continuum:

A Three Step Framework for Developing AI Systems in the right way



Executive Summary

- *The article introduces 'AI Capability Continuum', a three-step methodology for developing and managing the development of AI systems .*
- *Owing to the unique demands of AI system development, traditional software engineering methodologies like Waterfall, Spiral, RAID, Lean etc fall significantly short.*
- *The proposed methodology prioritizes the right metrics at each stage, thereby maximizing ROI from AI projects.*
- *The first phase involves laying the foundations.*
- *The second phase focuses on quickly moving from 'a' AI system to a 'very good' AI system.*
- *The third phase is about pushing boundaries & get to 'the' system.*
- *We discuss how availability of 'off-the-shelf intelligence' via LLMs such as ChatGPT, Llama has impacted AI system development & understand the same from the lens of AI Capability Continuum.*

In recent years, Artificial Intelligence (AI) has witnessed remarkable progress, with many breakthroughs now accessible via APIs and open-source solutions lowering the entry barrier. Thanks to this increased ease of implementation along with push from leadership, organizations — from startups to multinational corporations — are actively working on integrating AI into their products and services. However, despite this momentum, AI adoption remains fraught with challenges.

One major hurdle is the high failure rate of AI projects in the industry. According to a recent survey [1], a staggering 96% of AI projects encounter data issues during the training phase, preventing them from progressing further. Another survey [2] reveals that despite substantial investments, 8 out of 10 companies reported minimal or no Return on Investment (RoI) from their AI efforts. The reasons for such abysmal numbers are many. One of the key reasons is: ***lack of structured engineering methodologies for development of AI systems tailored to industry needs.*** Unlike academia and research labs, where AI development focuses on pushing the boundaries of state-of-the-art advancements, building AI systems in industry has a very different end goal and demands a more pragmatic approach.

In this article, we present “**AI Capability Continuum**”, a three-step framework tailored to help you conceptualize & execute the development of AI systems. To elucidate this framework effectively, we will utilize the notion of *capability curve*.

Traditional software engineering has long benefited from established methodologies—Waterfall, Spiral, Big Bang, Lean, Agile, etc.—to ensure structured development and efficient project execution.

The area of AI software development (a.k.a software 2.0) is still very nascent. There have been some attempts to create frameworks to capture inherent complexities of AI system development. These complexities necessitate a different methodology to model the development lifecycle of AI systems. Notable attempts are **Team Data Science Process (TDSP)** by Microsoft, **Cross-Industry Standard Process for Data Mining (CRISP-DM)**, **AI Ladder** by IBM. While they provide high-level guidance, they lack low level details. Further, TDSP is tightly integrated with Microsoft Azure, overly focused on Microsoft Ecosystem. CRISP-DM is data mining focused and outdated. IBM's AI Ladder is very high level and leans heavily on IBM's AI tools (Watson, Cloud Pak). This limits the broader applicability of these frameworks. They all lack a structured mechanism that paints an intuitive understanding of the process of AI system development for a non-technical person and is platform-independent.

To address this lacuna, we introduce the **AI Capability Continuum**, a three-phase framework that conceptualizes AI system development. To elucidate this - we use 'capability curve' (TBD - find references). This is a 2D plot where the system's *capability* is plotted on the Y-axis whereas time is plotted on X-axis. Interestingly this plot provides deep insights into the evolution, maturity, and optimization of AI systems.

This framework offers a systematic approach to AI system development, bridging the gap between fundamental advancements and practical implementation, ultimately guiding organizations toward sustainable AI success.

CAPABILITY CURVE OF TRADITIONAL SOFTWARE SYSTEM

Consider a traditional software system, S . Let us define its capability as the set of functionalities it can perform (what all it is capable of doing for the end user). When no code is written, there is no functionality at all (it's all on mere paper). As code is written, the system's starts to gain functionality. Now let's ask: *how does this growth unfold over time?* If one were to put a 2D plot with capability of S on the Y-axis and time on the X-axis and ask: *how does the shape of this capability-time curve evolve with time?* If you think on this question, you will realise that the shape of the curve pans out somewhat similar to the integral symbol (\int). Why so?

Initially, the progress on development of S is slow due to requirement gathering, scoping, budgeting, team formation etc. Since no implementation has started, **no real** capability has been accrued. This results in a flat slope. Once the development starts, Within a few days/ weeks of starting the development, one starts to see the gains materialize pretty quickly, creating a steep rise in the curve. Once the implementation starts, why do the gains accrue so quickly? Owing to our mastery over software developed along with the modern tools & the playbooks of best practices – capability accumulates very quickly; driving a steep acceleration in capability curve.

However, as one implements more and more software, complexity and technical debt accumulate, further enhancements requiring higher effort. The curve starts to taper off, reflecting diminishing returns. This trajectory is fundamental to understanding software system lifecycles (Fig. 1).

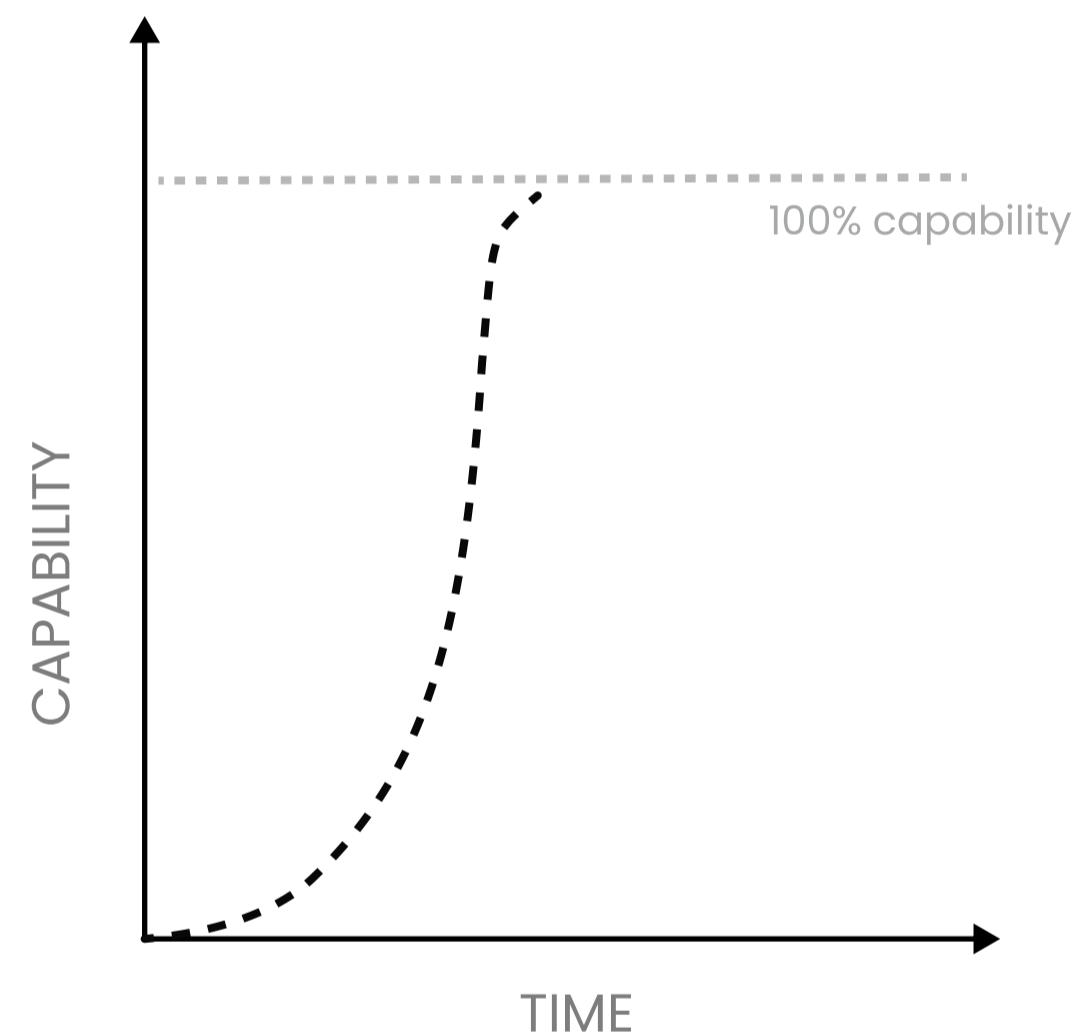


Fig 1: Capability curve for a typical software/IT system

At a high level (20,000 ft view), the capability curve appears smooth and continuous, as illustrated in Fig. 1. However, at a more granular level (20 ft view), this curve resembles a step function. Why? Consider implementing a simple calculator. As we develop the add() function, whether one-quarter or half of the function is written correctly, the system lacks addition capability until the function is fully implemented and operational. The capability does not increase incrementally but rather in discrete steps—either the functionality exists, or it does not. This makes the progression binary, with sudden jumps in capability rather than gradual improvements.

CAPABILITY CURVE OF AI SYSTEM (Pre GPT)

When it comes to the capability curve of a typical AI project/system, any guesses what the shape might look like? it is very different:

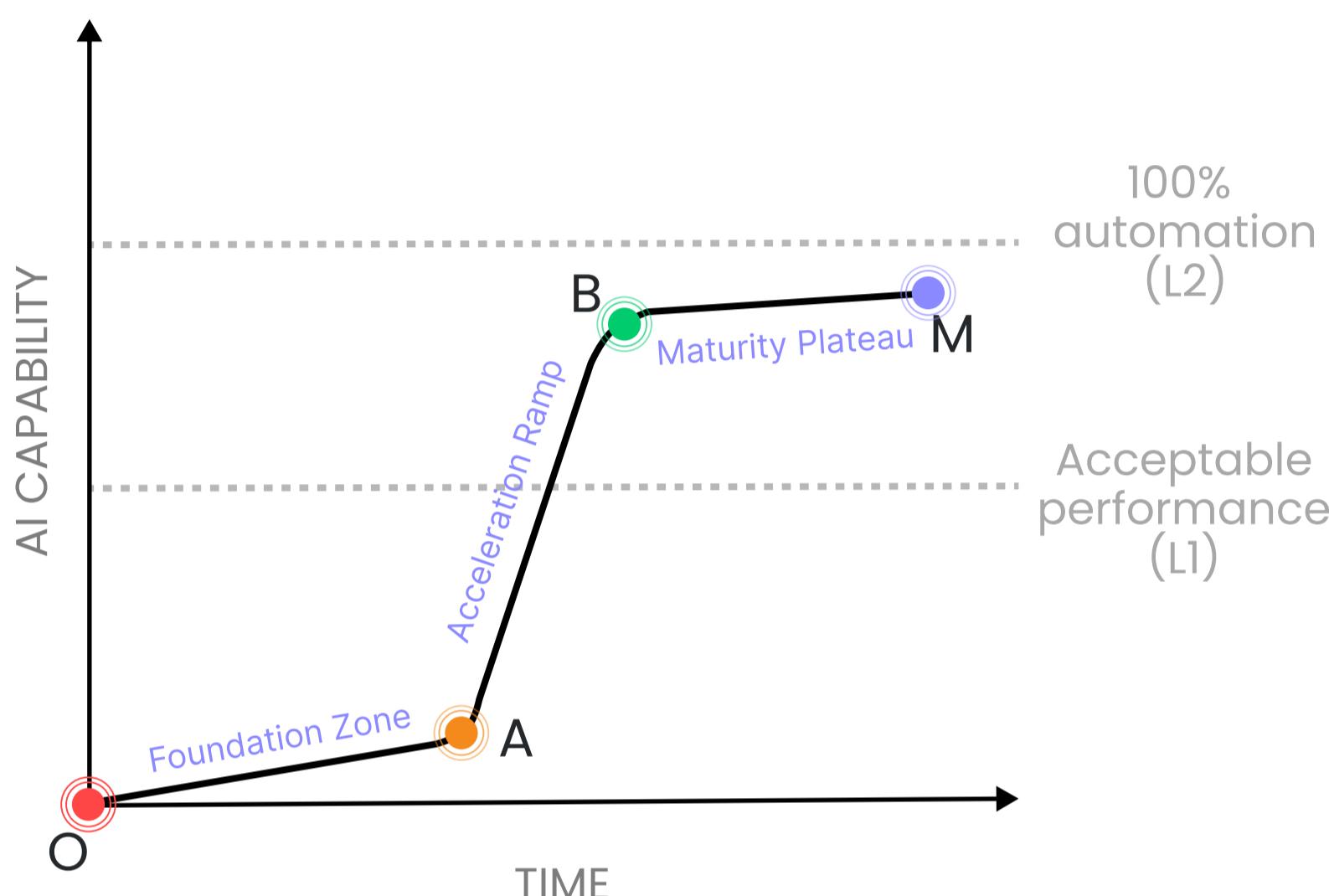


Fig 2: Capability curve for a typical AI system

The curve in Figure 2 shows distinct similarities and differences compared to Figure 1. Unlike the sharp rise in Figure 1 (on previous page), the initial segment in Figure 2 remains flat for a much longer period, giving it a more elongated shape. After this slow start, the curve rises quickly, but not as steeply as in Figure 1. What's most striking is the sharp stagnation toward the end, where further improvements in capability slow down sharply.

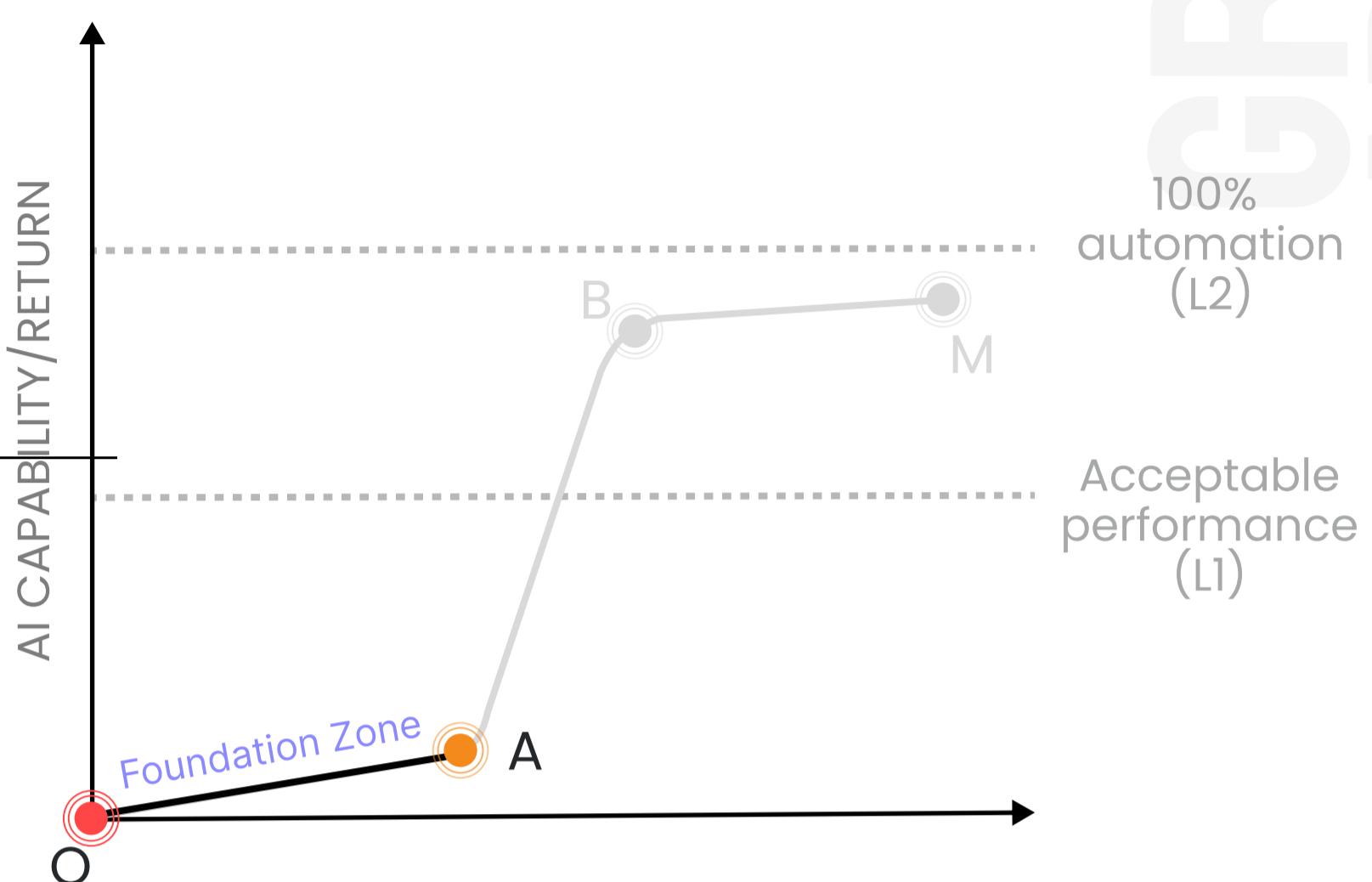
This shape of capability curve for AI surprises industry practitioners, particularly those with an extensive software engineering background. Founders, CXOs, and Managers typically expect AI systems' capability curve to follow the same steep hockey-stick trajectory as capability curve for traditional software systems. However, this is far from the reality.

The reason behind this difference lies in the fact that the well-established playbooks of traditional software development do not apply to AI development. This significantly affects the AI capability curve. To understand why the curve behaves this way, we divide it into three main segments: *Foundation Zone* (O-A), *Acceleration Ramp* (A-B), and *Maturity Plateau* (B-M). We'll examine each segment in detail to gain a deeper understanding of AI development and begin crafting its own playbook.

Foundation Zone (O-A)

Fig 3: Foundation Zone Phase of capability curve for a typical AI system

In the Foundation Zone, the focus is on setting up the groundwork for AI development. The key steps involved are:



- 1. Clarify the business problem** – Develop a better & deeper understanding of the (often vague) business problem statement.
- 2. Define the problem** – Transform the (vague) problem statement into a clear and well-defined business problem statement.
- 3. Evaluate AI suitability** – Assess if the problem statement (in 2) is even an AI problem
- 4. Set success metrics** – Define success metrics: both business and ML metrics.
- 5. Data requirements** – Understand the kind & quantity of data needed to solve the AI problem at hand.
 - a. **Data availability** – Check if you have the kind & quantity of data needed.
 - b. **Data preparation** – Collect, preprocess, and clean the data needed to create a v0 dataset from it.
- 6. AI problem type** – Determine the broader type of AI problem (e.g., supervised, unsupervised, reinforcement learning) at hand.
 - a. **Labelling** – In case of supervised learning, get the v0 dataset labeled.
- 7. Define constraints** – Understand the constraints any valid solution must adhere to:
 - a. Cost of mistake/wrong prediction,
 - b. Prediction time (real-time or batch),
 - c. compute location (cloud or edge)
- 8. Otherconstraints** - Any other constraints the solution must adhere to
 - a. Time to prediction, explainability of prediction etc
- 9. Build a model** – Develop a simple baseline model, or leverage third-party APIs.
- 10. Test business hypothesis** – Quickly validate if your solution addresses a major pain point for users (or business units)? How likely it is to find product-market fit (PMF).
 - a. **Market validation** – If successful, determine how much the market will be willing to pay for your solution?

The duration of the **Foundation Zone** varies based on the problem's complexity, the organization's AI maturity, and the time required to test the core thesis. This phase can take anywhere from **1 to 6 months**. The most challenging aspects are typically **preparing a dataset from data and validating the core business hypothesis**.

Observations:

- Number 1 mistake most teams make is *diving straight into building 'the' model, often aiming for state-of-the-art LLMs from day one*. Driven by FOMO & noise on social media platforms, *they believe anything less than state of the art Large Language Models (LLMs) is not 'innovative' enough thus unacceptable. This should never be the goal of the Foundation phase.*

Instead, this phase is about answering fundamental questions:

- Are we solving the right problem?
 - Is it a painkiller or a vitamin for the target users?
 - How much is the market willing to pay for it?
- Is this even an AI problem, or can it be solved traditionally?
- Do we have the right data to solve it effectively?

Why so? despite the amazing advances in last few years, AI endeavours is still expensive—**data, compute, and talent, internal realignment within the Organizations** don't come cheap. There's no point in building a **state-of-the-art model** if each prediction costs \$3 but the market will only pay **\$1** (or worse, has no interest at all).

Also, **building a great model is hard and takes time**. It requires deep problem understanding, the right skill set, quality datasets, and heavy compute. **Why invest at this level unless you're sure there's a viable business?**

Seasoned AI entrepreneurs know that in most cases **building a business is far harder than building a AI model**. So why fixate on a cutting edge model from day one?

- The goal of this phase is **not** to build the best model (unless you're a research lab). Instead, it's about tackling the hardest part of the problem: **the business viability & direction**. Key questions to answer:
 - Painkiller or vitamin?** are we building something that solve a major pain point?
 - Business viability:** How likely the AI system to meet its business objectives? (e.g., Alexa was a stellar AI product but failed to drive orders on amazon.com)
 - Market willingness:** Will users/clients pay for it? If so, how much?
 - Profitability & Sustainability:** Can you get enough LTV (Life Time Value) to offset high

dev costs, indirect expenses, and have large margins to build a sustainable business?

This is the core difference between AI in startups & product companies vs. AI in Academia & Research labs. The later aims to push the state-of-the-art; while the former needs viable, profitable AI solutions. To illustrate this, see the thought experiment on the next page.

- In organizations high on AI maturity, data is systematically stored and organized for seamless access by internal consumers like analytics & AI teams. This is akin to a well-organized pantry in a professional kitchen, enabling chefs to access ingredients quickly to create dishes swiftly. In contrast, data-immature organizations resemble a chaotic pantry—where retrieving specific slice of data becomes a project in itself, delaying AI initiatives. This is a **critical oversight** among founders and executives.

In most organizations that lack data maturity, most AI projects die in the Foundation phase itself! Thus, if you are serious about AI, fixing your data strategy is non-negotiable

- Many teams, founders, and executives fixate on the model while overlooking a critical step—**defining clear success metrics**. AI systems are probabilistic and error-prone, making it essential to establish both **AI and corresponding business metrics** from day one and ensure their alignment & progress in right direction.

Skipping this is like **building a rocketship without a control panel**—you won't know if you're on the right trajectory.

- You may wonder—**what about the model?** We never discussed it, and that's intentional. **Use whatever gets the job done very quickly**—a third-party API, open-source model, or even humans providing answers in real-time! You optimize for **time-to-market and not accuracy, scale or cost**.

As we emphasized earlier, **this is not the phase to build a great model**. The goal is to quickly assemble a system and test the market **immediately**.

- If you're *not training* your own v0 model, you can deprioritize dataset creation & labelling initially. However, once your project moves beyond Point A, **a high quality dataset becomes essential** for testing models. It's best to start early to assess potential risks and avoid setbacks later.

This phase highlights why the traditional corporate mantra of securing “early wins” doesn’t translate easily to AI projects. The Foundation phase is challenging, and quick wins are rare.

This phase can be summarized as “Start simple, Build quickly, Launch quickly, Learn quickly”

Thought Experiment

Imagine its 1920, the World War I has just concluded. For the first time in history, air bombers took to skies and influenced the outcome of any war. You are Richard Branson, a young, energetic and budding entrepreneur looking for your next big bold idea in your quest to create next unicorn. Given your sharp acumen, you quickly realize that one can modify air bombers to transport goods & people from one part of the world to another and charge the end customer for the same. You could be the first one in the world to usher the era of commercial aviation.

Your big challenge - getting first set planes customized for commercial needs. You have 2 options:

1. Quickly assemble an airplane and test the markets, gather early feedback, make amends in your offerings
OR
2. You will start building state-of-the-art of the engine? Strap your customer to THE engine you have build and fire it off?



If your answer is going to be (a), then why should it be any different while developing AI systems? Why this obsession with state-of-the-art LLMs from Day 1! Just as an airplane has over thousands of parts so does an AI system. One needs to get the whole AI system right to create the business wins. Getting to THE AI system is a journey. State of the art Model is necessary not but not sufficient.

Acceleration Ramp (A-B)

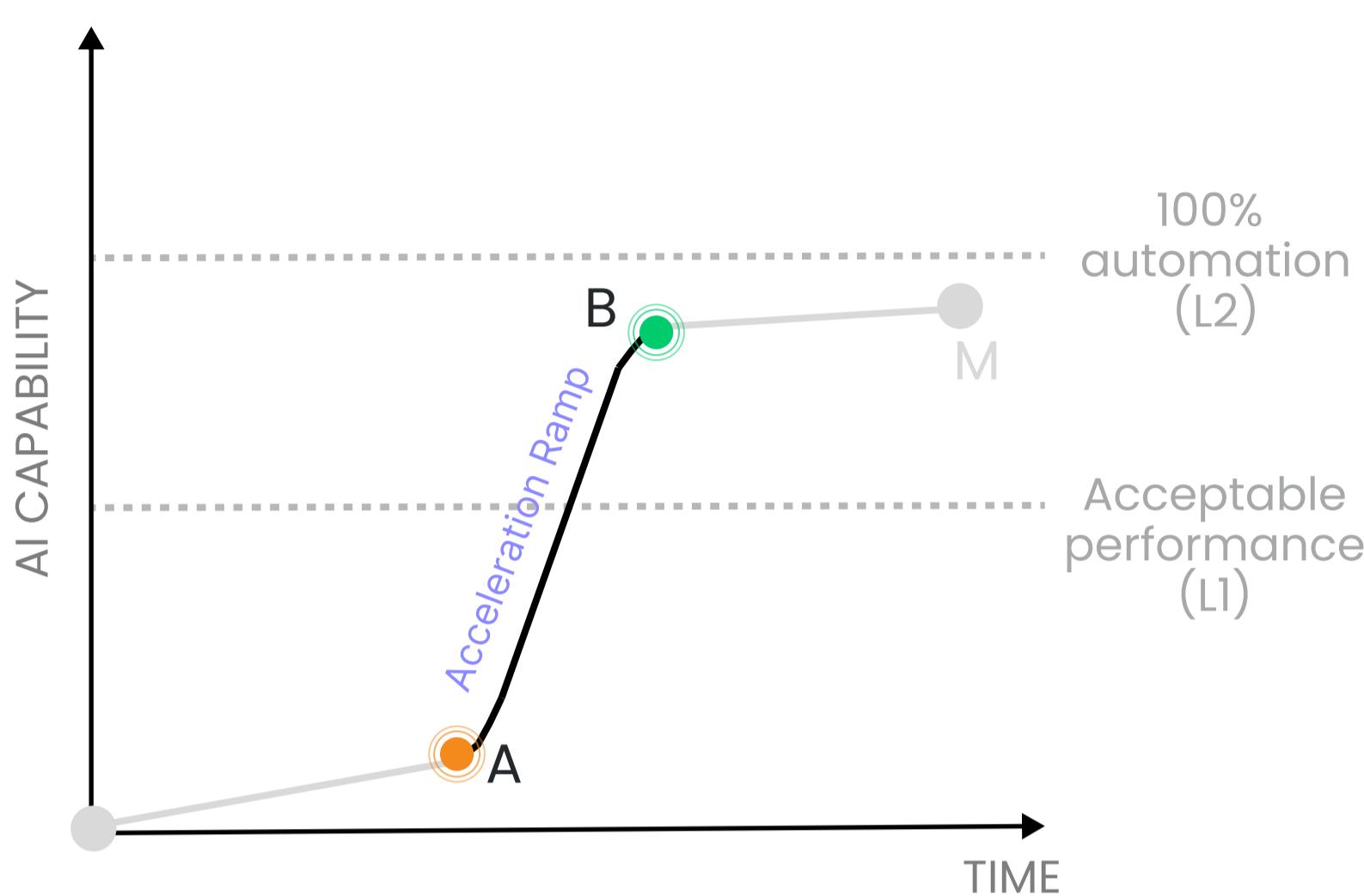


Fig 4: Acceleration Ramp Phase of capability curve for a typical AI system

This is the middle part of the curve in Fig. 4 - Acceleration Ramp. Here you get the highest progress/capability per unit effort.

A lot of hard work is already done into Foundation. You have already put in place a lot of key ingredients - refining problem statement, collecting data, operationalizing metrics & measurement methodology, and early validation from stakeholders (internal/external). In the next phase one focuses mainly on improving the model - going from *a* model to *the* model. Key steps in this phase:

1. You try various algorithms and build various models.
2. Rigorously benchmark the performance of every model built
3. Once your system crosses the acceptable performance level (L1), you take your AI system to production and expose predictions to end users
4. As you keep improving, you keep pushing out best model so far to production.
5. Test the new model and system thoroughly, replace the existing model with the new model, and monitor the gain in ML metrics and business metrics.

Keep Iterating previous steps. You will start moving quickly from a model to much better models. At some point, your gains will start to saturate. This is when you know that you are at point B. Depending on the problem at hand and AI maturity within the Org/Team, this phase can typically last from 3-12 months.

Observations:

- This phase starts, when your product/offering's value proposition starts to find traction in the market. The carefully orchestrated demos with which you tested the market landed well. Early customers have started to come, some even paid customers.

Now, given the traction, it is crucial that you must greatly ramp up the AI capabilities of your system. This is a great time to usher Acceleration Ramp phase. This is where you focus on the core - model!

- Note that this phase has a lot of iterations within it.
- This phase is all about going from *a* model (simpler approaches) to *the* model (complex approaches). Why not try the best algorithm upfront? Occam's razor - a fundamental tenet of AI. The objective is to find the simplest model that works the best.
- Since comparing 2 or more candidate models is a key part of this phase, the ground work we did on metrics, measure methodology & rigorous test sets in the previous phase forms the bed rock of this phase & comes super handy. Without that it becomes hard to critically compare various models.
- At each step, you closely analyze the kind of mistakes your model is making. Often, it is in this analysis lies the genesis of the next model.
- As you get to better models, you keep taking them to production. This is where you go from 1st version of your AI system to maybe 3rd or 4th version of your AI system.
- At some point, your gains will start to saturate, that's when you know you are close to point B.

Briefly, this phase is all about “Make it Better”

Maturity Plateau (B-M)

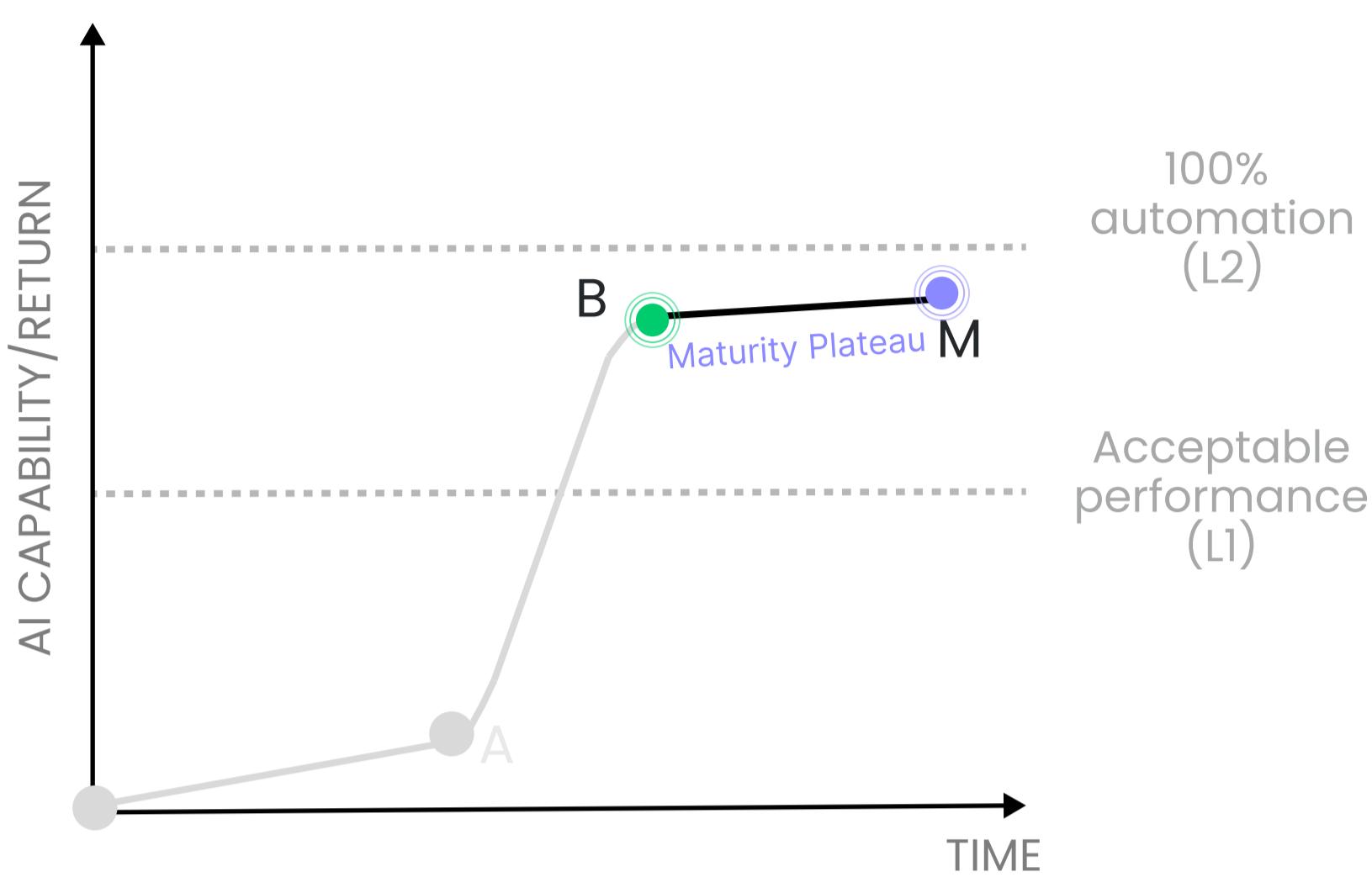


Fig 5: Maturity Plateau Phase of capability curve for a typical AI system

This is the final stretch - the tail end of the project lifecycle. The capability curve flattens as gains accumulate slowly. This phase is about pushing the system to its limits. Your team:

1. Builds the 20th, 30th, or even 40th model iteration; 5th/7th/10th version of the intended AI system.
2. Tries to push system performance to its absolute limits.
3. Analyzes and fixes every edge case that your AI system is getting wrong.
4. Experiments with novel approaches, algorithms & architectures, not just known AI algorithms.
5. Tweaks core mathematical formulations of AI models; even proposing new AI algorithms

Despite massive effort, improvements are often just 2-5%. This phase can last 6 to 24 months, depending on complexity.

Observations:

- This phase happens when the AI problem at hand is central to your value proposition, and your business is thriving with strong traction. You have customers that love your offering and are paying for it
- You are seen as market leader and your customers expect higher accuracy from your AI systems. Even 1-2% gain in the AI capability will further cement your position and move your business numbers significantly.

- Very few AI projects get to this stage.
- This phase is about **first principles approach to model building** - rethinking and rebuilding the model's mathematical formulation from the ground up.
- Notably, the **capability curve never reaches full automation (L2)**—today's AI lacks AGI's self-learning ability to continuously improve.

No matter the use case or model quality, AI will always struggle with a long tail of edge cases. AI lives in this long tail, constantly encountering failures. This has huge implications for profit margins—we address in “Economics of AI”

- **AI lives in the long tail of edge cases:** progress comes very slowly. Why? Complexity of handling edge cases. More advanced the model, greater its accuracy; necessitating higher-quality and more accurate data & more nuanced algorithms for further enhancements.
- **Instead of exponential improvement in performance, paradoxically one sees exponential increase in the expenses and efforts required for further improvements.** Ex: Self Driving Cars

In one line, this phase is about “Make it Great”.

Interestingly, each phase of an AI project demands distinct AI talent—more on this in ‘People’ section.

Now that we fully understand AI Maturity Continuum, let us look back at our original expectations on life cycle of a typical AI project. Our expectation:

- Take a business problem statement
- Build state of the art model, deploy it
- Done.

Reality: far from above! Fig. 6 sums this up:

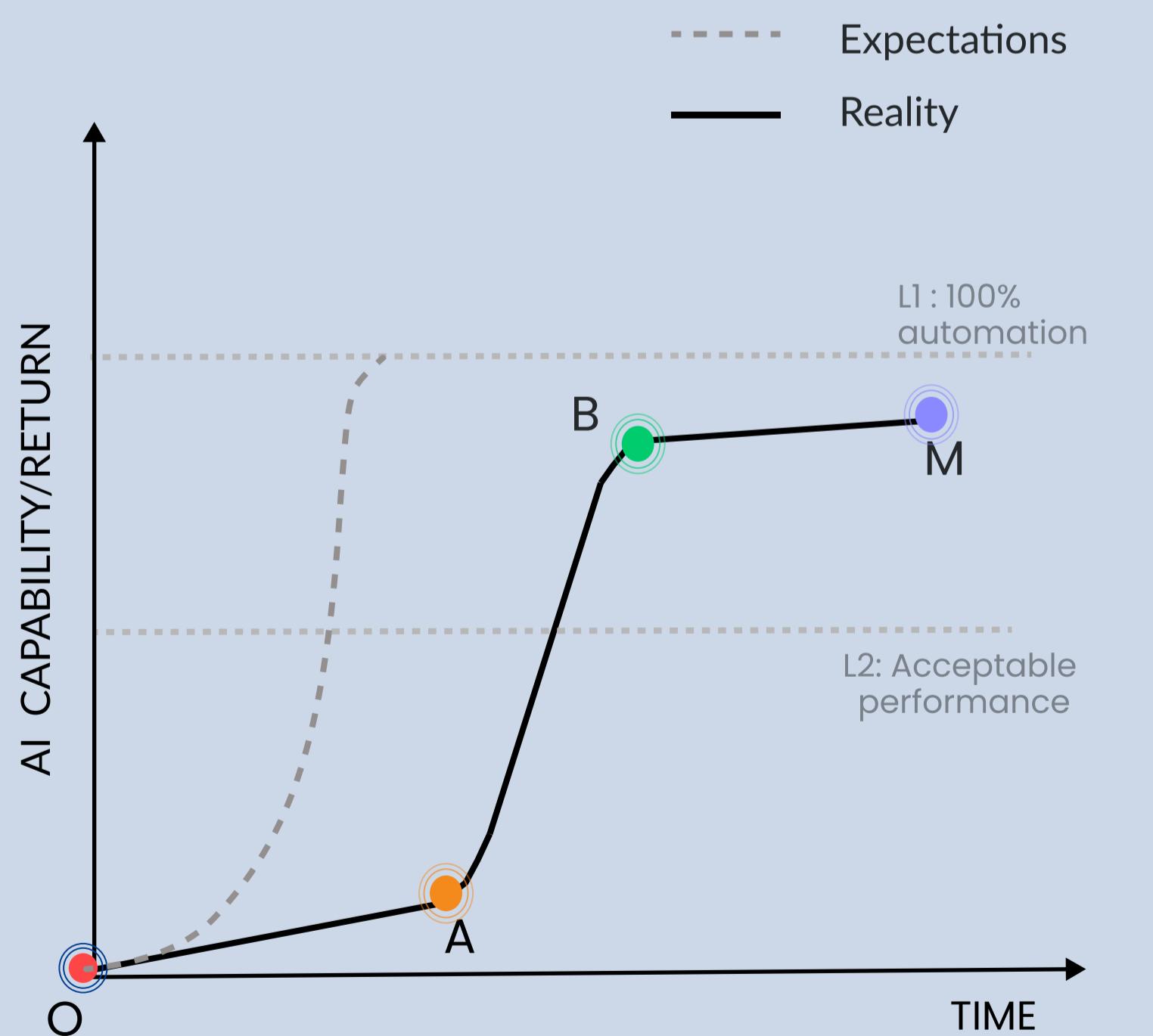


Fig 6: Capability curve for AI systems -
Expectation vs Reality

Impact of LLMs on the AI Development Lifecycle

Having understood the three phases of the AI development lifecycle, let's us explore how Large Language Models (LLMs) like chatGPT, Claude, Llama and other off-the-shelf foundational models have fundamentally reshaped the AI development lifecycle. Key shifts include:

- 1. Commoditization of Intelligence:** With the availability of foundational models via APIs and open-source models, **intelligence has been commoditized**. High levels of "intelligence" can now be accessed in a plug-and-play manner without building models from scratch.
- 2. AI Products Without proprietary AI models:** Today it is possible to build v0 of AI products without needing to build proprietary AI models.
- 3. AI models Without proprietary Datasets:** Historically, ability to curate large & high-quality labelled datasets was the biggest hurdle for building v0 of AI systems. Despite the "data-is-the-new-oil" narrative, most organizations still struggle to create good datasets. With commoditization of foundational models, teams can now build early versions of AI systems without proprietary data, circumventing this barrier.
- 4. Reduced Need for Specialized AI Talent:** Previously, developing even a basic AI model required AI scientists. Today, with prompt engineering and strategic use of APIs, smart business leaders and product managers with help from software engineers can assemble a functional early versions AI systems good enough to demo without deep expertise in AI.
- 5. Lower Entry Barrier and Faster Time to Market:** By leveraging off-the-shelf intelligence, teams can accelerate development cycles and bring AI products to market much faster, drastically reducing both cost and complexity.

Before proceeding further, it's essential to explicitly clarify a few points/terms:

- a. **High levels of Intelligence:** No foundational model gives you 100% accuracy—they all make mistakes. However, they give decent off-the-shelf accuracy. The exact number depends on the task at hand.
- b. With various techniques like Fine-tuning on Domain-Specific Data, transfer learning, LoRA (Low-Rank Adaptation), PEFT (Parameter Efficient Fine-Tuning), knowledge distillation and Multi-Step Reasoning (CoT - Chain of Thought) one can improve this number but not to 100%.
- c. Leveraging APIs is excellent for building early versions of AI systems. However, this approach is limited to initial versions & prototypes and cannot fully scale to highly mature production-grade AI systems. We'll delve deeper into this on the next page.

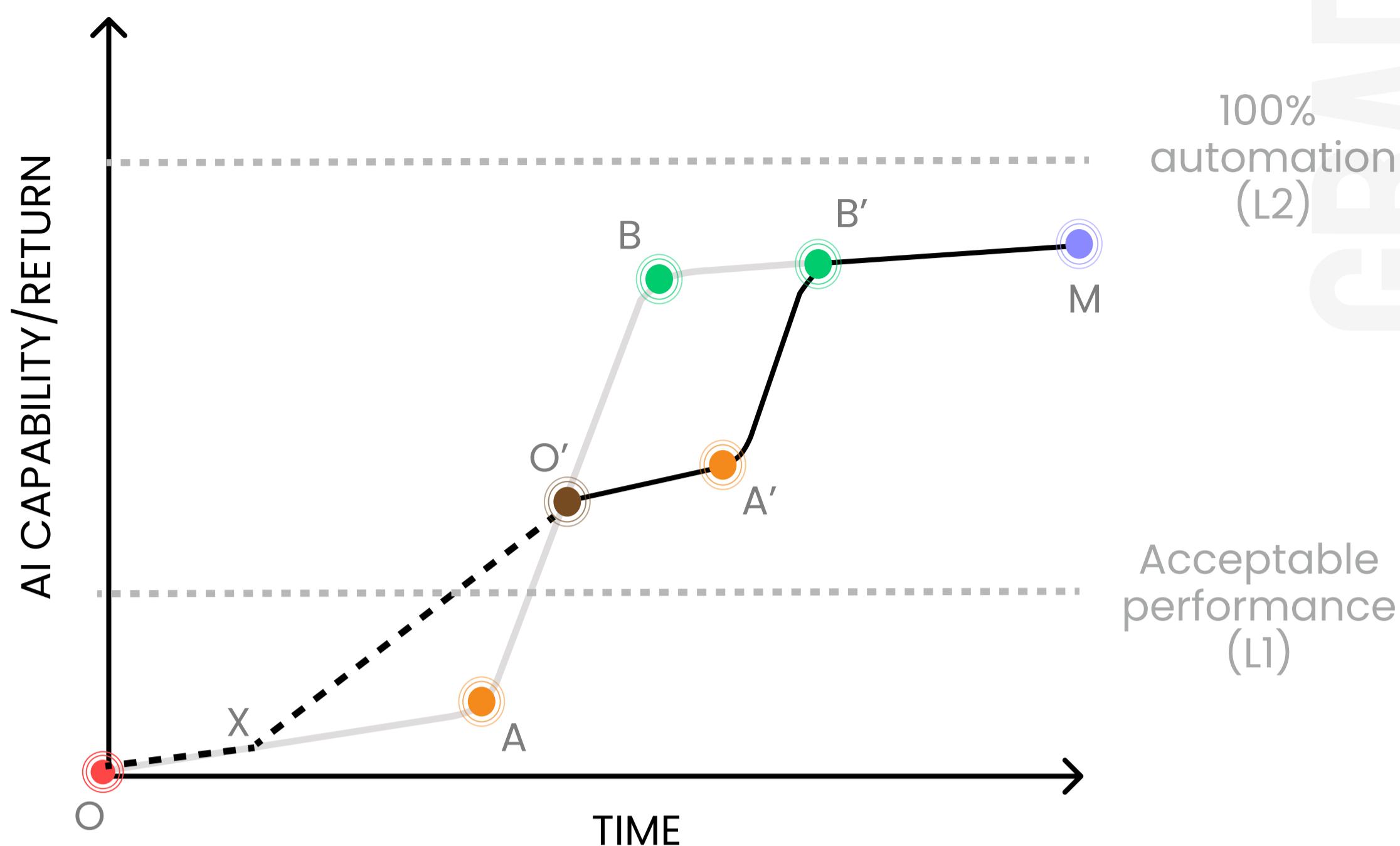


Fig 7: Impact of Off-the-shelf-LLMs on AI development lifecycle

Lets now return to capability curve. How does use of foundational models via APIs impacts the shape of capability curve? Before turning over the page, we encourage you to think.

As shown in Figure 7, turns out the entire curve translates (shifts) $[O \rightarrow O', A \rightarrow A', B \rightarrow B']$. Why so? Using chatGPT/off the shelf LLMs via API - one gets fairly high intelligence. This is represented by point O' in Figure 7. And since one can get to it very quickly (merely API calls), we have a straight line from pt O to pt O' . In most cases, this much intelligence is good enough to deliver an acceptable performance (not for all problems - ex: self driving cars) and you can start selling your product/offerings in the market. O to X represents initial project planning phase. However, since it doesnot involve the tedious phase of data collection, dataset preparation, labelling etc, it is shorter (faster) than OA .

If your offering is great and finds product market fit, at some point in time, you will have paying customers. As their number goes up, they will demand higher accuracy. Weather you use APIs or train proprietary models, its your problem. Your customers will demand for higher accuracies. More successful is your offering, higher will be this expectation.

Now chatGPTs of the world are generic AI systems trained on generic data, hence no matter how much prompt engineering you do it will take you only so far. To improve your systems further, your next logical choice will be to apply fine tuning/transfer learning on open source foundational models using your data. This will require you to gather data, build your own datasets. What after that? your only choice is to train your own proprietary models from

scratch. Note this exactly the journey we saw from *Foundation Zone, Acceleration Ramp & Maturity Plateau* (O-A-B-M) in Fig 4. only difference now will be the accuracies/ML metric values will be much higher, hence the curve takes exactly the same shape beyond O'.

Now as OpenAI, Meta, DeepMind, xAI and other research labs in industry & academia come up with newer & better techniques and push towards AGI, off-the-shelf intelligence will keep getting better - the point 'X' will keep on moving higher n higher. How fast will this happen? No one knows, it is anyone's guess.

Further, as mankind develops a more deeper understanding of AI development, OO' will become more steeper until it resembles capability curve of traditional software systems as shown in Fig 1. When will that happen? anyone's guess. We believe we are still 3-5 years away from that. Until then

It turns out that using the capability curve & its shape for AI projects one can answer some very crucial questions - what is the right process to develop AI systems, from a talent acquisition purpose when is the right time to bring in AI scientist with PhD pedigree, why profit margin of AI companies will never be more than 40% unlike SaaS companies that have 80-85% margins and many more.

We will answer these and many more in next set of articles. Adios until then.

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ABOUT US

We are the world's leading AI company, offering on-demand Chief AI Officer capability to accelerate your AI development, adoption and drive transformative business outcomes.

For example, a YC company partnered with us to build a critical AI system, this was showcased to Sam Altman (OpenAI) and Vinod Khosla (Khosla Ventures), leading to their Series B funding from Khosla Ventures. This AI system recently also featured at OpenAI's recent flagship event.

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