

INTRODUCTION TO AI AND GEN AI

Yogesh Haribhau Kulkarni



Outline

① AI INTRO

② GENAI INTRO

③ PROMPTENGG DEMO

④ CONCLUSIONS

⑤ REFERENCES



About Me

YHK

Yogesh Haribhau Kulkarni

Bio:

- ▶ 20+ years in CAD/Engineering software development
- ▶ Got Bachelors, Masters and Doctoral degrees in Mechanical Engineering (specialization: Geometric Modeling Algorithms).
- ▶ Currently doing Coaching in fields such as Data Science, Artificial Intelligence Machine-Deep Learning (ML/DL) and Natural Language Processing (NLP).
- ▶ Feel free to follow me at:
 - ▶ Github (github.com/yogeshhk)
 - ▶ LinkedIn (www.linkedin.com/in/yogeshkulkarni/)
 - ▶ Medium (yogeshharibhaukulkarni.medium.com)
 - ▶ Send email to [yogeshkulkarni at yahoo dot com](mailto:yogeshkulkarni@yahoo.com)



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Introduction to Artificial Intelligence

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“Houston, we have a problem!!”



50 Years Ago: “Houston, We’ve Had a Problem” – John Uri

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Whats the Problem?

- ▶ Along with some softer words like “disruption”, “passionate”, “excited” ...
- ▶ If you don't have word “innovation” in your talk/speech/conversation it's BIG problem.
- ▶ Irrespective of fields. You can be Corporate, Political, Social, etc.

And there is an addition of one more word, which is a must in every talk...and that is?

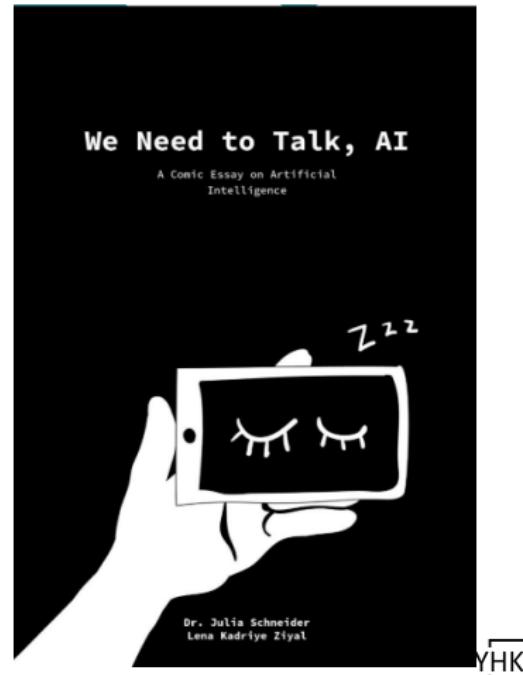


The Problem

Every company is claiming to be working in AI-ML

- ▶ Is it really so?
- ▶ What exactly is AI (ML)?
- ▶ What is not AI?

Or is it just a plain BIG hype?



What is the Core Idea?

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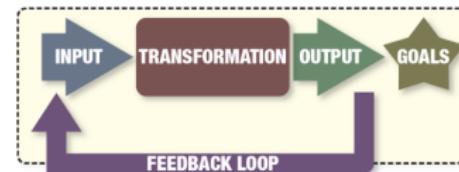
What's the core idea?

- ▶ behind problem solving?
- ▶ behind writing software algorithms?
- ▶ solving research problems?



Desire

- ▶ To find a “function”
- ▶ To find a relation
- ▶ To find a transformation
- ▶ To build a model
- ▶ From given inputs to desired outputs.
That's it.



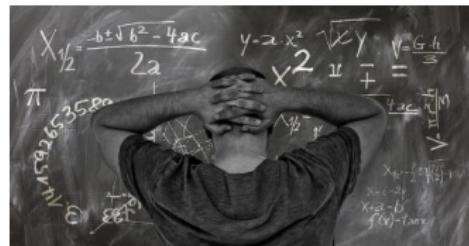
Functions

- ▶ Some functions are straight forward
- ▶ *"In summer, ice-cream sale goes up"*
- ▶ Cause and effect
- ▶ Relation (function, Mathematical model) is found out
- ▶ Here, simple rule based programming suffices



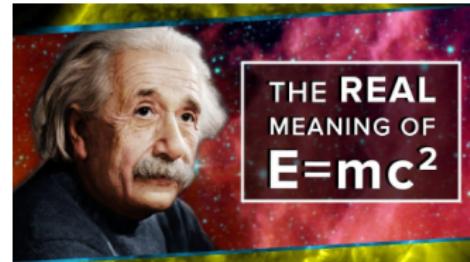
Functions

- ▶ But some functions are complex
- ▶ *"More you put efforts, your business flourishes."*
- ▶ Cause and effect again, but the relation is far too complex
- ▶ Too many variables
- ▶ Here, simple rule based programming not humanly possible.
- ▶ Lots of research needed to come up with equations.



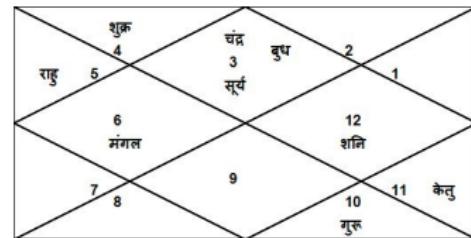
Functions

- ▶ $E = mc^2$
- ▶ What's this? a function?
- ▶ Input variable(s)?
- ▶ Output variable(s)?
- ▶ Parameters?
- ▶ How's the relation? linear?



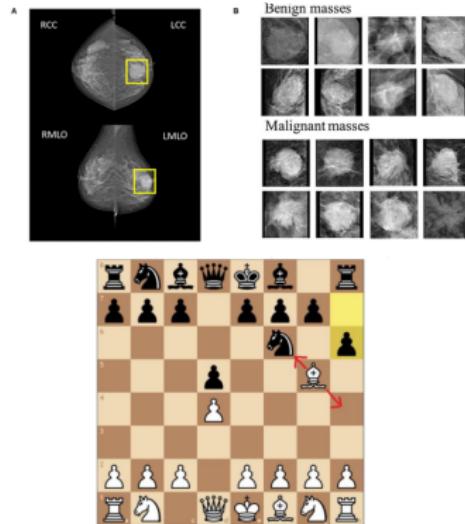
Controversial Example

- ▶ Even astrology is a model, based on the past cases.
- ▶ Could claim empirical evidence.
- ▶ Given this planetary position, it predicts.
- ▶ Represented by "Horoscope"
- ▶ Got weights for each planets (real or fictitious)
- ▶ Reliable??



Functions

- ▶ But most real-life functions are not deterministic
- ▶ Some are probabilistic, some non-linear.
- ▶ “*Detecting if the tumor is benign or malignant*”
- ▶ “*At any state in the game of chess, what's the next move?*”



Chess: next move?

- ▶ Needs extreme expertise
- ▶ Needs “intelligence”
- ▶ How do you get that?
 - ▶ Built by lots of training.
 - ▶ By studying lots of past games.
- ▶ This is how Humans build intelligence



Intelligence

- ▶ Can machine (software/program) also do the same?
- ▶ Can it play chess?
- ▶ Can it build intelligence?
- ▶ By looking at past experiences (data),
- ▶ Training Data: games played, moves used, etc.

Yes, it can!! That's Artificial Intelligence.



What is Artificial Intelligence?

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My definition

“If machines (or computer programs) start doing some/all of these “intelligent” tasks, then that’s Artificial Intelligence”



Intelligence: the differentiation

- ▶ Ability to think various domains
- ▶ Ability produce something new
- ▶ Ability to detect the unseen
- ▶ Ability to enhance knowledge (rules, patterns)



All these, AI has started doing. The AI era has arrived!!

Everyday usage

Artificial intelligence seems to have become ubiquitous.

- ▶ Replying to our emails on Gmail
- ▶ Learning how to drive our cars,
- ▶ Sorting our holiday photos.
- ▶ etc.



Too good to be true, isn't it, sort of Magical !!

But then ...

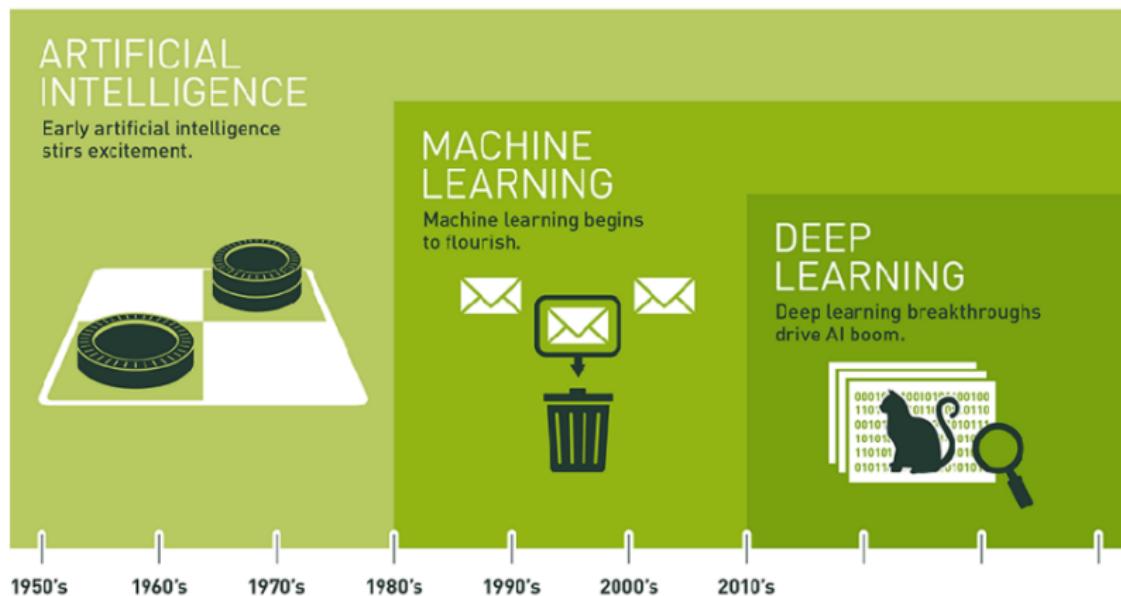
- ▶ When its too good, you start suspecting
- ▶ Is it for real!!
- ▶ How can such thing happen?
- ▶ How far will it go?



The next thing you know, people are worrying about exactly how and when AI is going to doom humanity.

AI, ML, DL ... Same?

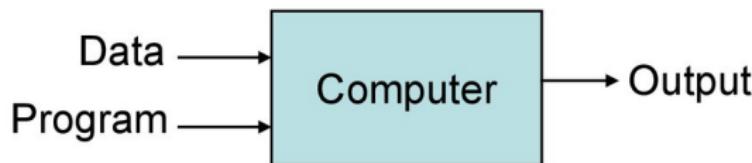
Or Relationship between them ?



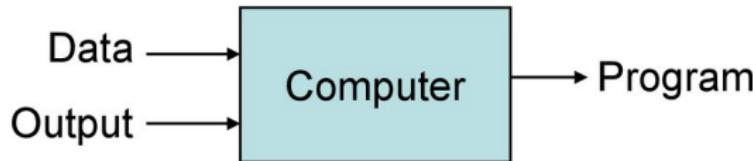
(Ref: <https://blogs.nvidia.com/blog/2016/07/29/whats-difference-artificial-intelligence-machine-learning-deep-learning-ai/>)

Traditional vs. Machine Learning?

Traditional Programming



Machine Learning



Why Machine/Deep Learning?

- ▶ Problems with High Dimensionality
- ▶ Hard/Expensive to program manually
- ▶ Techniques to model 'ANY' function given 'ENOUGH' data.
- ▶ Job \$\$\$

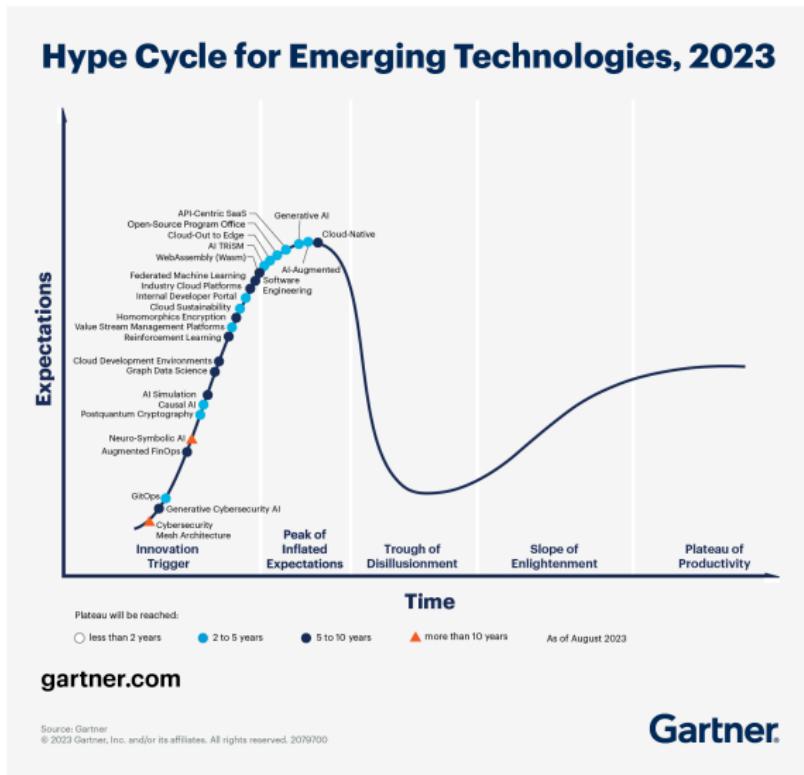


Why now?

- ▶ Flood of data (Internet, IoT)
- ▶ Increasing computational power
- ▶ Easy/free availability of algorithms
- ▶ Increasing support from industries



Gartner Hype Cycle Emerging Technologies 2023



Is AI a threat?

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Is AI a threat?

If you believe in what Elon Musk says, then YES.



Elon Musk recently commented on Twitter that artificial intelligence (AI) is more dangerous than North Korea

(Ref: What is Artificial Intelligence — Artificial Intelligence Tutorial For Beginners — Edureka)

Is AI a threat?

If you believe in these movies, then YES.



The Terminator



I, Robot



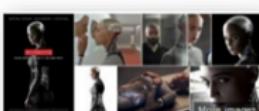
The Matrix



Tron: Legacy



War Games



Ex Machina

Well, AI based War robots are not impossible anymore.

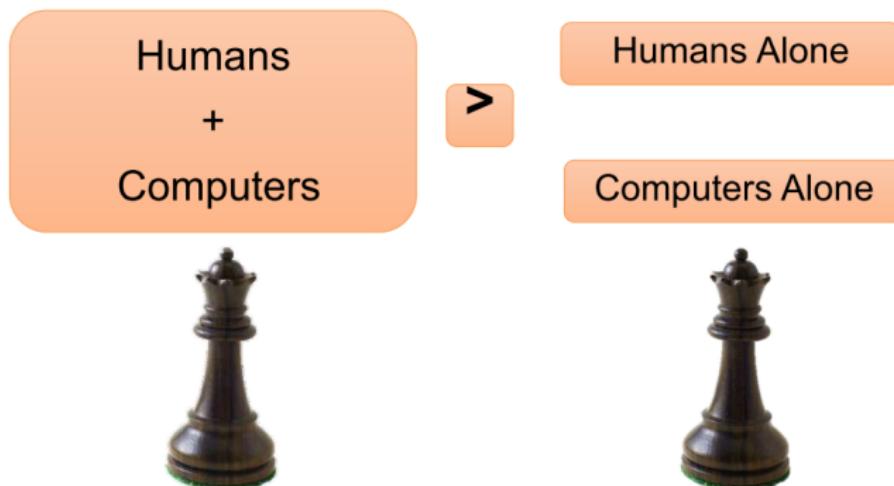
(Ref: What is Artificial Intelligence — Artificial Intelligence Tutorial For Beginners — Edureka)

Fear: Are we being replaced?

- ▶ Yes. in tasks that are repetitive
- ▶ But not which require complex thinking and creativity

Mostly

Technology Enhancing (Not Replacing) Humans



(Ref: "Artificial Intelligence Overview" - Harry Surden)

Limits on Artificial Intelligence

- ▶ Many things still beyond the realm of AI
- ▶ No thinking computers
- ▶ No Abstract Reasoning
- ▶ Often AI systems Have Accuracy Limits
- ▶ Many things difficult to capture in data
- ▶ Sometimes Hard to interpret Systems

Introduction to Generative AI

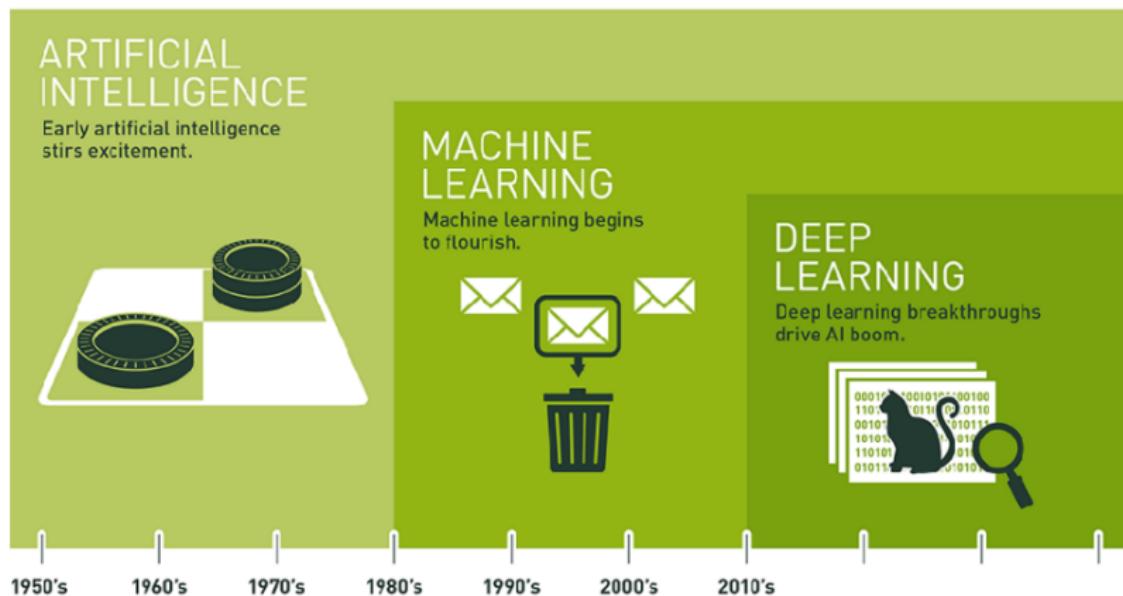
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Introduction

- ▶ What is Generative AI?
- ▶ What is not Generative AI?
- ▶ How is it related to AI-ML-DL?

Relationship between AI, ML, DL

First, let's see what's AI-ML-DL and relationship among them.



(Ref: <https://blogs.nvidia.com/blog/2016/07/29/whats-difference-artificial-intelligence-machine-learning-deep-learning-ai/>)

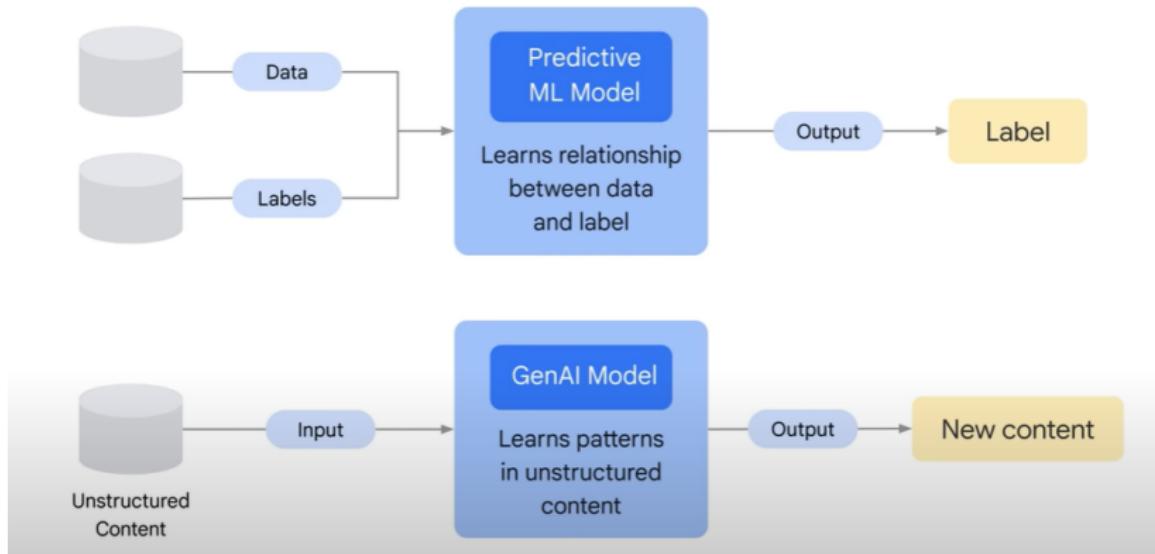
What is Gen AI wrt AI, ML, DL

Generative AI
is a **subset** of
Deep Learning



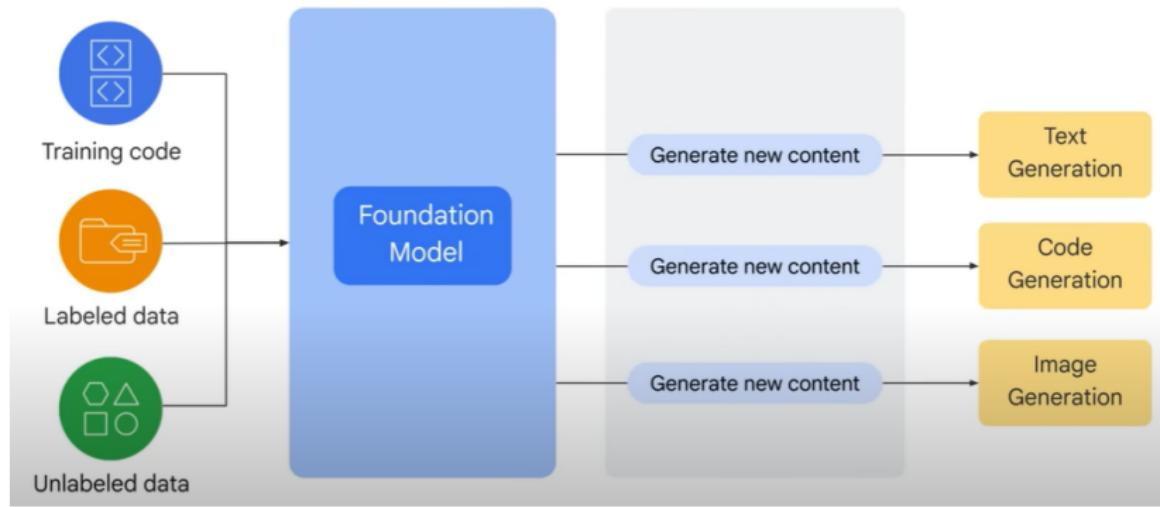
(Ref: Introduction to Generative AI - Google Cloud Tech)

Types of Approaches



(Ref: Introduction to Generative AI - Google Cloud Tech)

What is Foundation Model?



(Ref: Introduction to Generative AI - Google Cloud Tech)

Same Problem, using different Technologies

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Difference across technologies, old to new

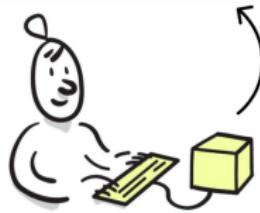
Lets see how the solutions to the problem of detecting a cat from images using traditional programming, deep learning, and generative AI, respectively.



Traditional Programming

- ▶ Traditional programming involves writing explicit rules to detect a cat in images.
- ▶ Features like color, texture, and shape can be used to define these rules.
- ▶ However, designing accurate rules for complex patterns like cat detection can be challenging.
- ▶ It requires extensive domain knowledge and might not generalize well to different images.

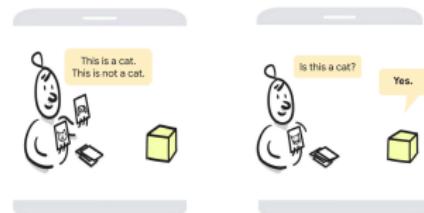
```
cat:  
  type: animal  
  legs: 4  
  ears: 2  
  fur: yes  
  likes: yarn, catnip
```



(Ref: Primer on LLM and Gen AI - Google Cloud)

Deep Learning

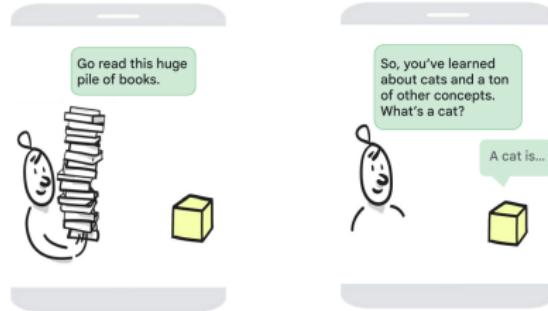
- ▶ Deep learning utilizes neural networks to automatically learn features for cat detection.
- ▶ Convolutional Neural Networks (CNNs) are particularly effective for image classification tasks.
- ▶ Large labeled datasets of cat images are used to train the network.
- ▶ The network learns to identify unique cat features and generalize them to detect cats in new images.
- ▶ Deep learning offers better accuracy and can handle complex patterns without explicit rule definition.



(Ref: Primer on LLM and Gen AI - Google Cloud)

Generative AI

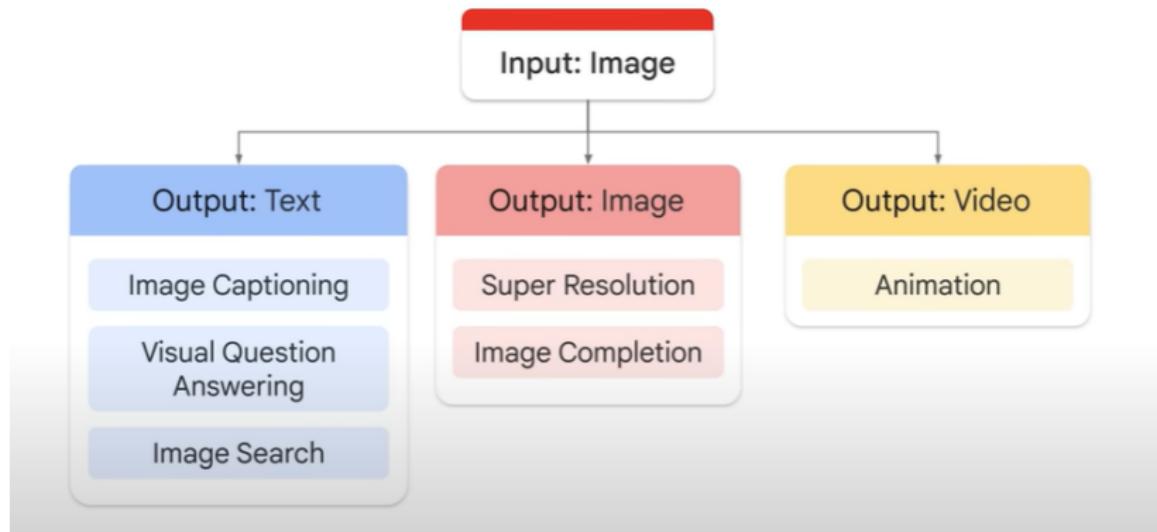
- ▶ Generative AI focuses on generating new data, including images of cats.
- ▶ Generative Adversarial Networks (GANs) are used to generate realistic cat images.
- ▶ The GAN consists of a generator and a discriminator that compete against each other.
- ▶ The generator learns to generate increasingly realistic cat images, while the discriminator learns to distinguish real from generated images.
- ▶ The generated cat images can be used to augment datasets for cat detection models.



(Ref: Primer on LLM and Gen AI - Google Cloud)

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Modalities in Generative AI

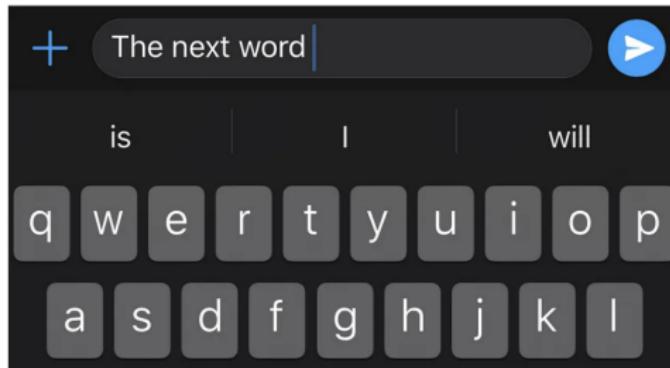


(Ref: Introduction to Generative AI - Google Cloud Tech)

Let's focus on the most popular modality ...

What is a Language Models?

- ▶ While typing SMS, have you seen it suggests next word?
- ▶ While typing email, have you seen next few words are suggested?
- ▶ How does it suggest? (suggestions are not random, right?)
- ▶ In the past, for “Lets go for a . . .”, if you have typed ‘coffee’ 15 times, ‘movie’ say 4 times, then it learns that. Machine/Statistical Learning.
- ▶ Next time, when you type “Lets go for a ”, what will be suggested? why?
- ▶ This is called Language Model. Predicting the next word. When done continuously, one after other, it spits sentence, called Generative Model.



Next word prediction using language modeling in keyboards(Mandar Deshpande)

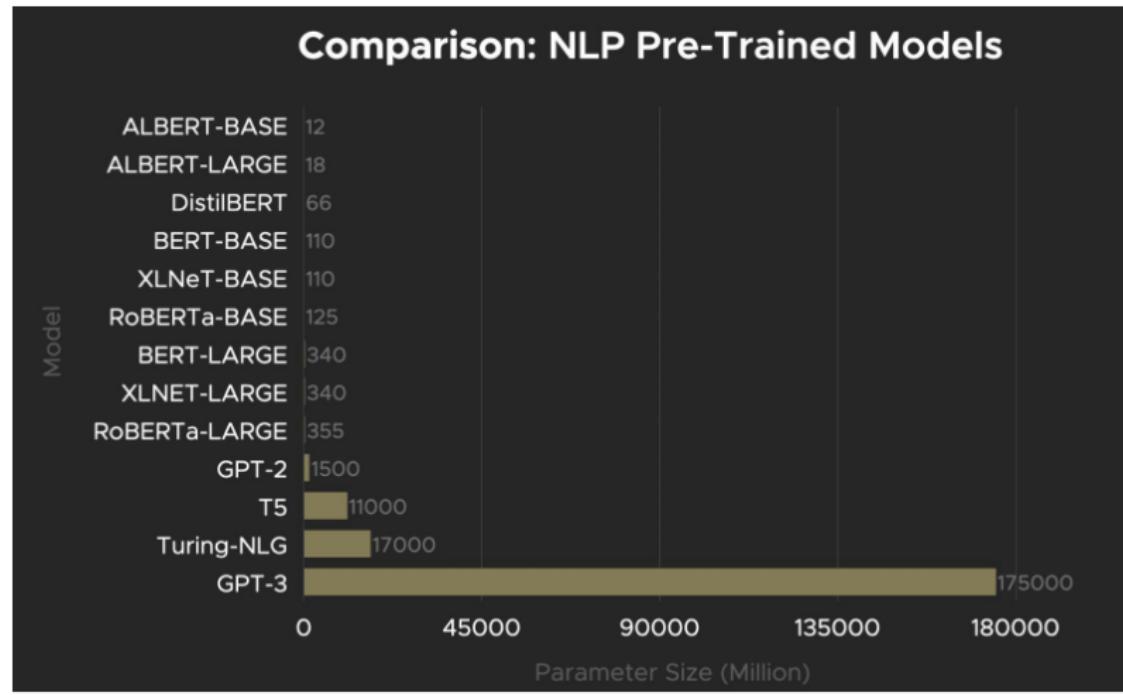
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Why they are called Large? Corpus

GPT: Generative Pre-trained Transformers

- ▶ GPT-1 is pre-trained on the BooksCorpus dataset, containing 7000 books amounting to 5GB of data
- ▶ GPT-2 is pre-trained using the WebText dataset which is a more diverse set of internet data containing 8M documents for about 40 GB of data
- ▶ GPT-3 uses an expanded version of the WebText dataset, two internet-based books corpora that are not disclosed and the English-language Wikipedia which constituted 600 GB of data

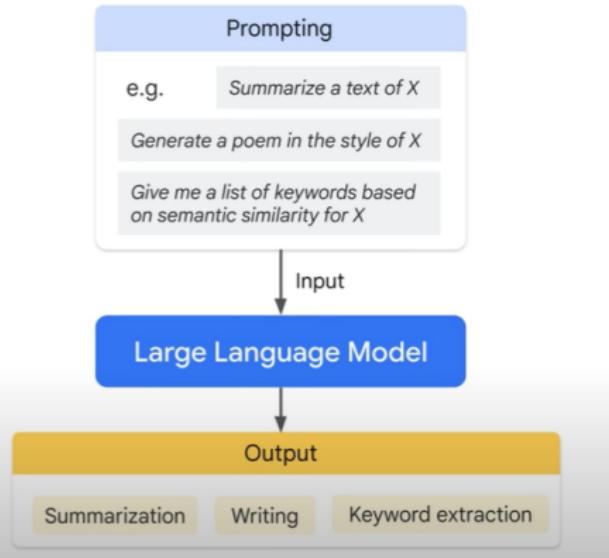
Why they are called Large? Parameters



(Ref: Deus.ai <https://www.deus.ai/post/gpt-3-what-is-all-the-excitement-about>)

Prompts driving Generative AI

Prompt Design:
the quality of the
input **determines** the
quality of the output.



(Ref: Introduction to Generative AI - Google Cloud Tech)

Thermal Engineering: AC Tonnage Calculation

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Basic

Calculate the air conditioning (AC) tonnage required for a small residential house.



Basic

Prompt: Calculate the air conditioning (AC) tonnage required for a small residential house.

Assistant response (simple, rule-of-thumb):

Use a common thumb-rule: *about 1 ton of cooling capacity per 400–600 (ft^2)*, depending on climate and building quality. Steps (concise):

- ▶ Measure conditioned floor area (ft^2).
- ▶ Choose a rule factor: use 1 ton for 500 (ft^2) as a neutral starting point.
- ▶ Divide area by the chosen factor and round up to the nearest 0.5 ton to provide margin.

Quick example: 1200 (ft^2) house → → $1200 / 500 = 2.4 \rightarrow$ choose 2.5 or 3.0 tons depending on climate (2.5 for moderate, 3.0 for hotter/humid).

Note: This is a high-level estimate. Final selection should consider insulation, windows, orientation, occupancy, and internal gains.

Adding Roles

As a HVAC engineer, explain to a junior student how to estimate the AC tonnage required for a residential house.



Adding Roles

Prompt: As a HVAC engineer, explain to a junior student how to estimate the AC tonnage required for a residential house.

Assistant response (mentoring tone, stepwise):

Measure and list inputs: conditioned floor area, ceiling height (standard 8 ft; if higher, note it), number and type of windows, wall/attic insulation quality, typical occupancy, major heat-producing appliances, and climate (warm/humid vs temperate).

Pick a baseline rule: start with 1 ton per 500ft^2 for a conservative neutral case.

Adjust qualitatively:

- ▶ Poor insulation or many west/south windows → increase capacity.
- ▶ Well insulated, shaded, or cooler climate → reduce slightly.
- ▶ High occupancy/appliances or south-facing glass → add margin.

Round and select equipment: round the calculated value up to the next common size (e.g., 2.5, 3.0 tons). Explain trade-offs: oversizing reduces dehumidification and can increase cycling; undersizing reduces comfort.

Document assumptions: write down the rule used and all qualitative adjustments so the estimate can be checked later.



Adding Constraints

Estimate the AC tonnage using simple thumb rules only. Do not use detailed equations or advanced heat load software.

Adding Constraints

Prompt: Estimate the AC tonnage using simple thumb rules only. Do not use detailed equations or advanced heat load software.

Assistant response (constrained, practical):

1. **Baseline factor:** use 1 ton per 500 (ft^2) for typical homes with average insulation.
2. **Simple modifiers (apply qualitatively):**
 - ▶ +20% capacity for poor insulation or many sun-exposed windows.
 - ▶ -10 – 15% for excellent insulation and heavy shading.
 - ▶ +0.5 ton if household often has 4+ occupants or many heat-generating appliances.
3. **Procedure:** compute base tons = area / 500, then adjust by one of the simple modifiers, finally round up to nearest 0.5 ton.

Constrained example (no equations beyond division): For a 1,200 ft^2 house with average insulation: $base = 1200 / 500 = 2.4 \rightarrow$ round up $\rightarrow 2.5$ ton. If insulation is poor, add 20%: $2.4 \times 1.2 = 2.88 \rightarrow$ round up $\rightarrow 3.0$ ton.

Adding Examples

Provide two example cases:

Example 1: A 1000 sq.ft. house with average insulation.

Example 2: A 1500 sq.ft. house with poor insulation.

Adding Examples

Prompt: Provide two example cases: Example 1: A 1000 sq.ft. house with average insulation. Example 2: A 1500 sq.ft. house with poor insulation.

Assistant response (worked examples, step-by-step arithmetic):

Rule used: 1 ton per 500 (ft^2) baseline. Poor insulation $\rightarrow +20\%$ capacity.

Example 1 - 1000(ft^2), average insulation:

- ▶ Base = $1000 / 500 = 2.0$ tons.
- ▶ No upward adjustment (average insulation).
- ▶ **Select 2.0 tons** (or 2.5 tons if you want extra margin in hot climates).

Example 2 - 1500 $f(f^2)$, poor insulation:

- ▶ Base = $1500 / 500 = 3.0$ tons.
- ▶ Apply poor-insulation modifier: $3.0 \times 1.20 = 3.6$ tons.
- ▶ Round up to common size \rightarrow **Select 4.0 tons** (3.5 might be available; 4.0 gives conservative margin).

Practical note: When capacity after adjustment is close to a common nominal size (e.g., 3.6 \rightarrow 3.5 or 4.0), consider climate and humidity: pick the larger if high humidity or frequent heat waves are expected.



Adding Contextual Information

You are designing HVAC for a middle-income residential building in a warm climate. Explain how you would estimate AC tonnage for one apartment.

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Incorporating Feedback

The homeowner reports that previous AC units felt insufficient during peak summer. Improve the tonnage estimation by considering practical real-world factors.



Time Constraints and Prioritization

Estimate the required AC tonnage quickly for an urgent site visit. Focus only on the most influential factors.



Incorporating Multidisciplinary Knowledge

Include effects from building orientation, sunlight exposure, occupancy, and electrical appliance heat gains while keeping the explanation simple and non-mathematical.

Addressing Regional and Climate Factors

Modify the tonnage estimation method for hot-humid, hot-dry, and moderate climate conditions.

Reflection and Iteration

Reflect on the estimation process and suggest how it could be improved for better comfort and energy efficiency.

Self-Criticism

Estimate the AC tonnage for a house. Then re-read your method, identify possible errors or oversimplifications, and refine it.

Chain-of-Thought

Estimate the AC tonnage required for a house. Let's think step by step from room size, heat gains, and climate to the final tonnage.



Self-Consistency

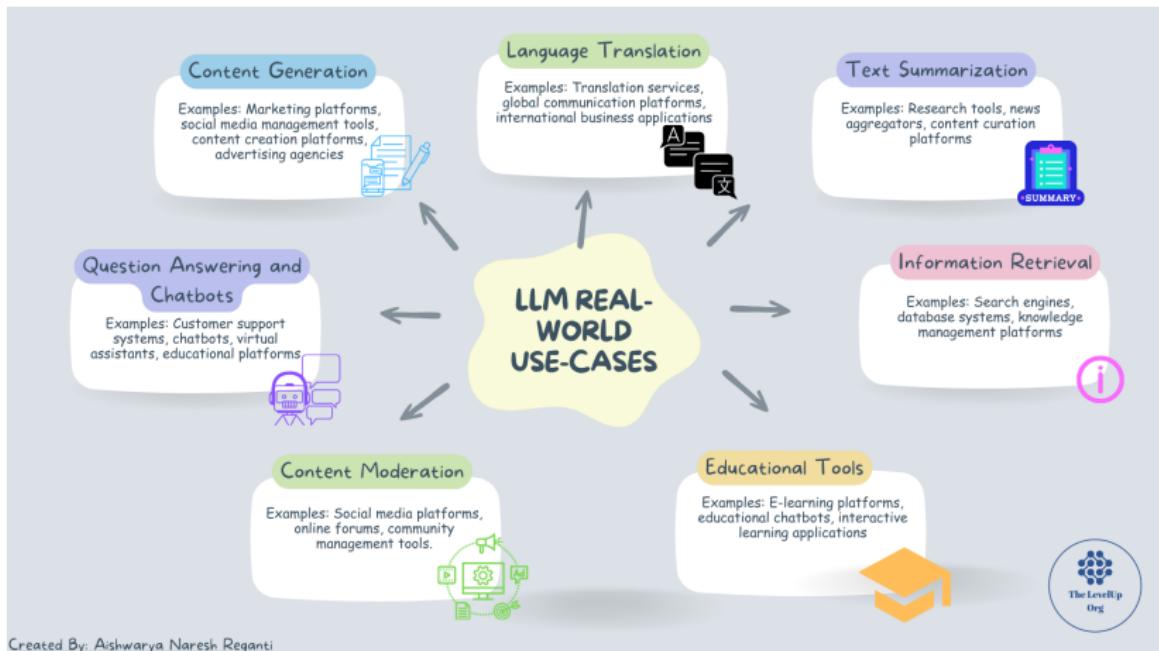
Here are three estimation methods for AC tonnage: Method A (area-based rule), Method B (volume-based rule), Method C (experience-based rule). Combine them into one consistent guideline.

Conclusions

(Ref: 2023 Kaggle AI Report on Generative AI, by Trushant Kalyanpur)



LLM Real World Use Cases



Created By: Aishwarya Naresh Reganti

(Ref: Applied LLMs Mastery 2024 - Aishwarya Reganti)



Advancements in Text-to-Image Generative AI

- ▶ Notable models: DALL-E/DALL-E 2, Midjourney, Stable Diffusion
- ▶ Creative expression, streamlined design
- ▶ Realistic, high-quality image generation
- ▶ Concerns: misuse, ethical implications
- ▶ Deepfakes, synthetic media for misinformation
- ▶ Risk of generating illegal, toxic content
- ▶ Challenges in ethical responsibility, moderation

Copilots: Revolutionizing Coding

- ▶ AI assistance for software developers
- ▶ 92% programmers use AI tools (Github survey)
- ▶ Copilot users 55% faster in project completion
- ▶ Potential \$1.5 trillion GDP boost (productivity study)
- ▶ AI tools like Copilot enhance speed, efficiency
- ▶ Fewer errors in coding processes

Industry Giants' Role in Text Generative AI

- ▶ Google, Meta, OpenAI - Pivotal contributions
- ▶ PaLM, Galactica, ChatGPT, GPT4 releases
- ▶ ChatGPT: Turning point in Text Generative AI
- ▶ LLMs for content creation, writing, storytelling
- ▶ Analyzing, organizing large textual data
- ▶ Efficient search engines, knowledge systems



Advancements in LLM Accessibility

- ▶ Meta's LLaMa: Open-source alternatives to ChatGPT
- ▶ Google's Bard: AI chatbot response to ChatGPT
- ▶ QLoRA: Fine-tuning LLMs on consumer GPUs
- ▶ Broadening access to advanced technology
- ▶ LLMs empower diverse applications
- ▶ LLMs: Bridging the gap between innovation and accessibility



References

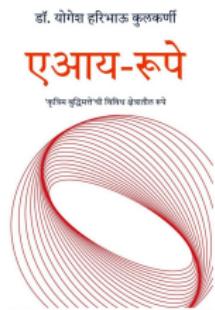
- ▶ Introduction to Generative AI - Google Cloud Tech
- ▶ Generative AI Presentation - Laura Worden

Newsletters to subscribe

- ▶ **The Batch by DeepLearning.AI:**
 - ▶ Summarizes diverse AI news with nuanced viewpoints.
 - ▶ Andrew Ng's thought leadership adds significant value.
- ▶ **The Rundown AI by Rowan Cheung:**
 - ▶ Go-to for generative AI events and product innovations.
 - ▶ Quick rundown with bullet point details for easy comprehension.
- ▶ **AI Supremacy by Michael Spencer:**
 - ▶ Personal writing style with in-depth exploration.
 - ▶ Offers multiple perspectives on AI topics.
- ▶ **Ahead of AI by Sebastian Raschka, PhD:**
 - ▶ Technical focus covering applied deep learning and generative AI.
 - ▶ Valuable insights for those seeking in-depth technical content.
- ▶ **To Data and Beyond by Youssef Hosni:**
 - ▶ Resource hub for hands-on projects, learning roadmaps, and research papers.
 - ▶ Ideal for those looking to dive into practical aspects of AI.



My First Book: AI-Rupe (Marathi)



Flipkart India



Amazon India



Notion Press

Pune AI Community (PAIC)

- ▶ Two-way communication:
 - ▶ Website puneaicommunity dot org
 - ▶ Email puneaicommunity at gmail dot com
 - ▶ Call + 9 1 9 8 9 0 2 5 1 4 0 6
 - ▶ LinkedIn:
<https://linkedin.com/company/pune-ai-community>
- ▶ One-way Announcements:
 - ▶ Twitter (X) @puneaicommunity
 - ▶ Instagram @puneaicommunity
 - ▶ WhatsApp Community: Invitation Link
<https://chat.whatsapp.com/LluOrhyEzuQLDr25ixZ>
 - ▶ Luma Event Calendar: puneaicommunity
- ▶ Contribution Channels:
 - ▶ GitHub: Pune-AI-Community and puneaicommunity
 - ▶ Medium: pune-ai-community
 - ▶ YouTube: @puneaicommunity



Website

Pune AI Community (PAIC) QR codes



Website



Medium Blogs



Twitter-X



LinkedIn Page



Github Repository



WhatsApp Invite



Luma Events



YouTube Videos



Instagram



Thanks ...

- ▶ Office Hours: Saturdays, 3 to 5 pm (IST);
Free-Open to all; email for appointment to
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(<https://www.github.com/yogeshhk/>)

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