Introduction to Generative AI

Yogesh Haribhau Kulkarni

Outline

1. Overview
2. Implementations
3. Frameworks
4. Applications
5. Conclusions
6. Preparation
7. References

About Me

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

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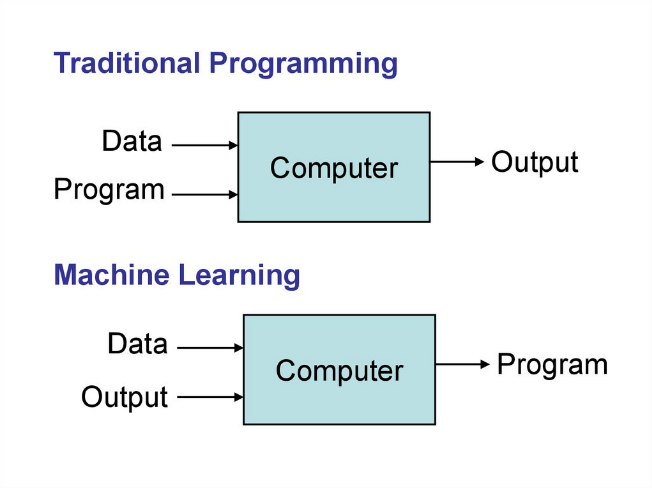
Introduction to Generative AI

Introduction

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

Traditional vs. Machine Learning?

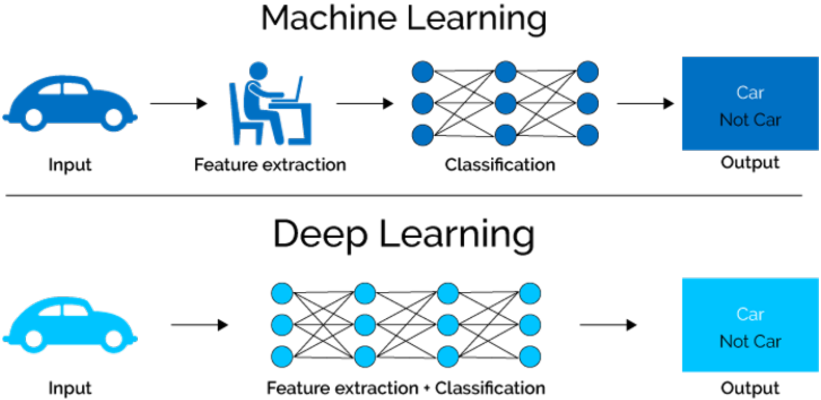


Why Machine Learning?

- Problems with High Dimensionality
- Hard/Expensive to program manually
- Job $$$

ML vs DL: What's the difference?

Deep learning algorithms attempt to learn (multiple levels of) representation by using a hierarchy of multiple layers



(Reference: https://www.xenonstack.com/blog/static/public/uploads/media/machine-learning-vs-deep-learning.png)

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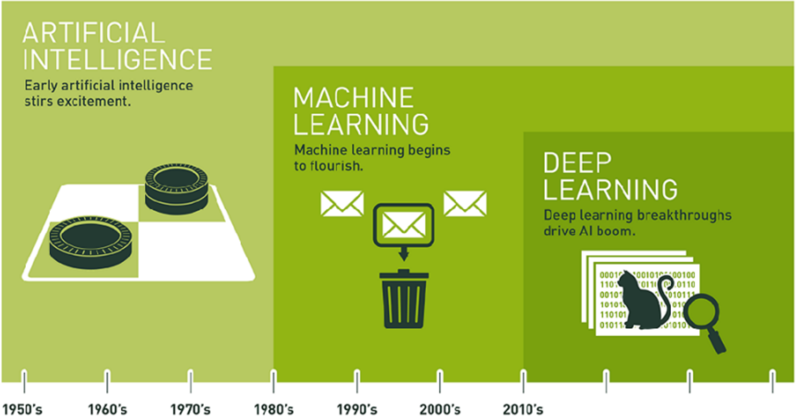
Use Deep Learning When . . .

- You have lots of data (about 10k+ examples)
- The problem is "complex" - speech, vision, natural language
- The data is unstructured
- Techniques to model 'ANY' function given 'ENOUGH' data.

(Ref: Introduction to TensorFlow 2.0 - Brad Miro)

Relationship between AI, ML, DL

First, lets see whats 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/)

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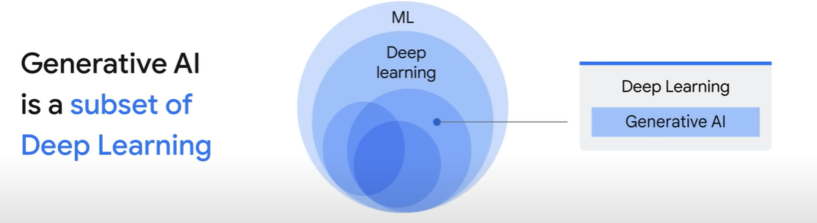
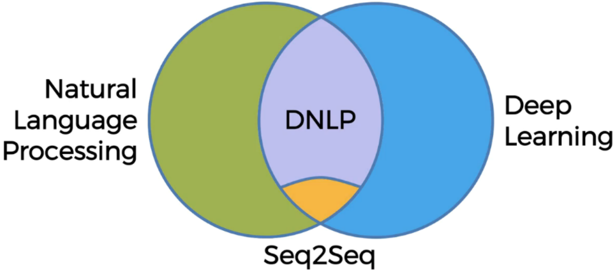
What is Gen AI wrt AI, ML, DL



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

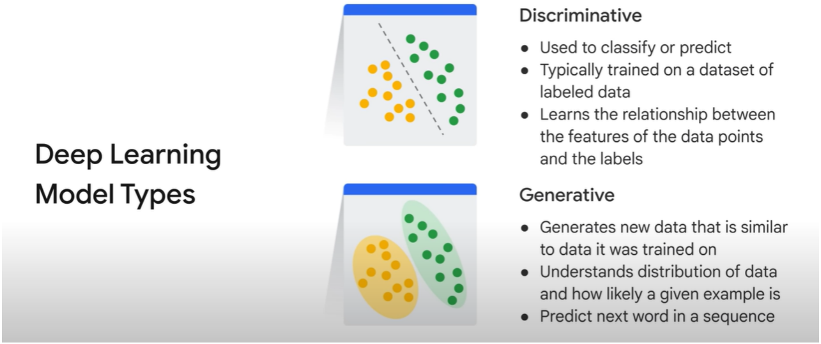
What is Deep NLP



(Ref: Deep Learning and NLP A-Z - Kirill Eremenko)
(Note: Size is not indicative of importance)

Seq2Seq is heavily used technique of DNLP for sequence to sequence modeling, eg Translation, Q & A, etc. Thats the basis of Large Language Models (LLMs)

Types of Approaches



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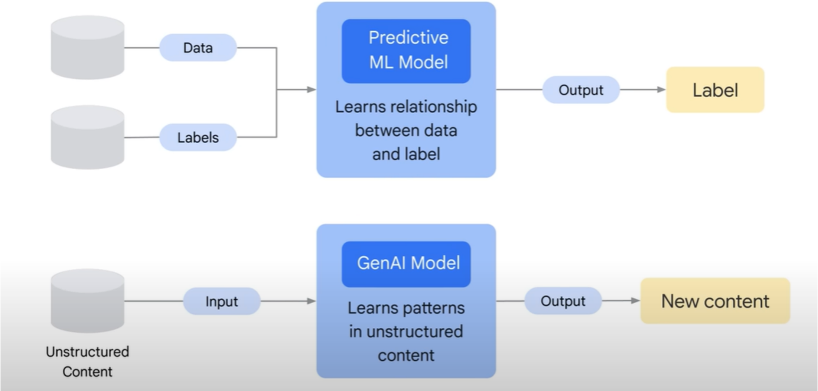
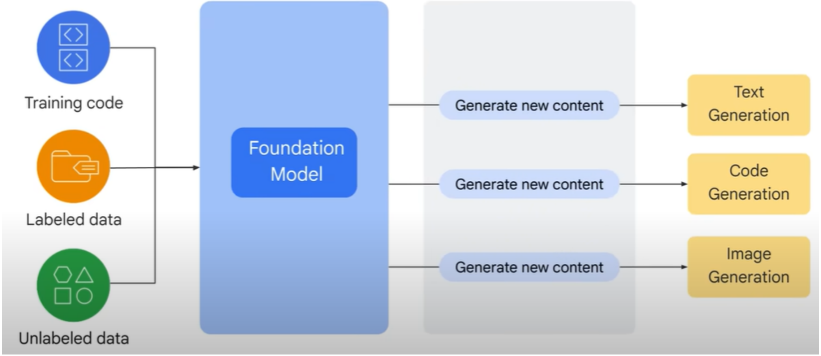
Types of Approaches



(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

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.

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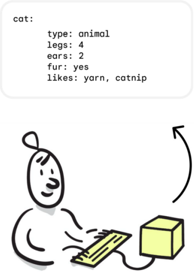
Traditional Programming

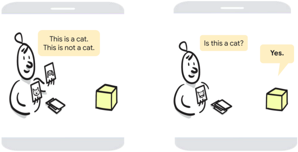
- Traditional programming involves writing explicit rules to detect a cat in images.
- Features like color, texture, and shape can be used to define these rules.
- However, designing accurate rules for complex patterns like cat detection can be challenging.
- It requires extensive domain knowledge and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



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

Deep Learning

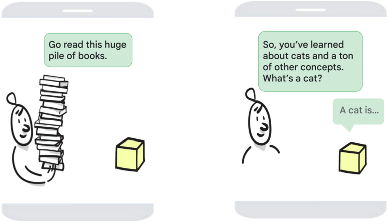
- Deep learning utilizes neural networks to automatically learn features for cat detection.
- Convolutional Neural Networks (CNNs) are particularly effective for image classification tasks.
- Large labeled datasets of cat images are used to train the network.
- The network learns to identify unique cat 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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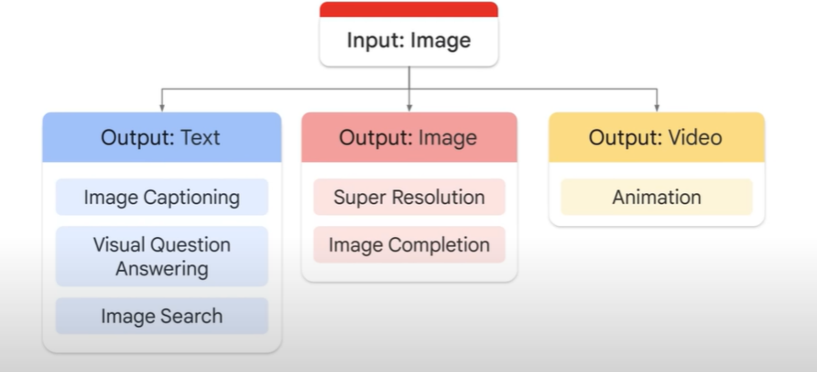
Modalities in Generative AI

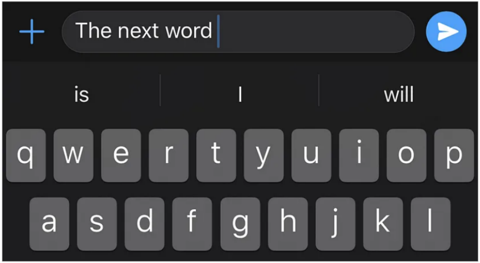


(Ref: Introduction to Generative AI - Google Cloud Tech)

Let's foucs 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.



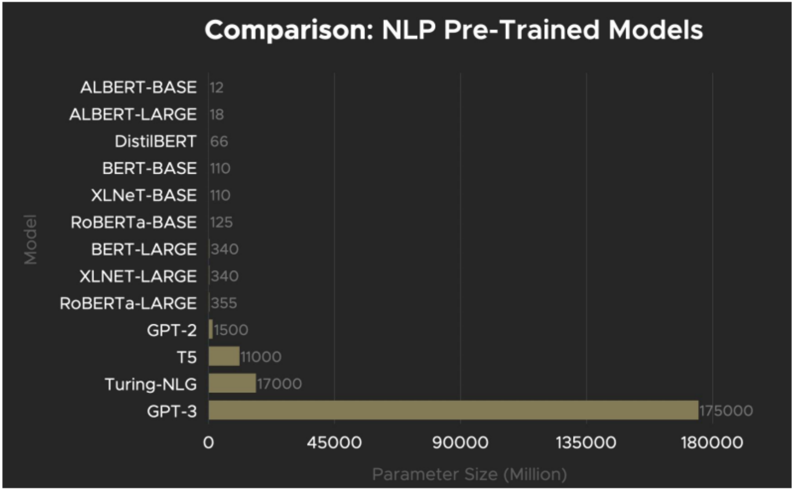
Next word prediction using language modeling in keyboards(Mandar Deshpande)

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

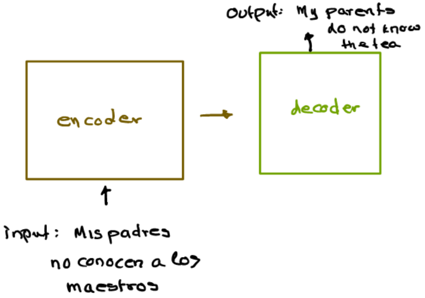
Why they are called Large? Parameters



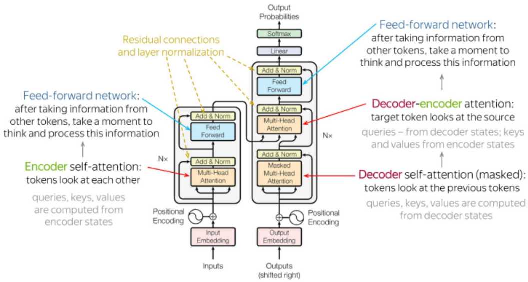
(Ref: Deus.ai https://www.deus.ai/post/gpt-3-what-is-all-the-excitement-about)

Underlying Architecture: Transformers

- In its heart it contains an encoding component, a decoding component, and connections between them.
- The Transformer is a model that uses attention to boost the speed with which seq2seq with attention models can be trained.
- The biggest benefit, however, comes from how The Transformer lends itself to parallelization. How?



Transformer Models

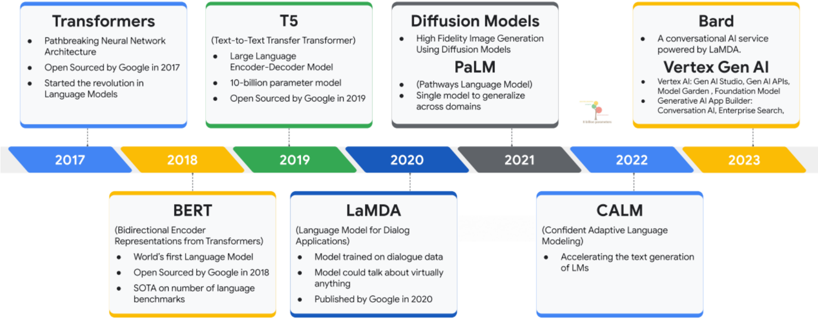


(Ref: The Complete Prompt Engineering for AI Bootcamp (2023))

- No recurrence, so parallelization possible
- Context information captured via attention and positional encodings
- Consists of stacks of layers with various sublayers

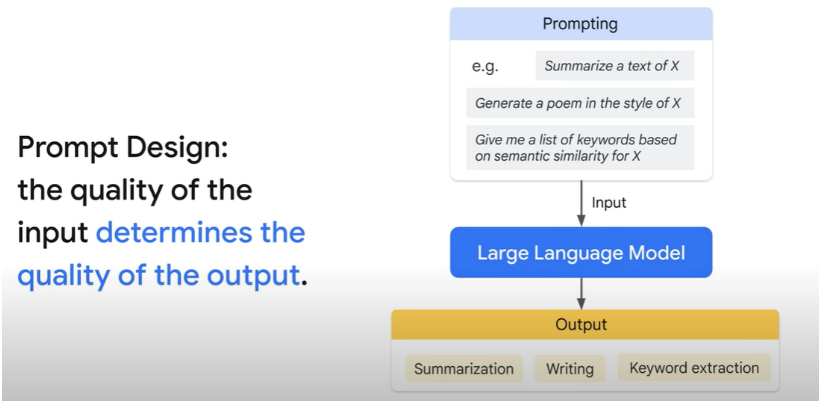
Transformers are basis of (the most) Large Language Models

The Progress of Models . . .



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

Prompts driving Generative AI

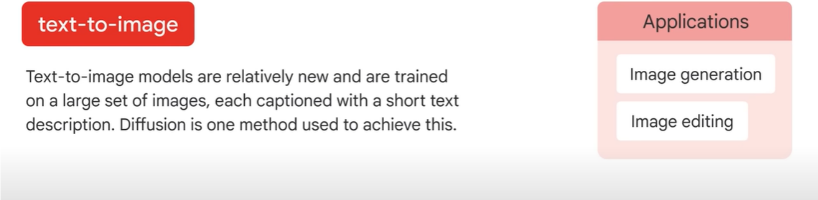


(Ref: Introduction to Generative AI - Google Cloud Tech)

Model Types

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

Model Types



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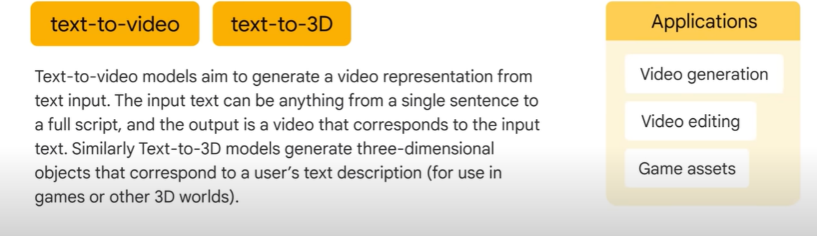

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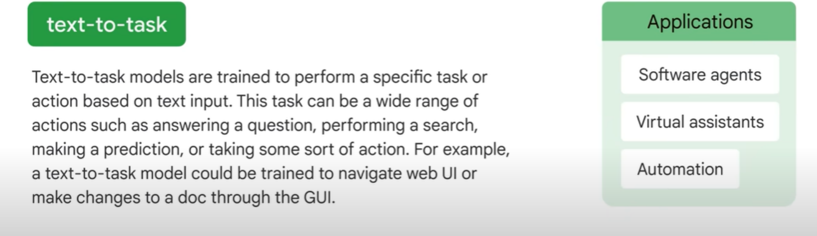
Model Types



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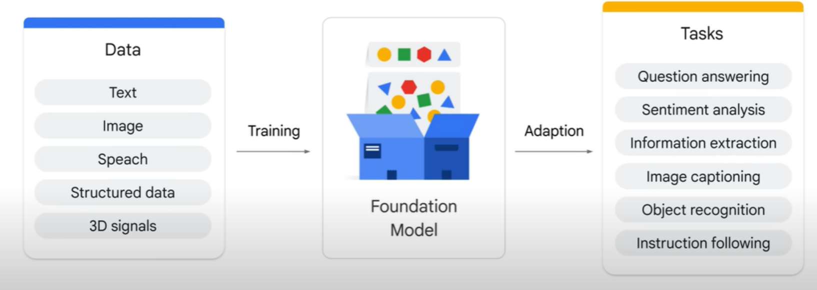
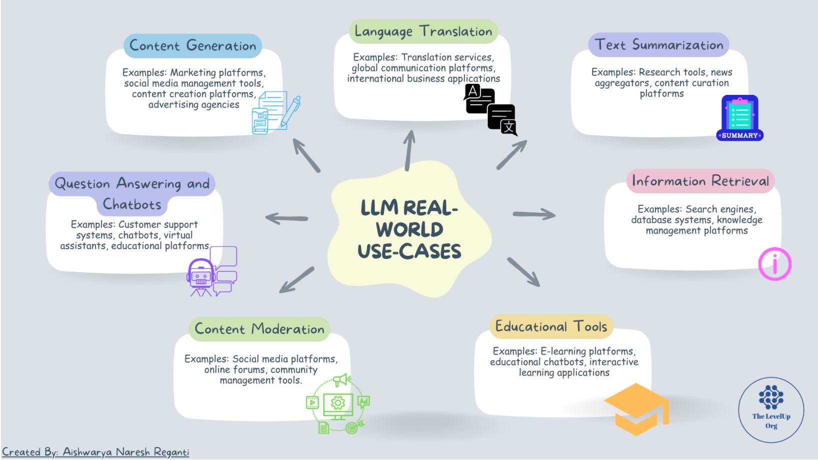
Model Types

Foundation Model:



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

LLM Real World Use Cases



(Ref: Applied LLMs Mastery 2024 - Aishwarya Reganti)

LLM Challenges

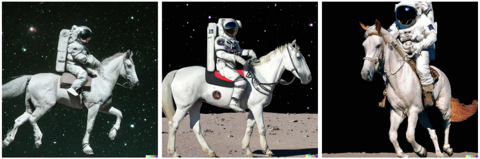
(Ref: Applied LLMs Mastery 2024 - Aishwarya Reganti)

What's IN these days . . .

2021: Dall-E

Zero-Shot Text-to-Image Generation

- OpenAI's 2021 release: DALL-E
- Text-to-image generation model
- Implementation of GPT-3
- Generates images from text descriptions
- Utilizes text-image dataset



"An astronaut riding a horse in a photorealistic style." Credit: OpenAI

(Ref: Example prompt "An astronaut riding a horse in photorealistic style" using DALL-E: Open AI)

ChatGPT - A Tipping Point for Generative AI

- Released by OpenAI in November 2022
- Generative AI chatbot
- Rapid worldwide popularity
- 1 million users in 5 days
- Netflix took 3.5 years for same user count
- 100 million monthly active users by January 2023
- Fastest-growing application in history

What's Inside?

Technical Details

- Based on GPT3.5 Instruct architecture
- Estimated 175 billion parameters
- Fine-tuned on chat-specific task
- Curated dataset for fine-tuning

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Improving ChatGPT with RLHF

- Key technique: Reinforcement Learning from Human Feedback (RLHF)
- Trains language model to align with human preferences
- Collects human feedback on model-generated text
- Updates model's parameters using feedback
- Enhances ChatGPT responses' quality
- Increases factual, informative, and creative output

Midjourney: Image Generation Model

- Developed by Midjourney Inc.
- Released in July 2022
- Architecture details undisclosed
- High-quality image generation
- Wide variety of styles and genres

Meta Releases LLaMA

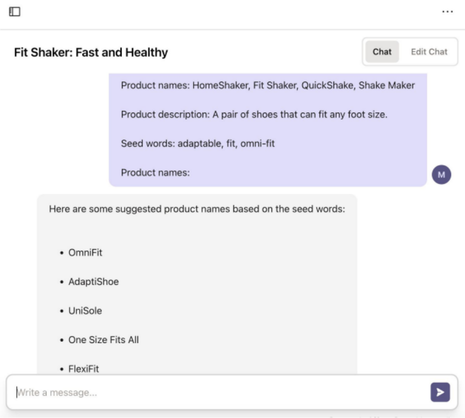
Open Source LLMs Explode!

- February 2023: Meta releases LLM "LLaMA"
- LLaMA: 65-billion parameter model
- Trained on extensive text and code dataset

Significance of LLaMA Release

- One of the largest public LLMs
- Suited for complex and challenging tasks
- Open source, initially for research purposes
- Model weights leaked online, accessible to all
- Sparked development of numerous open source LLMs

Anthropic Claude



(Ref: The Complete Prompt Engineering for AI Bootcamp (2023))

- Uses Constitutional AI rather than RLHF
- Constitutional AI trains to follow a set of high-level principles or rules, such as a constitution, that specify the desired behavior and outcomes of the system.
- RLHF uses human feedback, such as ratings, preferences, or corrections, to optimize a language model or an agent's policy using reinforcement learning

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Google is not behind

Google Releases Bard

- March 2023: Google introduces Bard chatbot
- Built on LLM framework
- Fine-tuned model based on PaLM 2
- PaLM 2: Around 340 billion parameters
- Bard trained on dataset 10 times larger than ChatGPT

Bard's Unique Features

- Access to the internet
- Continuous learning and knowledge update
- More up-to-date and accurate than ChatGPT
- ChatGPT limited to training dataset info
- Bard surpasses ChatGPT's knowledge scope

Domain and Task Adaptation

(Ref: Applied LLMs Mastery 2024 - Aishwarya Reganti)

Using LLMs Effectively

- General AI models like ChatGPT excel in diverse text generation but may lack depth for specific domains.
- They might generate inaccurate or contextually inappropriate content, known as hallucinations.
- Task-specific and domain-specific LLMs are crucial for specialized domains, possessing industry-specific knowledge.
- Domain-specific LLMs ensure accurate interpretation of specialized terminology and practices.

Benefits of Domain-specific LLMs

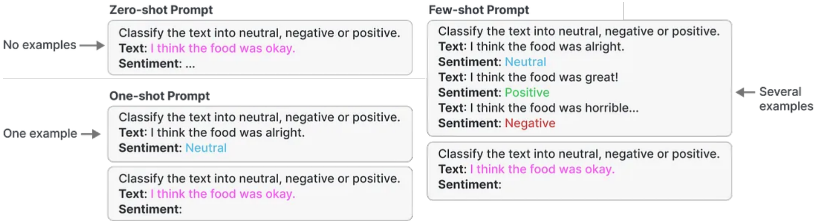
- Depth and Precision: Tailored for understanding industry-specific terminology, ensuring precision.
- Overcoming Limitations: Excel in accuracy and context relevance, overcoming general LLM limitations.
- Enhanced User Experiences: Provide tailored and personalized responses for better user experiences.
- Improved Efficiency: Streamline operations, automate tasks, and boost productivity for businesses.
- Addressing Privacy Concerns: Ensure data protection and privacy adherence in sensitive industries.

Methods

- Few Shots prompting
- Retrieval Augmented Generation
- Domain Specific pre-training (ie full, from scratch on own data)
- Domain Specific fine-tuning (with change in weights or additional adopter weights)

(Ref: 3 Easy Methods For Improving Your Large Language Model - Towards Data Science - Maarten Grootendorst)

Prompt Engineering



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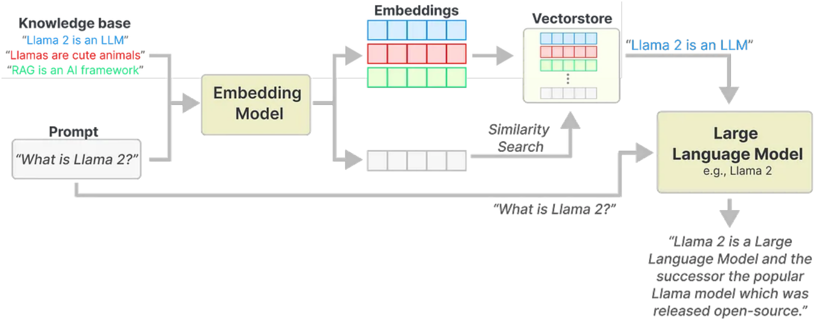
Retrieval Augmented Generation (RAG)



(Ref: 3 Easy Methods For Improving Your Large Language Model - Towards Data Science - Maarten Grootendorst)

Retrieval Augmented Generation (RAG)

- Training Duration: Not required.
- No model weights; relies on external information retrieval system.
- External knowledge provided as context in the prompt.
- Advantages: No training costs, low expertise requirement, and easy updating of knowledge base.

Retrieval Augmented Generation (RAG)

- **Definition:** Enhances LLM-generated responses by incorporating up-to-date and contextually relevant information from external sources.
- Addresses inconsistency and lack of domain-specific knowledge in LLMs, reducing hallucinations.
- **Two Phases:**
  1. Retrieval: Searches and retrieves relevant external information.
  2. Content Generation: LLM synthesizes an answer based on retrieved information and internal training data.
- **Fundamental RAG Pipeline:**
  1. Ingestion: Documents segmented into chunks, embeddings generated, and stored in an index.
  2. Retrieval: System retrieves top-k documents based on embedding similarity.
  3. Synthesis: LLM utilizes contextual knowledge from chunks to formulate accurate responses.
- **No Training Requirement:** Unlike previous domain adaptation methods, RAG doesn't require model training when specific domain data is provided.

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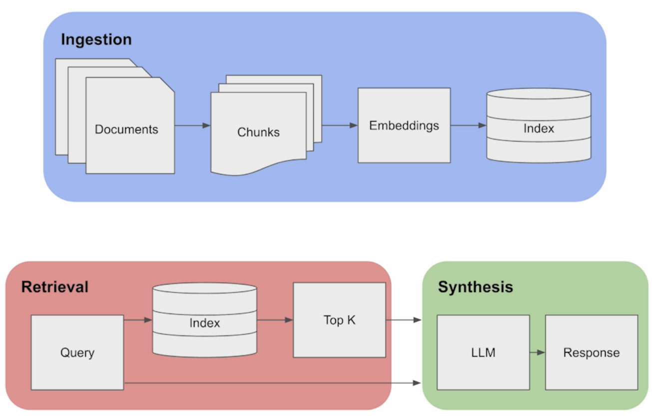
Retrieval Augmented Generation (RAG)



(Ref: Applied LLMs Mastery 2024 - Aishwarya Reganti)

Retrieval Augmented Generation (RAG)

Advantages of RAG	Disadvantages of RAG
Information Freshness: RAG addresses the static nature of LLMs by providing up-to-date or context-specific data from an external database.	Complex Implementation (Multiple moving parts): Implementing RAG may involve creating a vector database, embedding models, search index etc. The performance of RAG depends on the individual performance of all these components
Domain-Specific Knowledge: RAG supplements LLMs with domain-specific knowledge by fetching relevant results from a vector database	Increased Latency: The retrieval step in RAG involves searching through databases, which may introduce latency in generating responses compared to models that don't rely on external sources.
Reduced Hallucination and Citations: RAG reduces the likelihood of hallucinations by grounding LLMs with external, verifiable facts and can also cite sources	
Cost-Efficiency: RAG is a cost-effective solution, avoiding the need for extensive model training or fine-tuning	

(Ref: Applied LLMs Mastery 2024 - Aishwarya Reganti)

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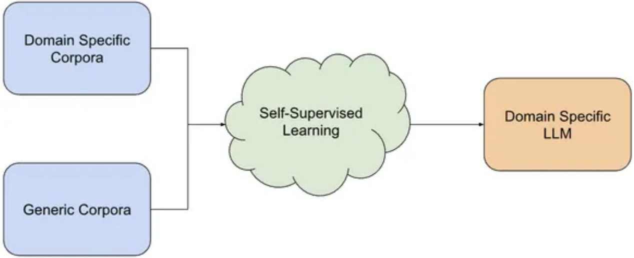
Domain-Specific Pre-Training

- Training Duration: Days to weeks to months.
- Requires extensive domain training data.
- Allows customization of model architecture, size, tokenizer, etc.
- Examples: PaLM 540B, GPT-3, LLaMA 2.

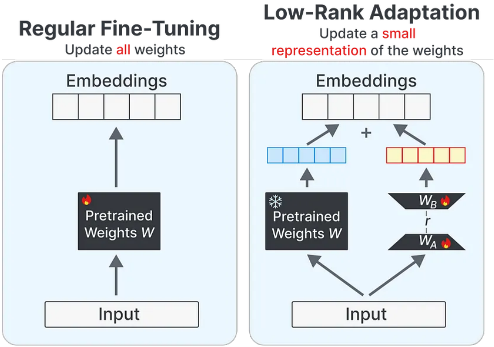
Domain-Specific Pre-Training



(Ref: Applied LLMs Mastery 2024 - Aishwarya Reganti)

Parameter-Efficient Fine-Tuning

Instead of fine-tuning the model's billions of parameters, we can leverage PEFT instead, Parameter-Efficient Fine-Tuning. As the name implies, it is a subfield that focuses on efficiently fine-tuning an LLM with as few parameters as possible.



(Ref: 3 Easy Methods For Improving Your Large Language Model - Towards Data Science - Maarten Grootendorst)

Domain-Specific Fine-Tuning

- Training Duration: Minutes to hours.
- Involves adding domain-specific data and tuning for specific tasks.
- Updates the pre-trained LLM model.
- Examples: Alpaca, xFinance, ChatDoctor.

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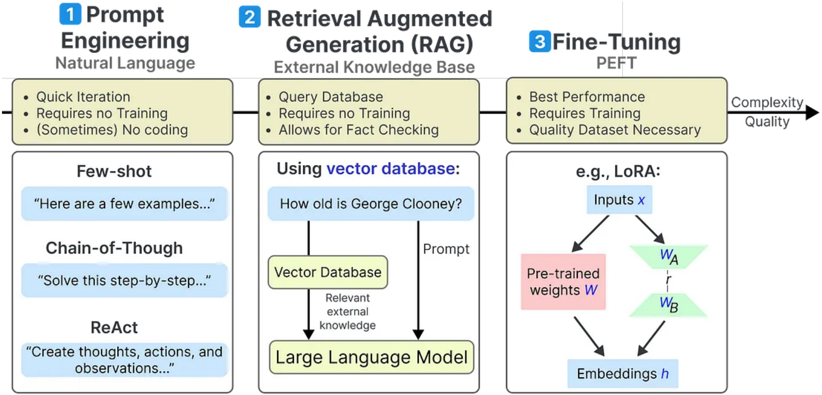
Choosing Adaptation Methods



(Ref: 3 Easy Methods For Improving Your Large Language Model - Towards Data Science - Maarten Grootendorst)

Introduction to LangChain

What is LangChain?

Framework built to help you build LLM-powered applications more easily by providing

- a generic interface to a variety of different foundation models,
- a framework to help you manage your prompts
- a central interface to long-term memory , external data , other LLMs , and other agents for tasks an LLM is not able to handle (e.g., calculations or search).

It is an open-source project (https://github.com/hwchase17/langchain) created by Harrison Chase.

(Ref: Getting Started with LangChain: A Beginner's Guide to Building LLM-Powered Applications by Leonie Monigatti)

What can you do with LangChain?

- Models: Choosing from different LLMs and embedding models
- Prompts: Managing LLM inputs
- Chains: Combining LLMs with other components
- Indexes: Accessing external data
- Memory: Remembering previous conversations
- Agents: Accessing other tools

(Ref: Getting Started with LangChain: A Beginner's Guide to Building LLM-Powered Applications by Leonie Monigatti)

Models: Choosing from different LLMs and embedding models

LangChain offers integration to a wide range of models and a streamlined interface to all of them. LangChain differentiates between three types of models that differ in their inputs and outputs:

- LLMs take a string as an input (prompt) and output a string (completion).
- Chat models are similar to LLMs. They take a list of chat messages as input and return a chat message.
- Text embedding models take text input and return a list of floats (embeddings), for calculating similarities between texts (e.g., movie summaries).

Hugging Face: Choosing from different LLMs and embedding models

```python
from langchain import HuggingFaceHub
llm = HuggingFaceHub(repo_id = "google/flan-t5-xl")

# The LLM takes a prompt as an input and outputs a completion
prompt = "Alice has a parrot. What animal is Alice's pet?"
completion = llm(prompt)

from langchain.embeddings import HuggingFaceEmbeddings
embeddings = HuggingFaceEmbeddings(model_name =
     "sentence-transformers/all-MiniLM-L6-v2")

# The embeddings model takes a text as an input and outputs a list of floats
text = "Alice has a parrot. What animal is Alice's pet?"
text_embedding = embeddings.embed_query(text)
```

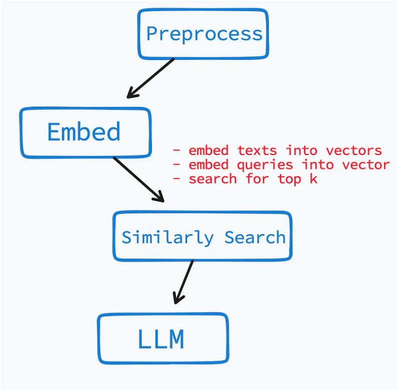
LangChain Usecases

- Personal assistants
- Question answering over database(s)
- Chatbots
- Querying tabular data
- Interacting with APIs
- Model Evaluation

(Ref: Linkedin Post by Munjal Patel)

How LangChain Works?

- Text is preprocessed by breaking it down into chunks or summaries,
- embedding them in a vector space,
- searching for similar chunks when a question is asked.



(Ref: Getting started with LangChain - Avra)

Applications of Generative AI in Business Services & Outsourcing and Digital Services

Business Use Cases for Generative AI

- Natural Language Access to own Accounting data
- Intelligent audit assistance in Advisory services, prompts/query bank
- Chatbot-based customer support in Financial services
- Agent based Financial planning and analysis

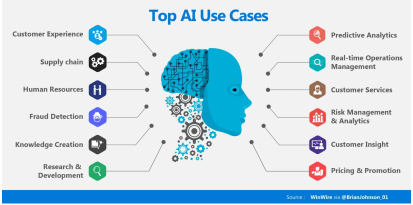


FIGURE: How to use generative AI in business — Hibernian Recruitment

Generative AI in Accounting

- Prompt-based wizard for financial statement preparation
- Intelligent data extraction from documents
- Chatbot-based audit tasks and procedures
- Forecasting and budgeting assistance
- Tailored client reporting and communication

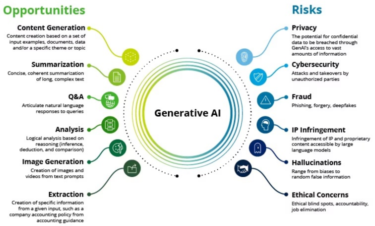


FIGURE: Generative AI in Accounting - Deloitte

Generative AI in Advisory Services

- Intelligent data analysis and insights generation
- Personalized client recommendations and advice
- Automated report writing and presentation creation
- Predictive modeling for strategic decision-making
- Knowledge base curation and retrieval

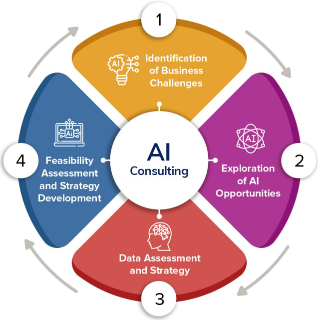


FIGURE: Generative AI in Management Consulting: Revolutionizing Decision-Making and Client Services — by Harry Kang — Medium

Generative AI in Outsourcing

- Personalized customer interaction and support
- Automated task assignment and workflow management
- Multilingual content generation and translation
- Predictive analytics for resource planning

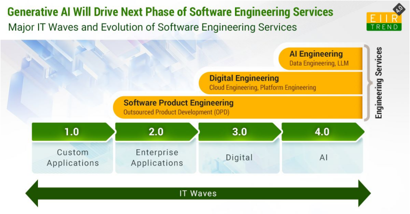


FIGURE: Generative AI in Outsourcing - EIIR Trend

Generative AI in Financial Services

- Chatbot-based customer support and engagement
- Automated financial planning and analysis
- Personalized investment recommendations
- Fraud detection and risk management
- Regulatory compliance and reporting

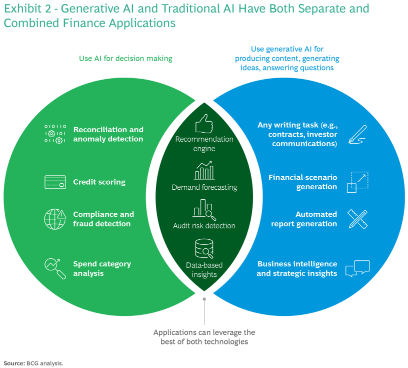


FIGURE: Generative AI in Financial Services - BCG

Applications of Generative AI in Product development

GenAI in Product Development

- Code generation with GitHub Copilot
- Automated software testing and QA
- Synthetic test data generation
- Accelerated prototyping and iteration
- Intelligent code refactoring and optimization

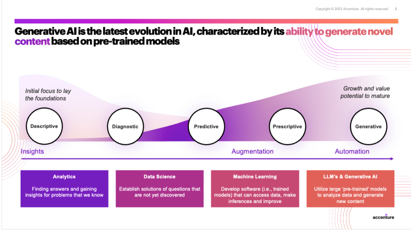


FIGURE: Revolutionizing Product Management: Unleashing the Power of GenAI for Innovation and Success — by Sebastian Straube — Product Coalition

Code Generation with GitHub Copilot

- Automate repetitive coding tasks
- Suggest relevant code snippets
- Maintain code style and best practices
- Accelerate development workflows
- Enhance developer productivity

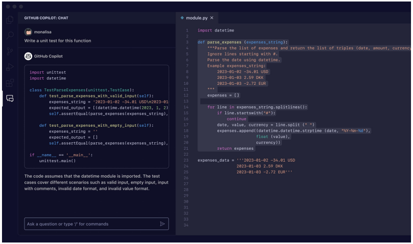


Figure: GitHub Copilot for Code Generation

Automated Software Testing and QA

- Generate comprehensive test cases
- Automate regression testing scenarios
- Identify potential edge cases and bugs
- Optimize test coverage and efficiency
- Integrate with CI/CD pipelines

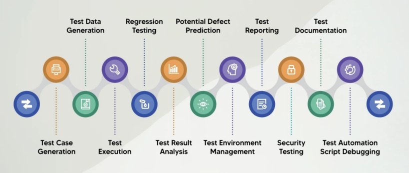


FIGURE: Generative AI in QA Automation - Kellton

Synthetic Test Data Generation

- Create diverse and realistic test data
- Protect sensitive information with anonymization
- Simulate complex data relationships and scenarios
- Reduce the need for manual data generation
- Integrate with test automation frameworks

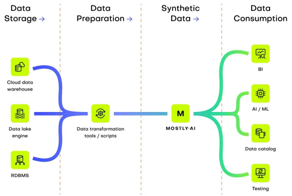


FIGURE: Generative AI for Synthetic Test Data - Mostly.AI

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Accelerated Prototyping and Iteration

- Devin, Devika's of the world. Crew AI, AutoGen etc
- Generate interactive mockups and wireframes
- Create product demonstrations and explainer videos
- Iterate on design ideas and user experiences
- Validate concepts with stakeholders and end-users
- Facilitate rapid experimentation and feedback loops

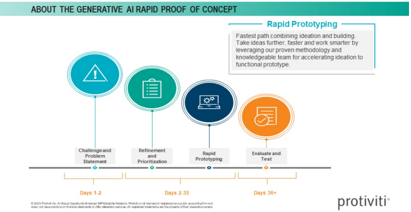

FIGURE: Generative AI in Product Prototyping

Applications of Generative AI in Business Functions

Generative AI for Sales

- Prompt banks for sales pitches and proposals
- Automated lead qualification and nurturing
- Sales forecasting and pipeline management
- Intelligent customer insights and segmentation

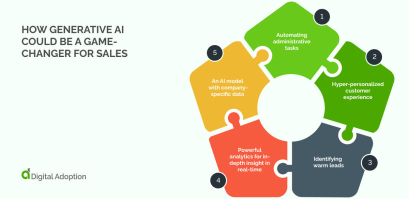

FIGURE: Generative AI in Sales - Digital Adoption

Generative AI for Marketing

- Prolific content generation for campaigns
- Automated social media and email marketing - Tools calling APIs
- Intelligent customer segmentation and targeting

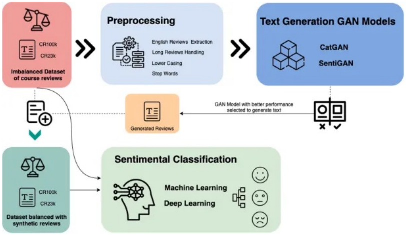

FIGURE: Generative AI in Marketing - Research AI Multiple

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Generative AI for HR

- Intelligent job description and posting generation
- Candidate screening and resume summarization
- Personalized employee onboarding and training
- HR policy and procedure documentation
- Employee feedback and sentiment analysis

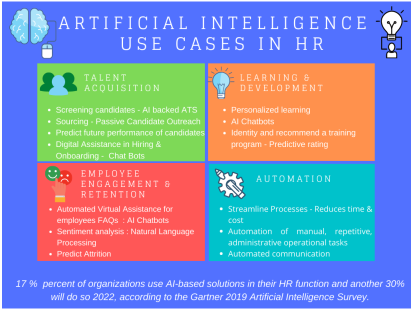

FIGURE: Generative AI in HR - People Matters

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Conclusions of Generative AI

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

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

Learning Path, Roadmap

Resources

- First : try Free Online resources, see how much you grasp
- No expensive (read, fees in lakhs) certification courses, to start with
- Test waters, gain some understanding of yourself then decide.

Start Playing the Role

- Wish to be a Data Scientist? Start playing that role today.
- Take specific actions to embody the desired role.
- Tone of the suggestion: Begin playing the coveted role immediately.

Build Foundation

- Take courses in necessary mathematics, programming, ML, and DL.
- Engage in assignments to solidify foundational knowledge.
- Lay the groundwork for a strong understanding of key concepts.

Kaggle Competitions

- Participate in Kaggle competitions across various domains.
- Explore NLP, Image Processing, Time-Series, and more.
- Gain practical experience and exposure to diverse challenges.

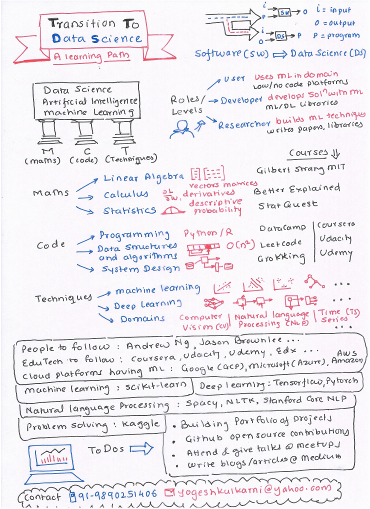
Specialize and Apply

- Choose a specific area, e.g., NLP, and go deep into it.
- Apply your expertise to problems from different domains (legal, medical, etc.).
- Develop a comprehensive and specialized skill set.

Build a GitHub Portfolio

- Showcase your work, courses, and projects on GitHub.
- Portfolio serves as a self-assessment tool and demonstrates your grasp.
- Discuss it during interviews, providing concrete evidence of your skills.
- Your GitHub repo is your real resume – proxies like education and gender matter less.

My Sketchnote



(Ref: How to become a Data Scientist? - Yogesh Kulkarni)

Summary Steps

Prep:

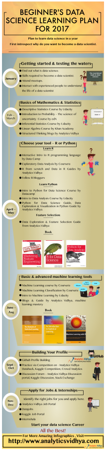
- Mathematics: Statistics, Calculus, Linear Algebra
- Programming: Python, Data Structure & Algorithms, Tools
- ML/DL: algorithms & frameworks

Practice: Kaggle, Hackathons, projects on Github, blogs, Meetups-talks, etc.

Analytics Vidhya Learning Path 2017

- An year long schedule
- Mostly free resources
- Followed it myself
- Separate paths for:
  - Beginner: Not much experience in programming but just college maths
  - Transitioner: Decent experience programming, but no ML and just college maths
  - Intermediate: Knows ML, comfortable with programming and maths.

https://www.analyticsvidhya.com/blog/2017/01/the-most-comprehensive-data-science-learning-plan-for-2017/



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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.

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Thanks . . .

- Search **"Yogesh Haribhau Kulkarni"** on Google and follow me on LinkedIn and Medium
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