臺北市立大學資訊科學系
碩士班Seminar

Agentic AI for ESG and Digital Sustainability Innovation (代理式 AI 於 ESG 與數位永續創新)

Time: 13:10-15:00, **Wednesday, April 30, 2025**
Place: R314, Gongcheng Building, Department of Computer Science, **University of Taipei**
Host: Prof. Ching-Tai Chen

NVIDIA University Ambassador Certified Instructor

aws educate Cloud Ambassador 2020 Cohort

aws academy Accredited Educator

aws certified Cloud Practitioner

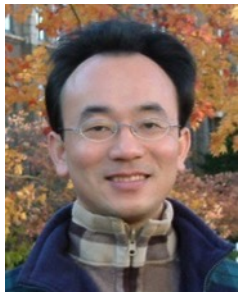
aws certified Solutions Architect Associate

戴敏育 教授 (Prof. Min-Yuh Day)

國立臺北大學 資訊管理研究所 教授
金融科技暨綠色金融研究中心 主任
永續辦公室 永續發展組 組長

2025-04-30

NTPU
國立臺北大學
National Taipei University



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Professor, Information Management, NTPU

Director, Intelligent Financial Innovation Technology, IFIT Lab, IM, NTPU

Director, Fintech and Green Finance Center (FGFC), NTPU

Division Director, Sustainable Development, Sustainability Office, NTPU

Visiting Scholar, IIS, Academia Sinica

Ph.D., Information Management, NTU

Publications Co-Chairs, International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2013-)

Program Co-Chair, IEEE International Workshop on Empirical Methods for Recognizing Inference in TExt (IEEE EM-RITE 2012-)

Publications Chair, The IEEE International Conference on Information Reuse and Integration for Data Science (IEEE IRI 2007-)

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Outline

1. Agentic AI
2. ESG Data Analytics
3. Digital Sustainability Innovation

衡量企業永續關鍵指標
臺北大學獨創ESG永續評鑑系統

社會(S)	經濟(E)	環境(E)	揭露(D)
1.人權 2.員工溝通與福利 3.人力資本發展 4.多元組成與包容性 5.供應鏈社會面向控管 6.客戶關係管理 7.產品安全 8.企業公民與慈善	1.股東權益 2.董事會結構與運作 3.行為準則與內控 4.風險及危機管理 5.永續金融 6.ESG創新	1.環境系統與治理 2.空氣管理 3.能源與氣候變遷 4.水管理 5.原物料與廢棄物管理/資源與廢棄物管理 6.生物多樣性 7.供應商及產品生命週期管理/供應鏈環境面向管理	1.ESG 揭露

Source: https://www.aacsb.ntpu.edu.tw/twsvi/view.php?id=Nzc=

國立臺北大學
National Taipei University

國立臺北大學商學院
企業永續發展研究中心
Center for Corporate Sustainability

SEED
台灣永續評鑑

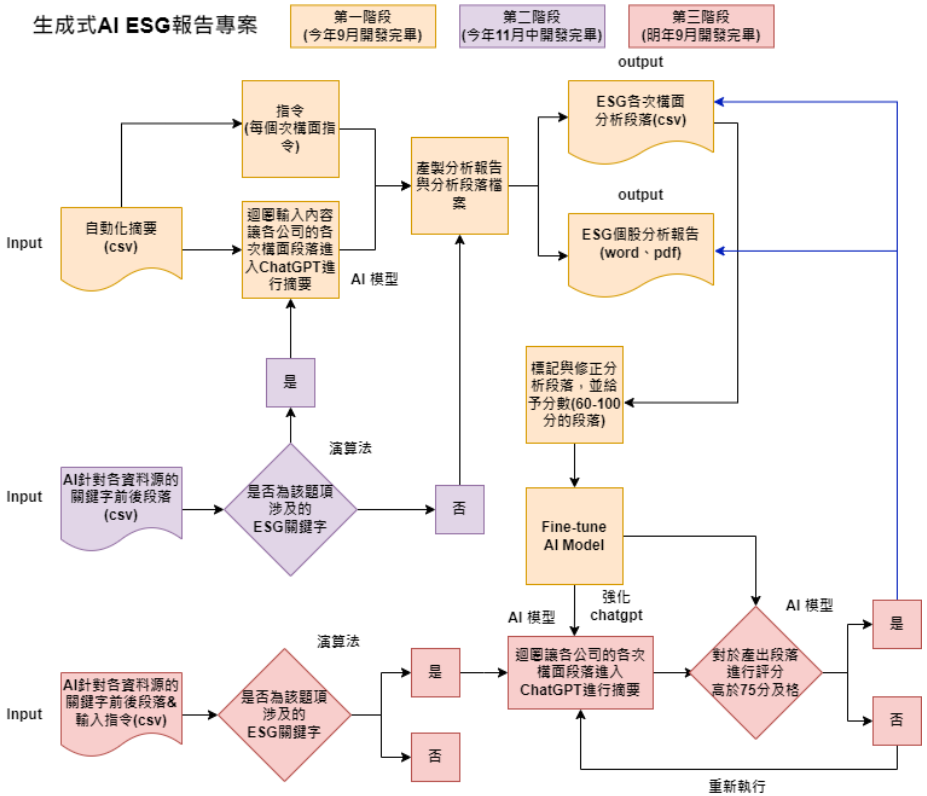
台灣永續評鑑

國立臺北大學商學院企業永續發展研究團隊

透過 AI SEED 提升評鑑效率

國立臺北大學 National Taipei University
國立臺北大學商學院 企業永續發展研究中心 Center for Corporate Sustainability

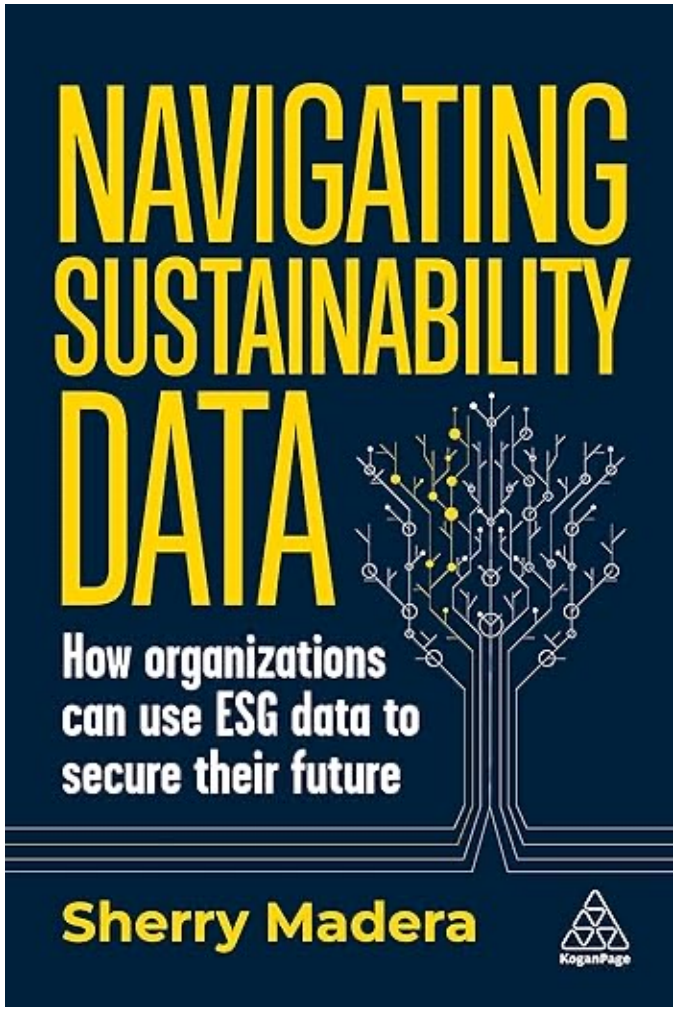
為使評鑑效率提升，與國立臺北大學資管所及資工所合作，開發相關程式，
已有25%題項自動或半自動化，大幅提升評鑑效率，並持續開發機械學習，持續透過AI 輔助評鑑進行。
另也透過AI SEED團隊持續將部分流程自動化，提升評鑑正確性，減少人力出錯可能。



題號	題目關鍵字	完成度
2-1-15	僅分派董監酬勞未分派股利	100%
2-2-3	獨董達董事席次1/2以上	100%
2-2-4	至少兩名獨董任期不超過9年	100%
2-2-14	設提名委員會且半數以上為獨董	100%
2-2-30	董事長兼任總經理	100%
2-2-31	1/3以上董事任期超過15年	100%
2-3-8	破產 / 面臨下市	100%
2-3-15	資安長或資訊安全委員會	100%
2-4-7	無保留意見	100%

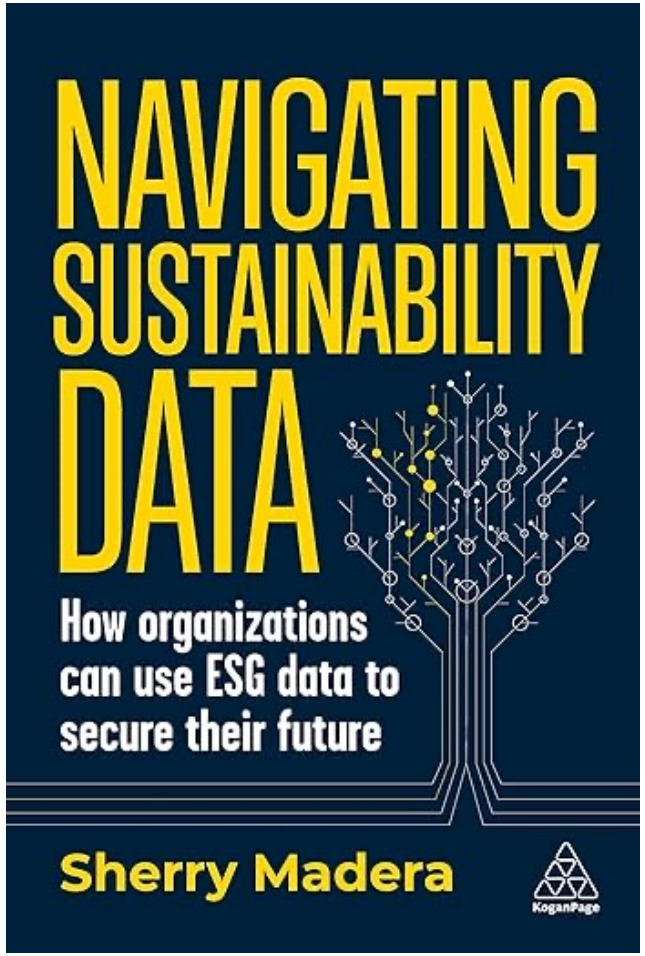
SEED 台灣永續評鑑

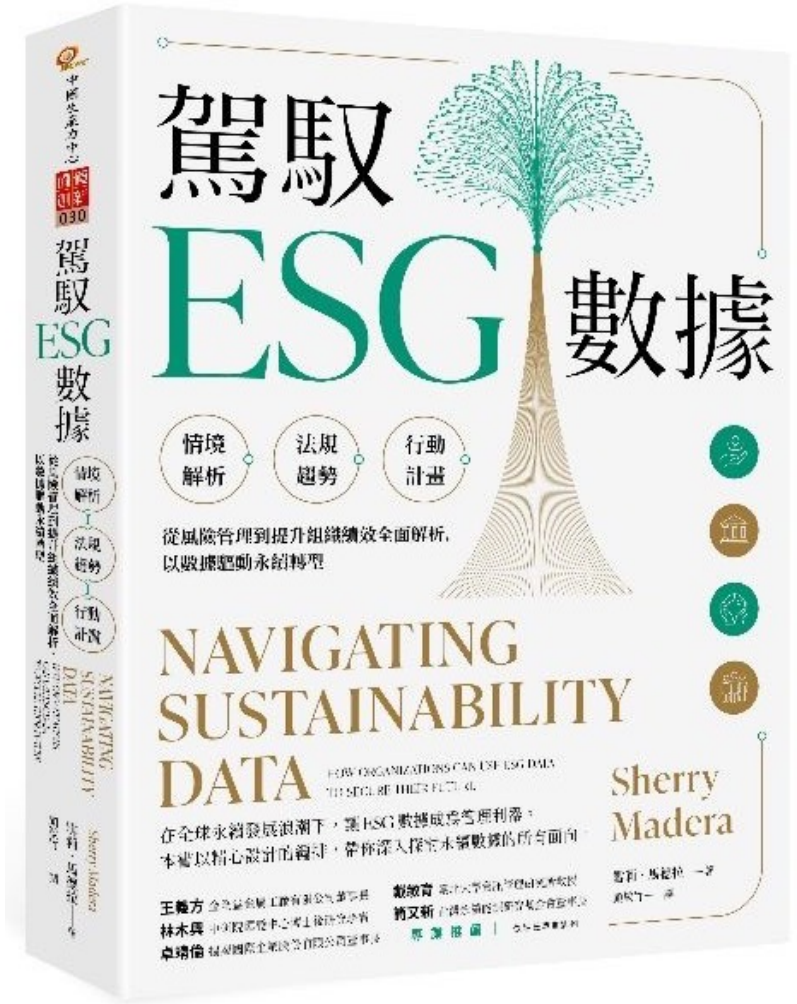
Sherry Madera (2024),
Navigating Sustainability Data: How Organizations can use ESG Data to Secure Their Future, Kogan Page



Source: https://www.amazon.com/Navigating-Sustainability-Data-Organizations-Secure/dp/1398612243/

雪莉．馬德拉 (Sherry Madera) (顏敏竹 譯) (2024),
駕馭ESG數據 (Navigating Sustainability Data),
財團法人中國生產力中心





專業推薦：
王義方
（金全益金屬工廠有限公司董事長）
林木興
（中研院環變中心博士後研究學者）
卓靖倫
（揚秦國際企業股份有限公司董事長）
戴敏育
（國立臺北大學資訊管理研究所教授）
簡又新
（台灣永續能源研究基金會董事長）

Source: https://www.eslite.com/product/1001201176268268892900 2

Innovative Agentic AI Technology for Autonomous ESG Report Generation

Industrial Technology Research Institute (ITRI),
Fintech and Green Finance Center (FGFC, NTPU),
NTPU-114A513E01, 2025/03/01~2025/12/31

Generative AI-Driven ESG Report Generation Technology

Industrial Technology Research Institute (ITRI),
Fintech and Green Finance Center (FGFC, NTPU),
NTPU-113A513E01, 2024/03/01~2024/12/31

Agentic AI
Powering Digital Sustainability Innovation

Generative AI, Agentic AI, Physical AI

2012 AlexNet
Deep learning breakthrough

Perception AI
Speech recognition
Deep recommender systems
Medical imaging

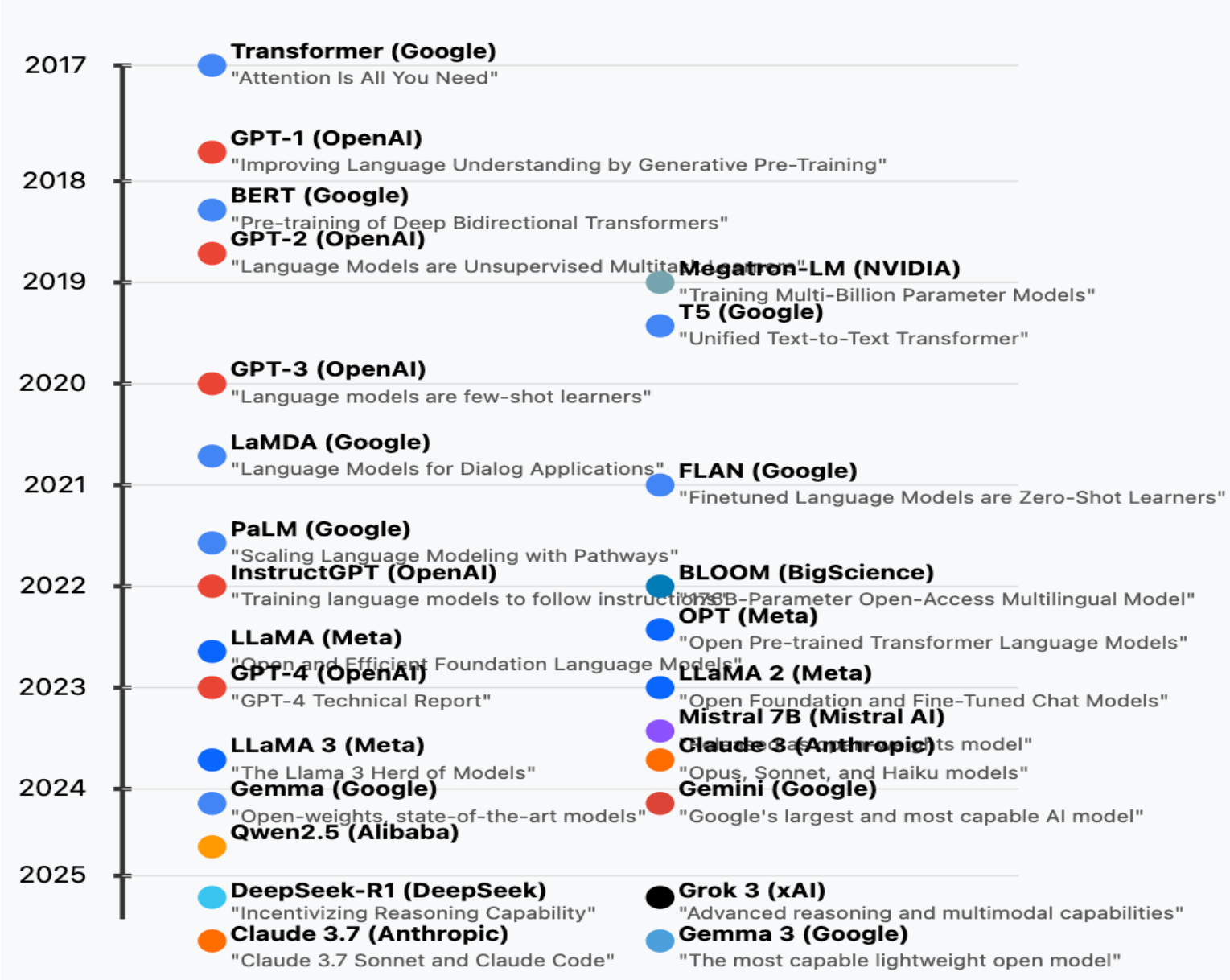
Generative AI
Digital marketing
Content creation

Agentic AI
Coding assistants
Customer service
Patient care

Physical AI
Self-driving cars
General robotics

Source: NVIDIA (2025), GTC March 2025 Keynote with NVIDIA CEO Jensen Huang, https://www.youtube.com/watch?v=_waPvOwL9Z8

Generative AI LLMs (2017-2025)



Key Organizations

- Google
- OpenAI
- Meta
- Mistral AI
- Alibaba
- xAI
- Anthropic
- NVIDIA
- BigScience

Key Milestones

2017: Transformer architecture

2018: First-gen GPT, BERT

2020: GPT-3 (175B parameters)

2022: Emergent abilities, instruction tuning

2023: GPT-4, multimodal models

2024: Open-weights race, Mamba2

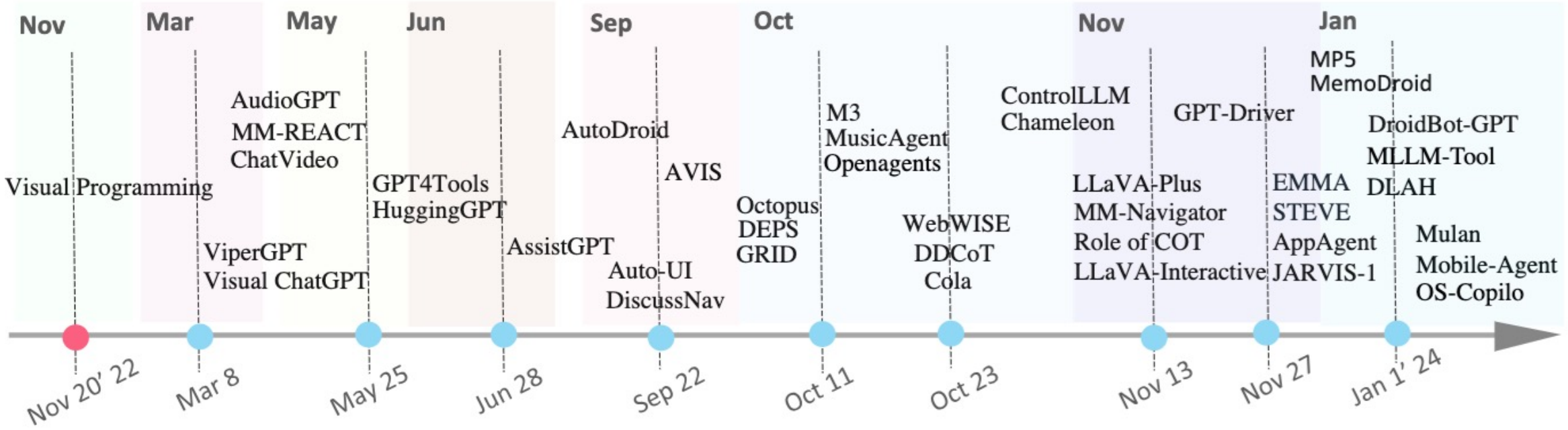
2025: DeepSeek-R1, Grok 3

Claude 3.7, Gemma 3

Source: https://github.com/Hannibal046/Awesome-LLM

LLM-powered Multimodal Agents

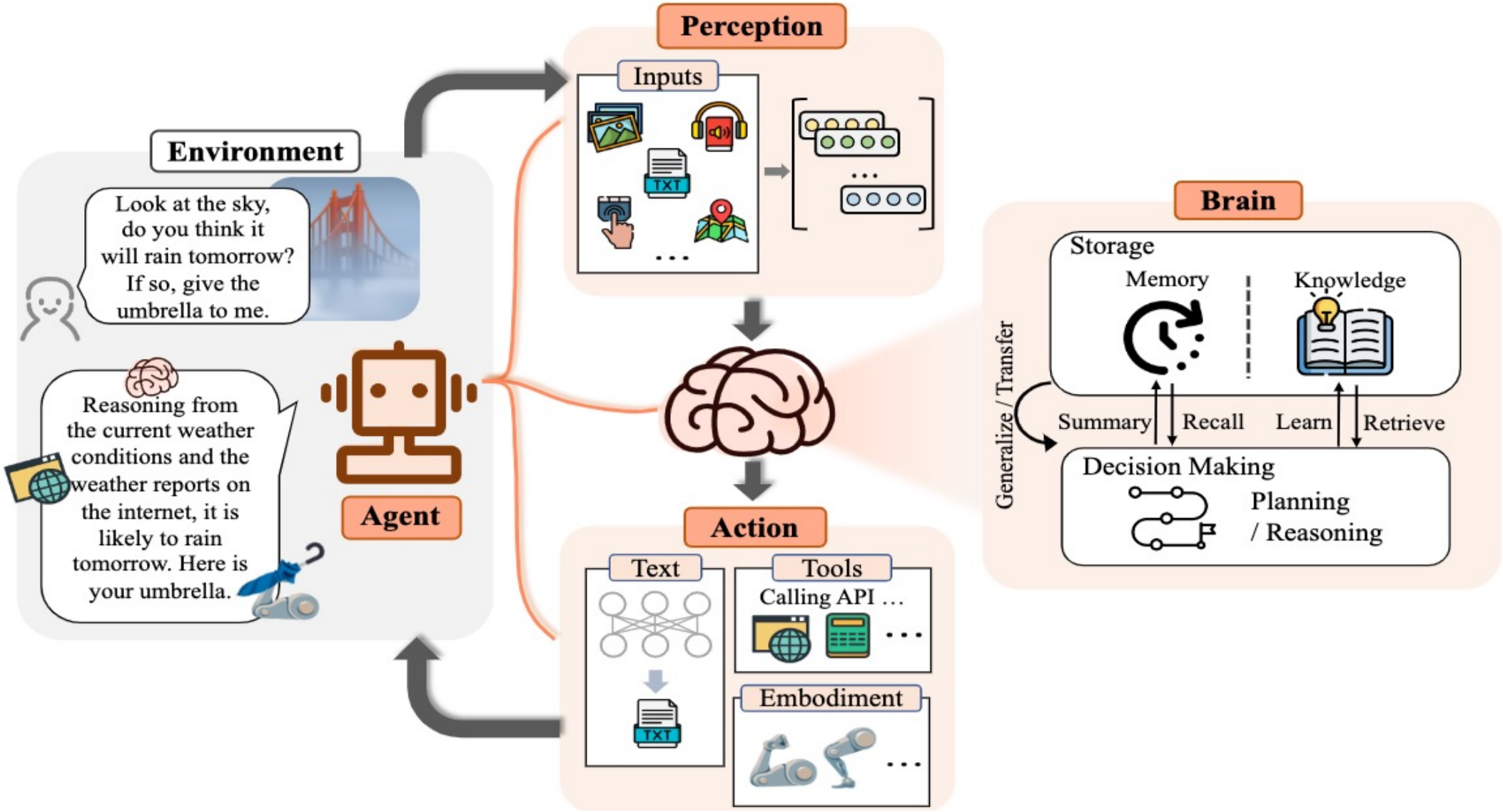
Large Multimodal Agents (LMAs)



2022 2023 2024

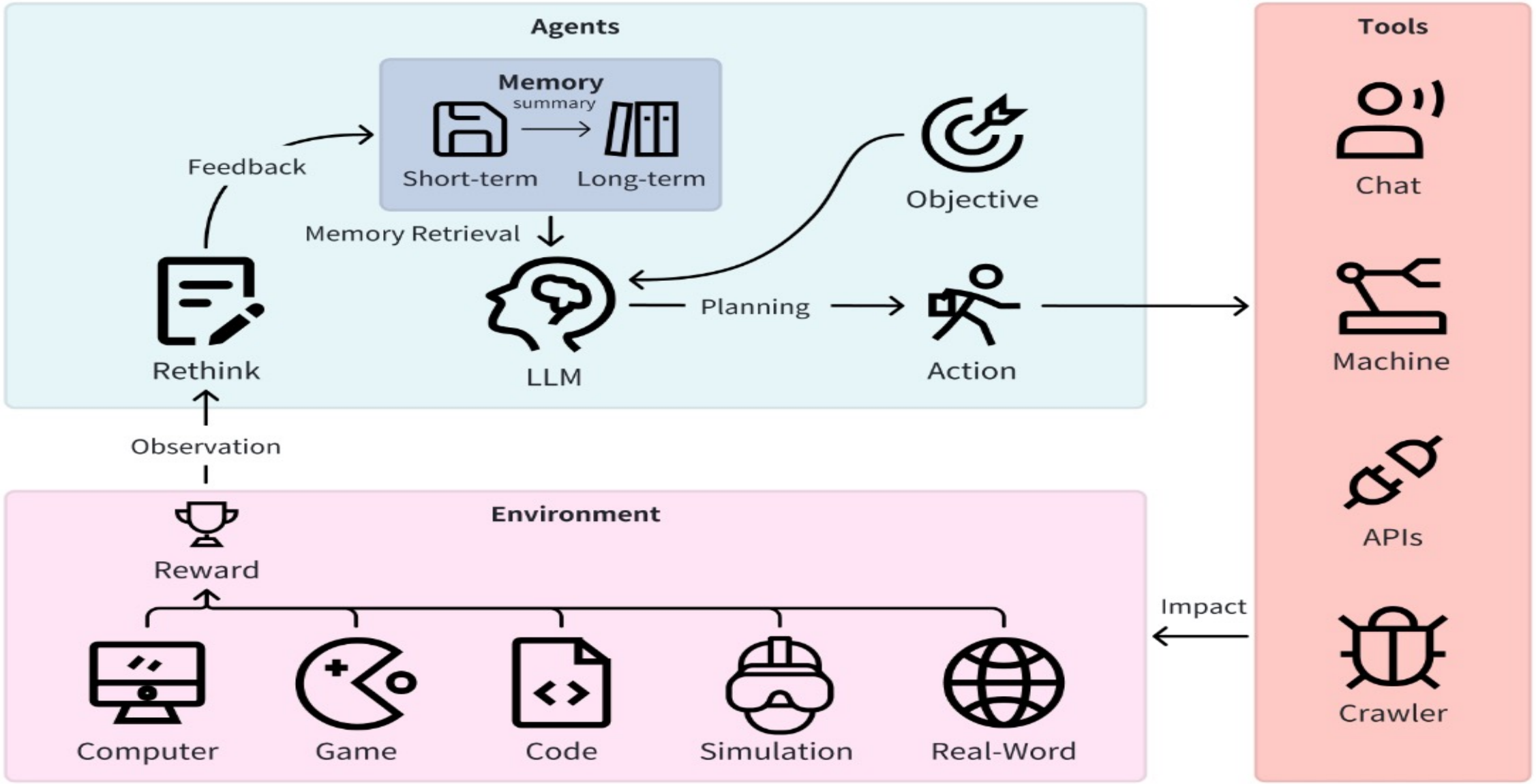
Source: Xie, Junlin, Zhihong Chen, Ruifei Zhang, Xiang Wan, and Guanbin Li. "Large Multimodal Agents: A Survey." arXiv preprint arXiv:2402.15116 (2024).

Large Language Model (LLM) based Agents



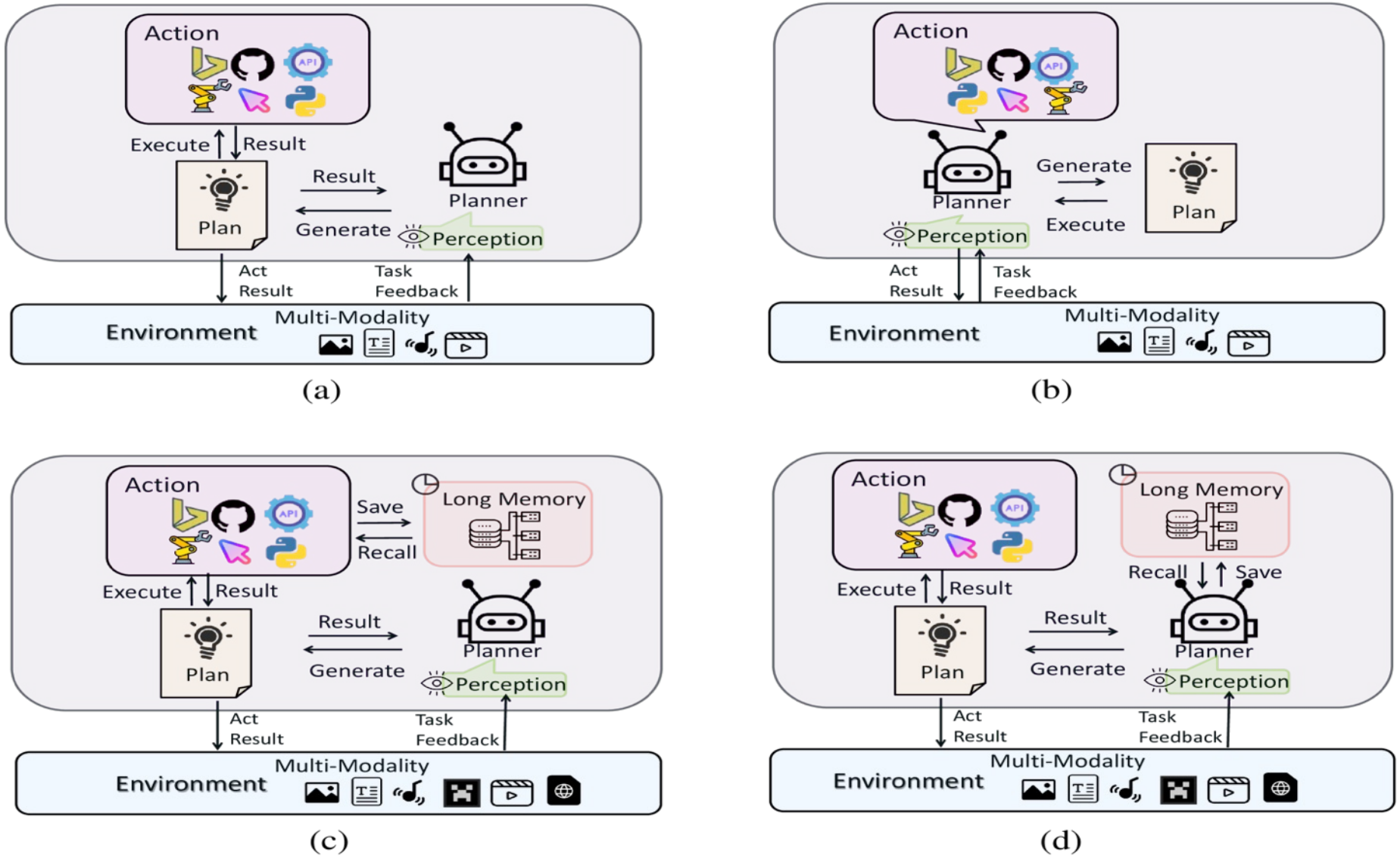
Source: Xi, Z., Chen, W., Guo, X., He, W., Ding, Y., Hong, B., ... & Gui, T. (2023). The rise and potential of large language model based agents: A survey. arXiv preprint arXiv:2309.07864.

LLM-based Agents



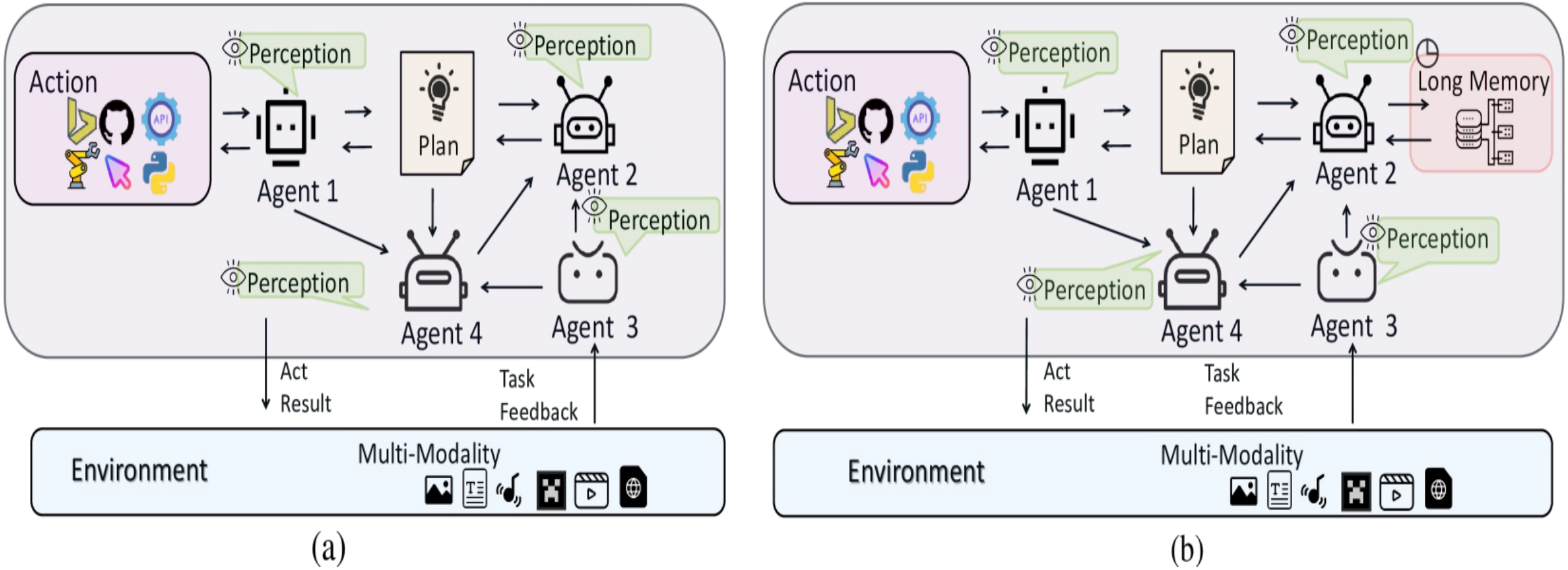
Source: Cheng, Yuheng, Ceyao Zhang, Zhengwen Zhang, Xiangrui Meng, Sirui Hong, Wenhao Li, Zihao Wang et al. "Exploring large language model based intelligent agents: Definitions, methods, and prospects." arXiv preprint arXiv:2401.03428 (2024).

Large Multimodal Agents (LMA)



Source: Xie, J., Chen, Z., Zhang, R., Wan, X., & Li, G. (2024). Large Multimodal Agents: A Survey. ArXiv, abs/2402.15116.

Large Multimodal Agents (LMA)



Source: Xie, J., Chen, Z., Zhang, R., Wan, X., & Li, G. (2024). Large Multimodal Agents: A Survey. ArXiv, abs/2402.15116.

Agentic AI Cloud Architecture

Microservices and Serverless Architecture

Containers (Docker, Kubernetes)
Serverless platforms (AWS Lambda, Google Cloud Functions)

APIs and Tooling Integration via MCP

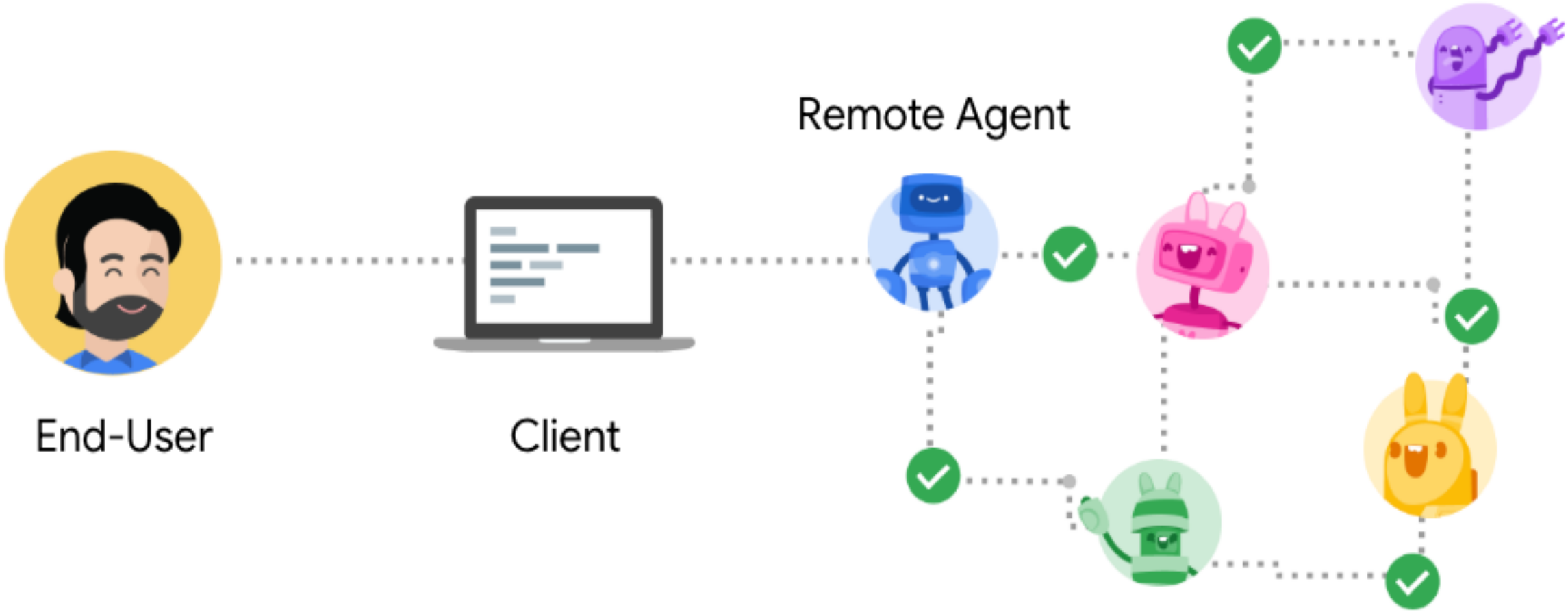
Agents access tools (e.g., databases, APIs, CRMs, payment gateways)
using Model Context Protocol (MCP)
Enhances tool-using behavior of LLM agents

Tools and Frameworks

LangChain, AutoGen, CrewAI: for orchestrating LLM agents
Anthropic's MCP, Google's A2A: communication protocols
Vector DBs (Pinecone, Weaviate): for agent memory

Agent2Agent Protocol (A2A)

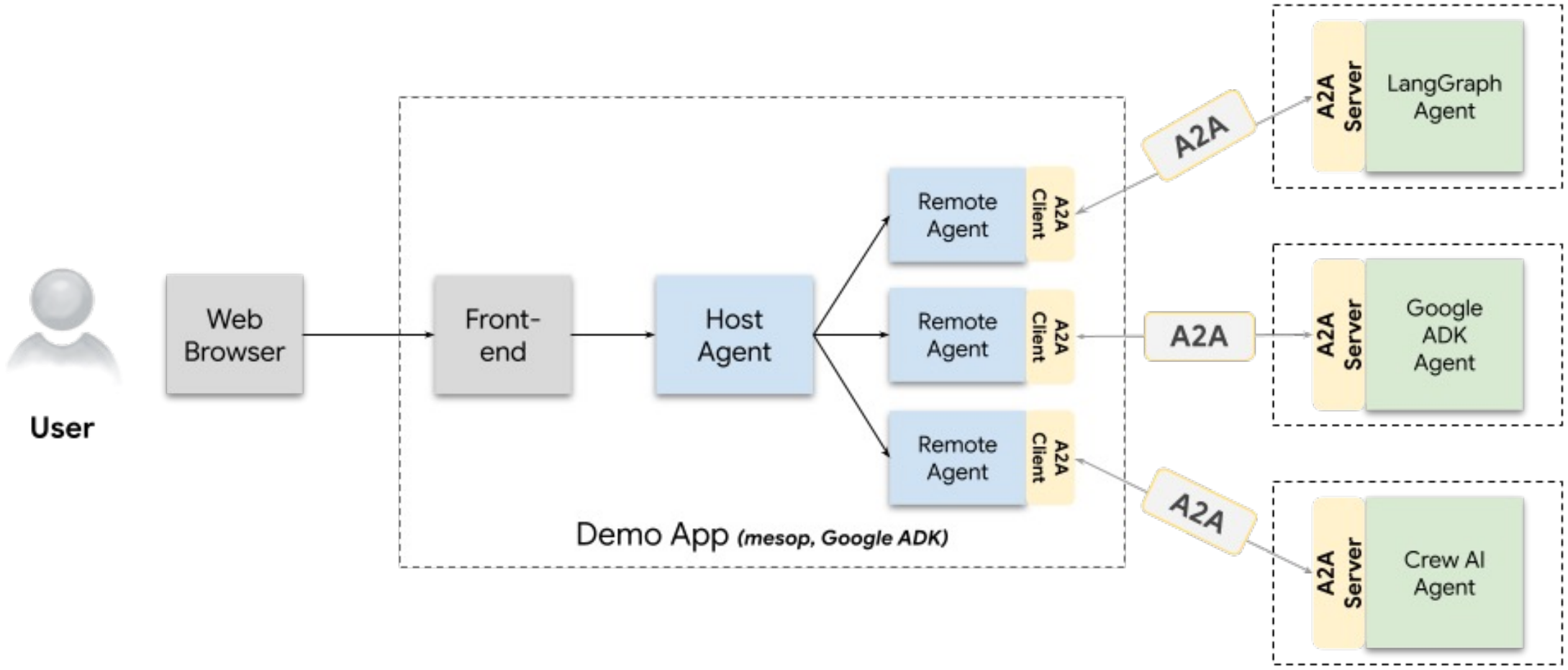
An open protocol enabling Agent-to-Agent interoperability, bridging the gap between opaque agentic systems



Source: https://google.github.io/A2A/

A2A Demo Web App

Agents talking to other agents over A2A



Source: https://github.com/google/A2A/blob/main/demo/README.md

A2A

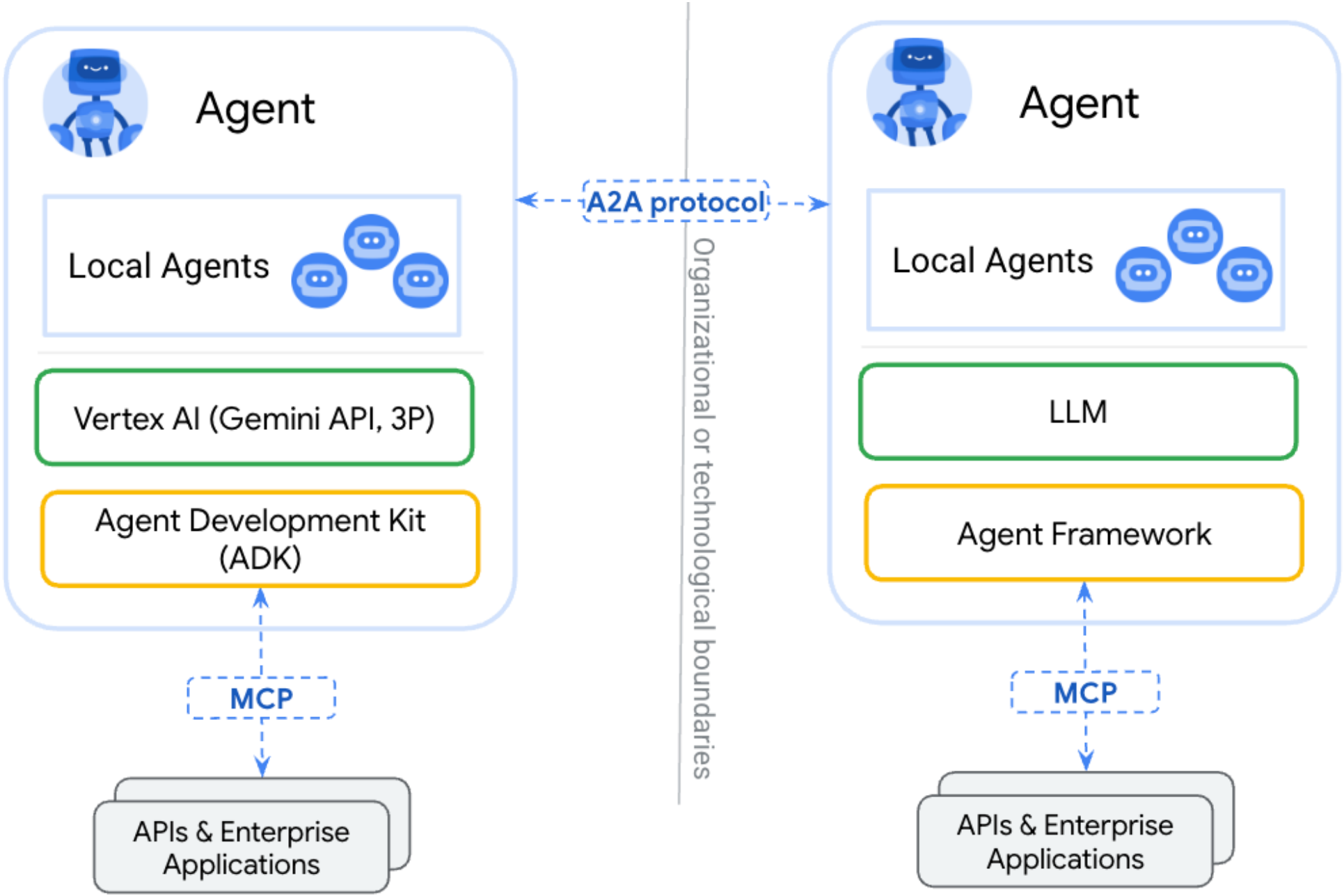
(Agent2Agent Protocol)

for agent-agent collaboration

MCP

(Model Context Protocol)

for tools and resources



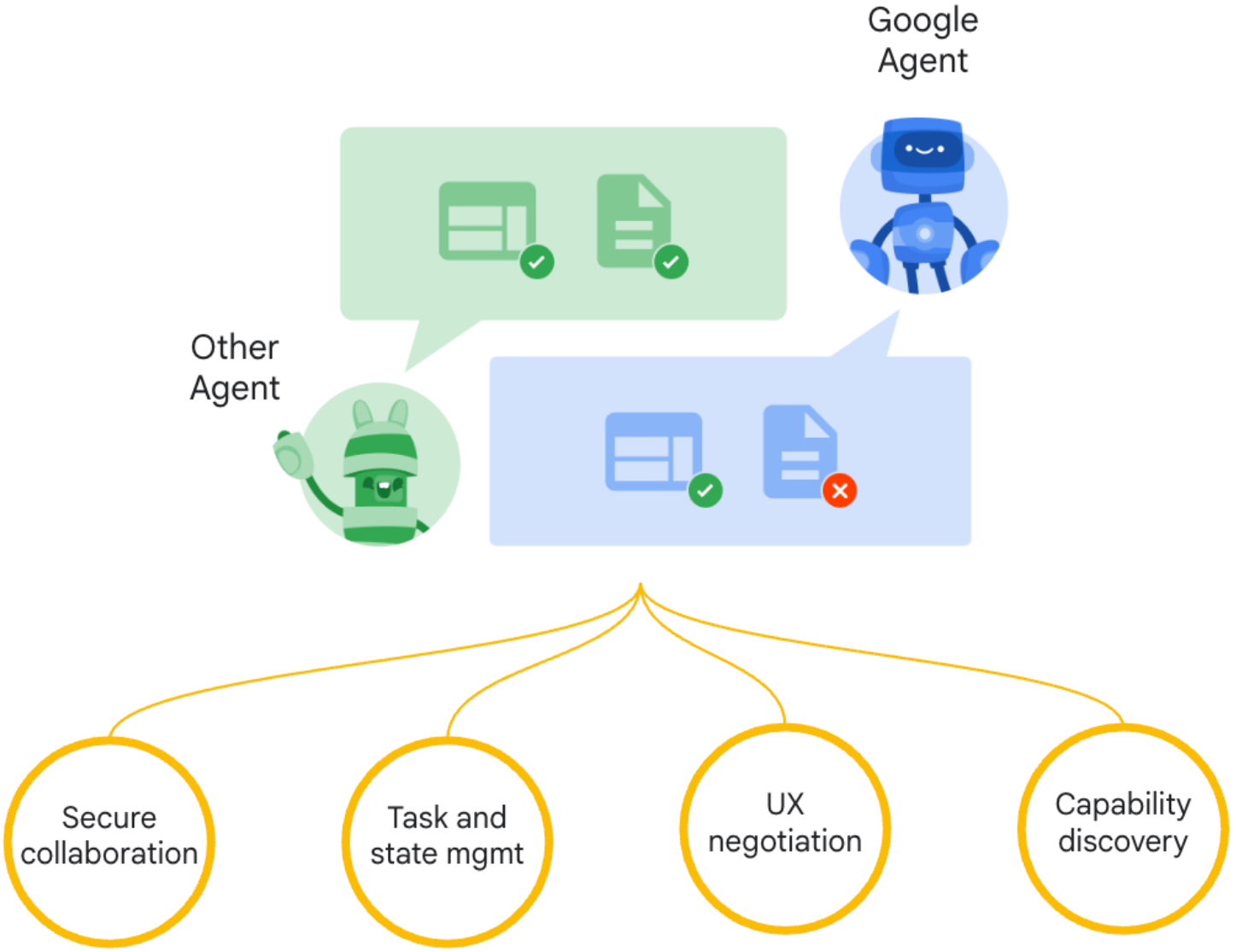
Source: https://google.github.io/A2A/

Google A2A (Agent2Agent Protocol)

Seamless Agent Collaboration

Simplifies Enterprise Agent Integration

Supports Key Enterprise Requirements

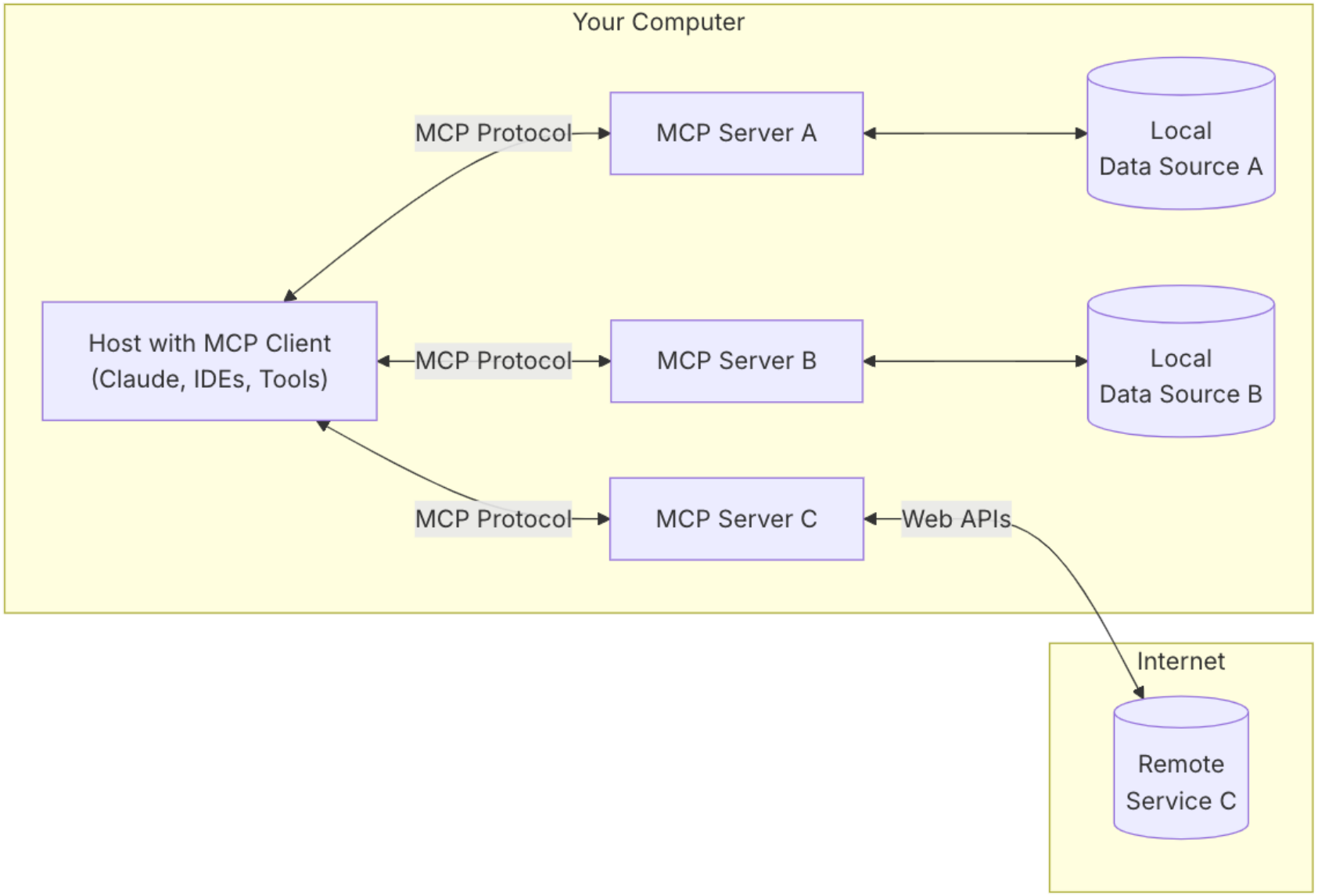


Source: https://google.github.io/A2A/

MCP (Model Context Protocol)

MCP is a open protocol that standardizes how applications provide context to LLMs.

MCP: USB-C port for AI applications.



Source: https://modelcontextprotocol.io/introduction

MCP and A2A

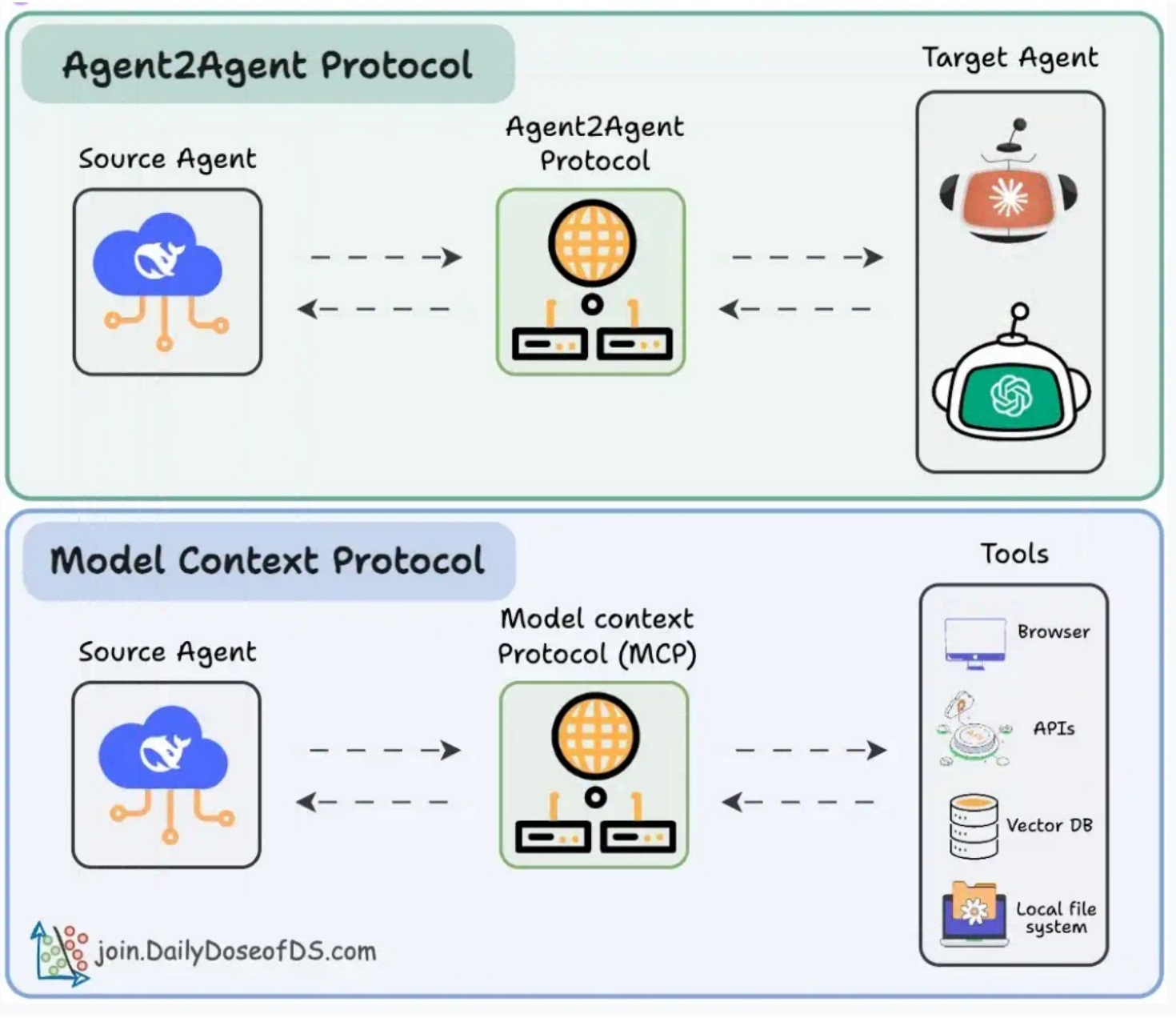
- MCP (Model Context Protocol) for tools and resources
  - Connect agents to tools, APIs, and resources with structured inputs/outputs.
  - Google ADK supports MCP tools. Enabling wide range of MCP servers to be used with agents.
- A2A (Agent2Agent Protocol) for agent-agent collaboration
  - Dynamic, multimodal communication between different agents without sharing memory, resources, and tools
  - Open standard driven by community.
  - Samples available using Google ADK, LangGraph, Crew.AI

Source: https://google.github.io/A2A/

Agentic applications require both A2A and MCP

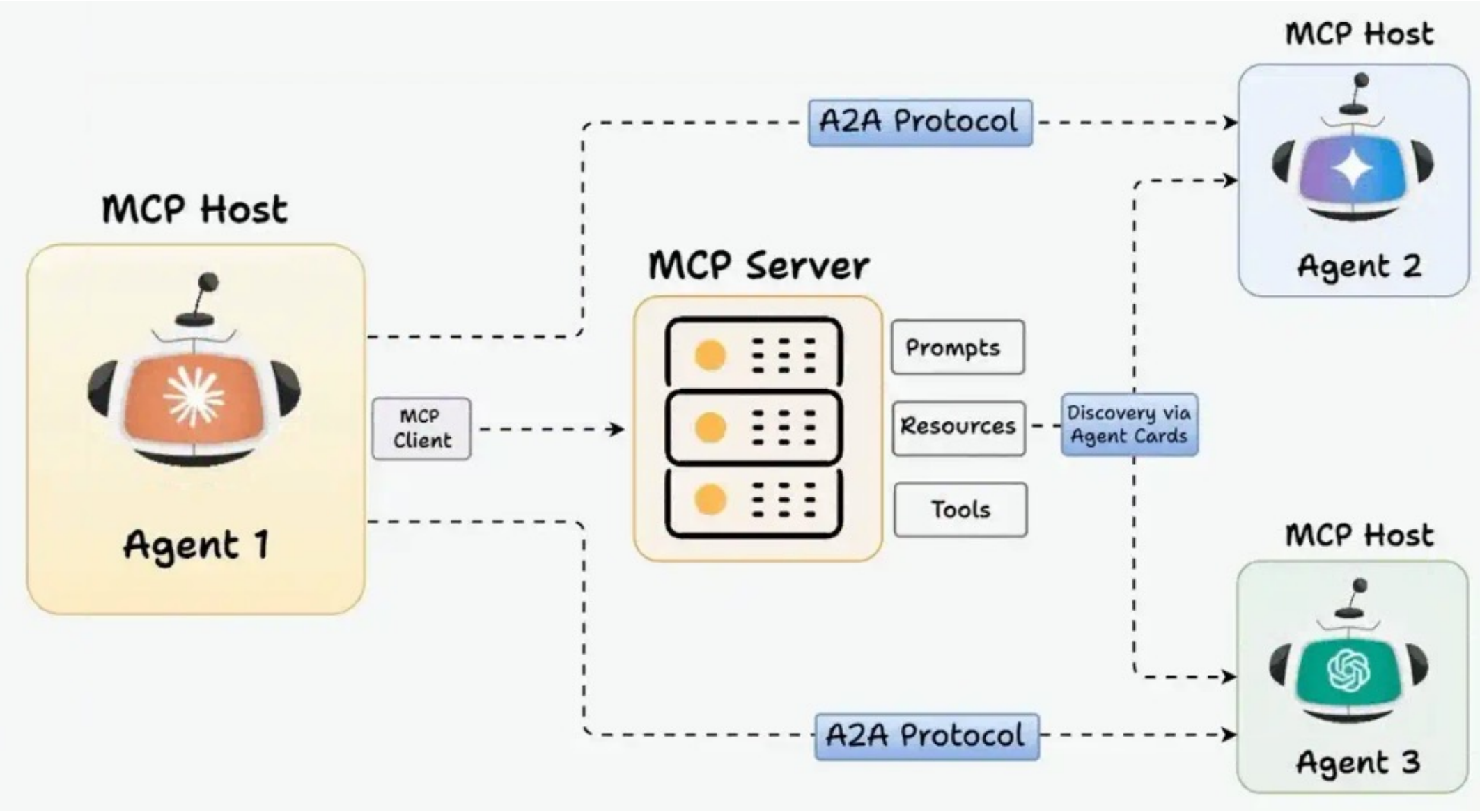
A2A allows agents to connect with other agents and collaborate in teams.

MCP provides agents with access to tools



Source: https://blog.dailydoseofds.com/p/a-visual-guide-to-agent2agent-a2a

MCP and A2A Protocol for AI Agents



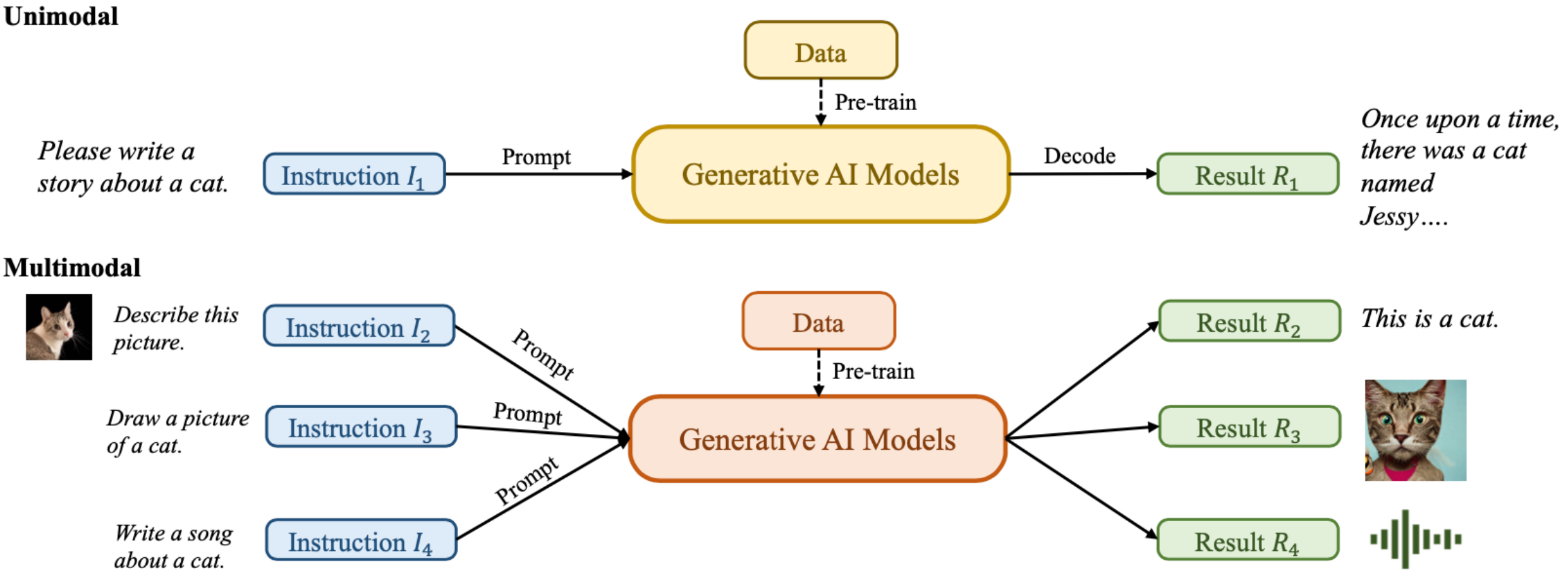
Source: https://blog.dailydoseofds.com/p/a-visual-guide-to-agent2agent-a2a

Generative AI (Gen AI)

AI Generated Content (AIGC)

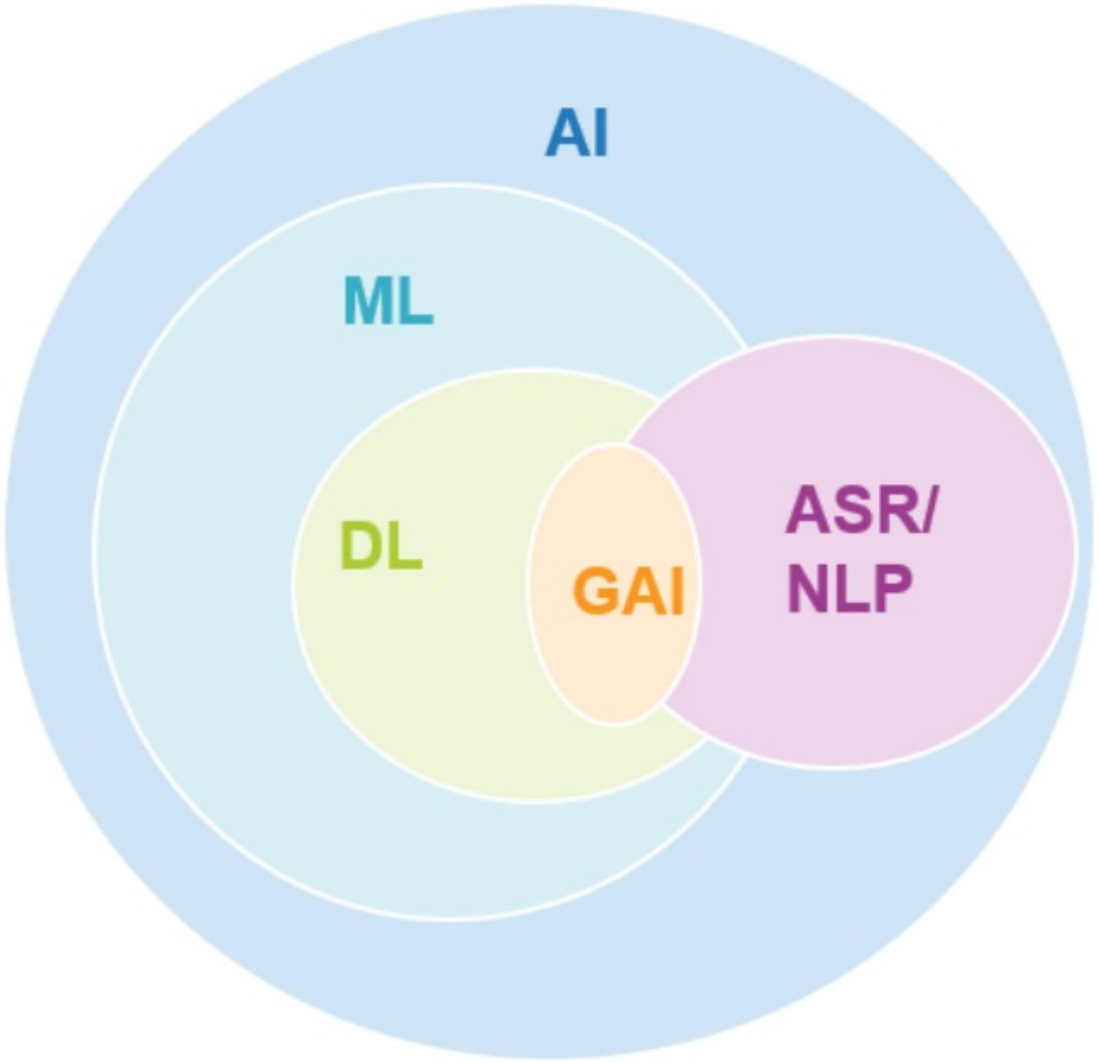
Generative AI (Gen AI)

AI Generated Content (AIGC)



Source: Yihan Cao, Siyu Li, Yixin Liu, Zhiling Yan, Yutong Dai, Philip S. Yu, and Lichao Sun (2023). "A Comprehensive Survey of AI-Generated Content (AIGC): A History of Generative AI from GAN to ChatGPT." arXiv preprint arXiv:2303.04226.

AI, ML, DL, Generative AI



- Artificial Intelligence
- Machine Learning
- Deep Learning
- Automatic Speech Recognition, Natural Language Processing
- Generative AI

Source: Jeong, Cheonsu. "A Study on the Implementation of Generative AI Services Using an Enterprise Data-Based LLM Application Architecture." arXiv preprint arXiv:2309.01105 (2023).

Definition of Artificial Intelligence (A.I.)

Artificial Intelligence

"… the science and engineering of making intelligent machines"

(John McCarthy, 1955)

Source: https://digitalintelligencetoday.com/artificial-intelligence-defined-useful-list-of-popular-definitions-from-business-and-science/

Artificial Intelligence

"… technology that thinks and acts like humans"

Source: https://digitalintelligencetoday.com/artificial-intelligence-defined-useful-list-of-popular-definitions-from-business-and-science/

Artificial Intelligence

"… intelligence exhibited by machines or software"

Source: https://digitalintelligencetoday.com/artificial-intelligence-defined-useful-list-of-popular-definitions-from-business-and-science/

4 Approaches of AI

2. **Thinking Humanly:** **The Cognitive Modeling Approach**	**3.** **Thinking Rationally:** **The "Laws of Thought" Approach**
1. **Acting Humanly:** **The Turing Test Approach (1950)**	**4.** **Acting Rationally:** **The Rational Agent Approach**

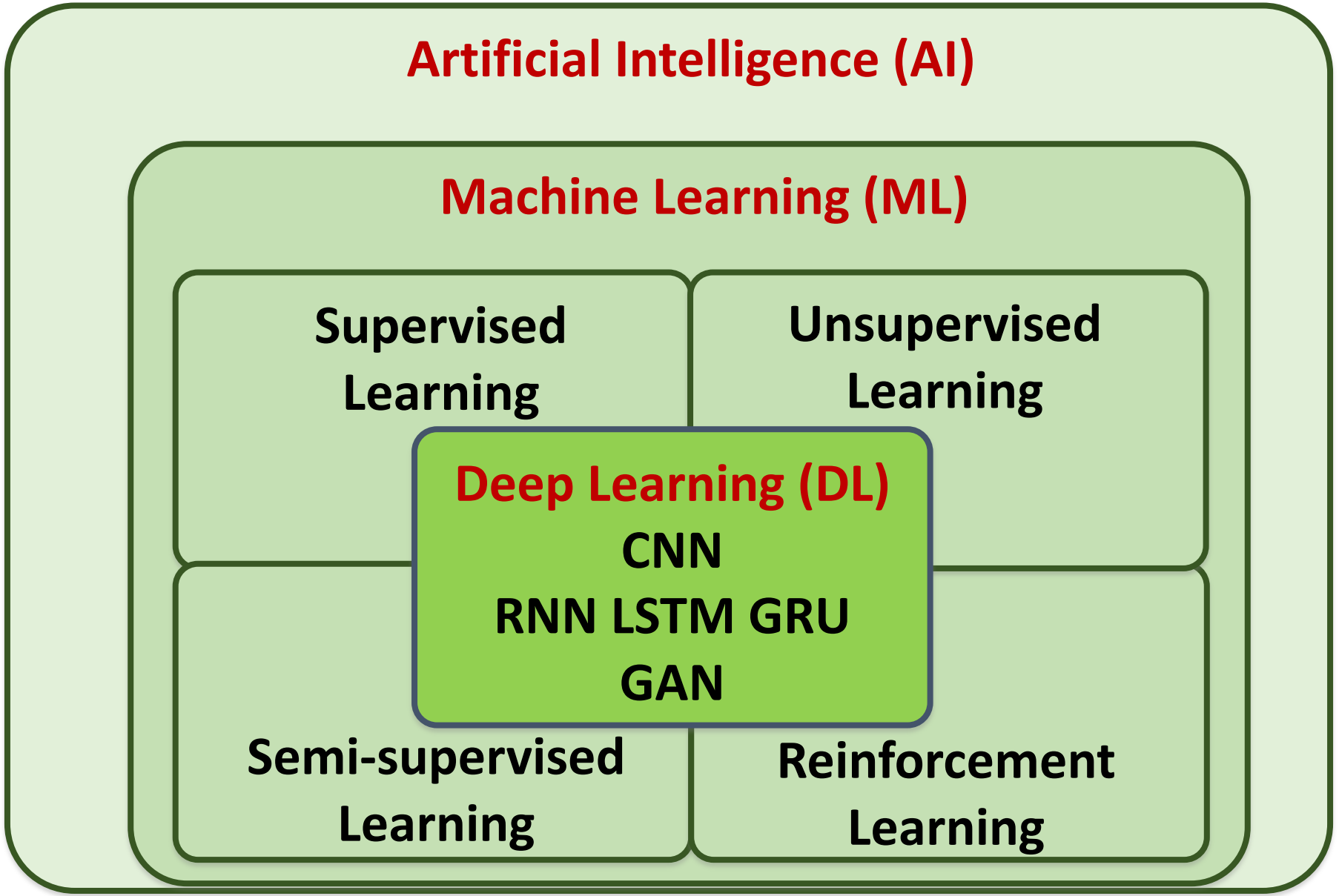
Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

AI Acting Humanly: The Turing Test Approach (Alan Turing, 1950)

- Knowledge Representation
- Automated Reasoning
- Machine Learning (ML)
  - Deep Learning (DL)
- Computer Vision (Image, Video)
- Natural Language Processing (NLP)
- Robotics

Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

AI, ML, DL



Source: https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/deep_learning.html

Comparison of Generative AI and Traditional AI

Feature	Generative AI	Traditional AI
Output type	New content	Classification/Prediction
Creativity	High	Low
Interactivity	Usually more natural	Limited

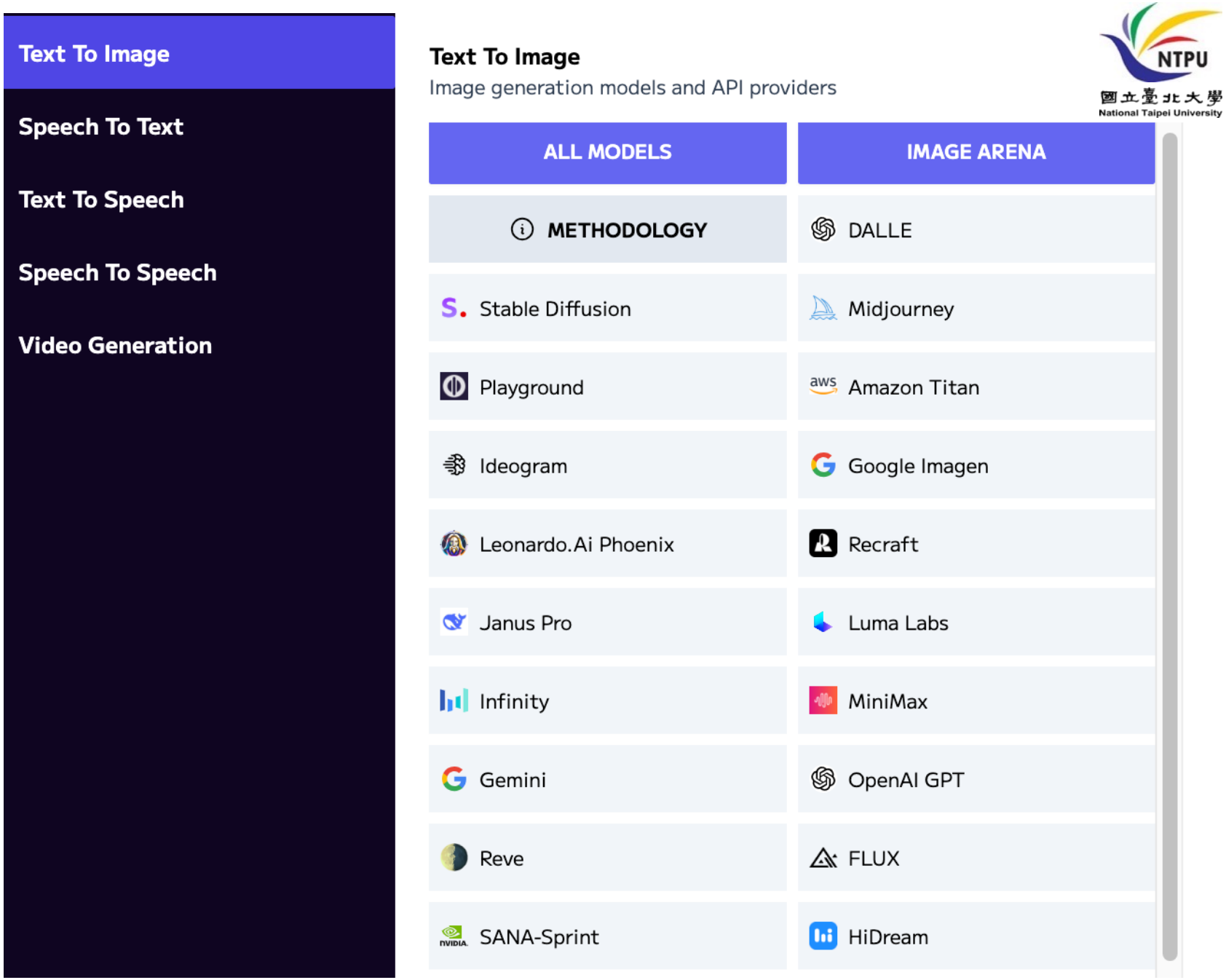
Generative AI

- Generative AI: The Art of Creation
- Definition: AI systems capable of creating new content
- Characteristics: Creativity, interactivity

Generative AI
Large Language Models (LLMs)
Foundation Models

Language Models

Text
Image
Speech
Video
Models



https://artificialanalysis.ai/

Generative AI (Gen AI)

AI Generated Content (AIGC)

Image Generation

Instruction 1:
An astronaut riding a horse in a photorealistic style.

Instruction 2:
Teddy bears working on new AI research on the moon in the 1980s.

Figure 1

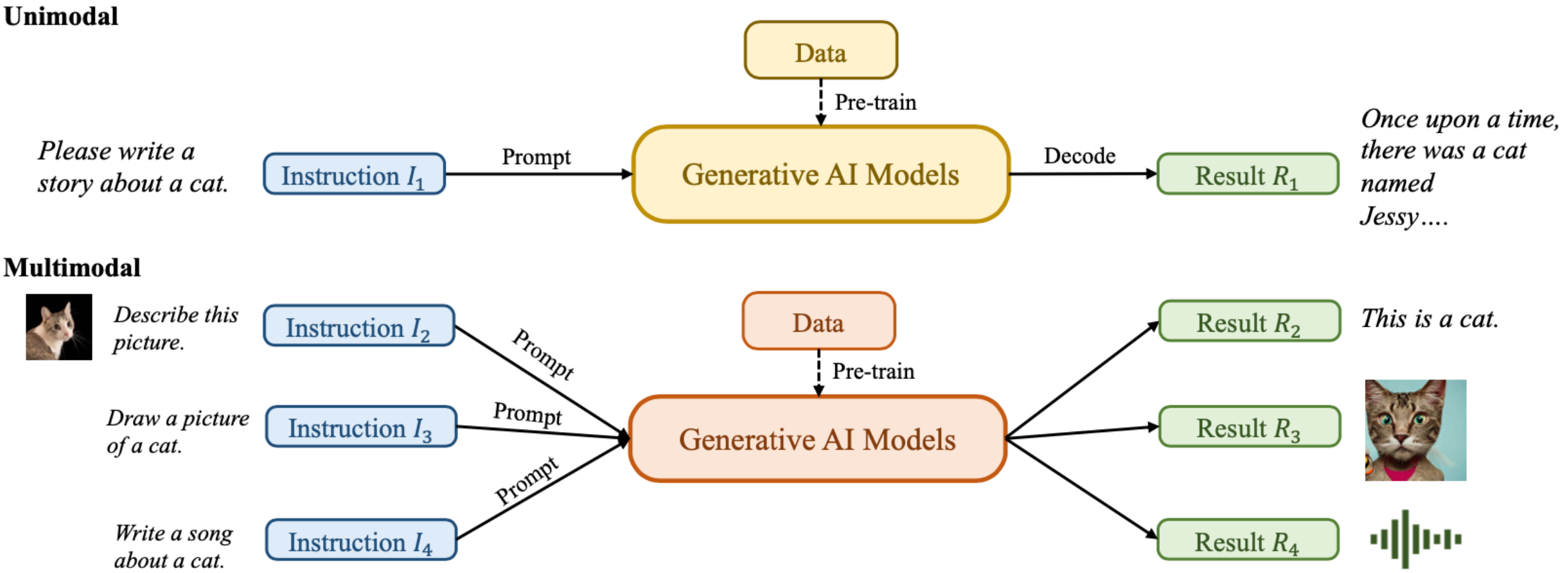
Figure 2

OpenAI DALL·E 2

Source: Yihan Cao, Siyu Li, Yixin Liu, Zhiling Yan, Yutong Dai, Philip S. Yu, and Lichao Sun (2023). "A Comprehensive Survey of AI-Generated Content (AIGC): A History of Generative AI from GAN to ChatGPT." arXiv preprint arXiv:2303.04226.

Generative AI (Gen AI)

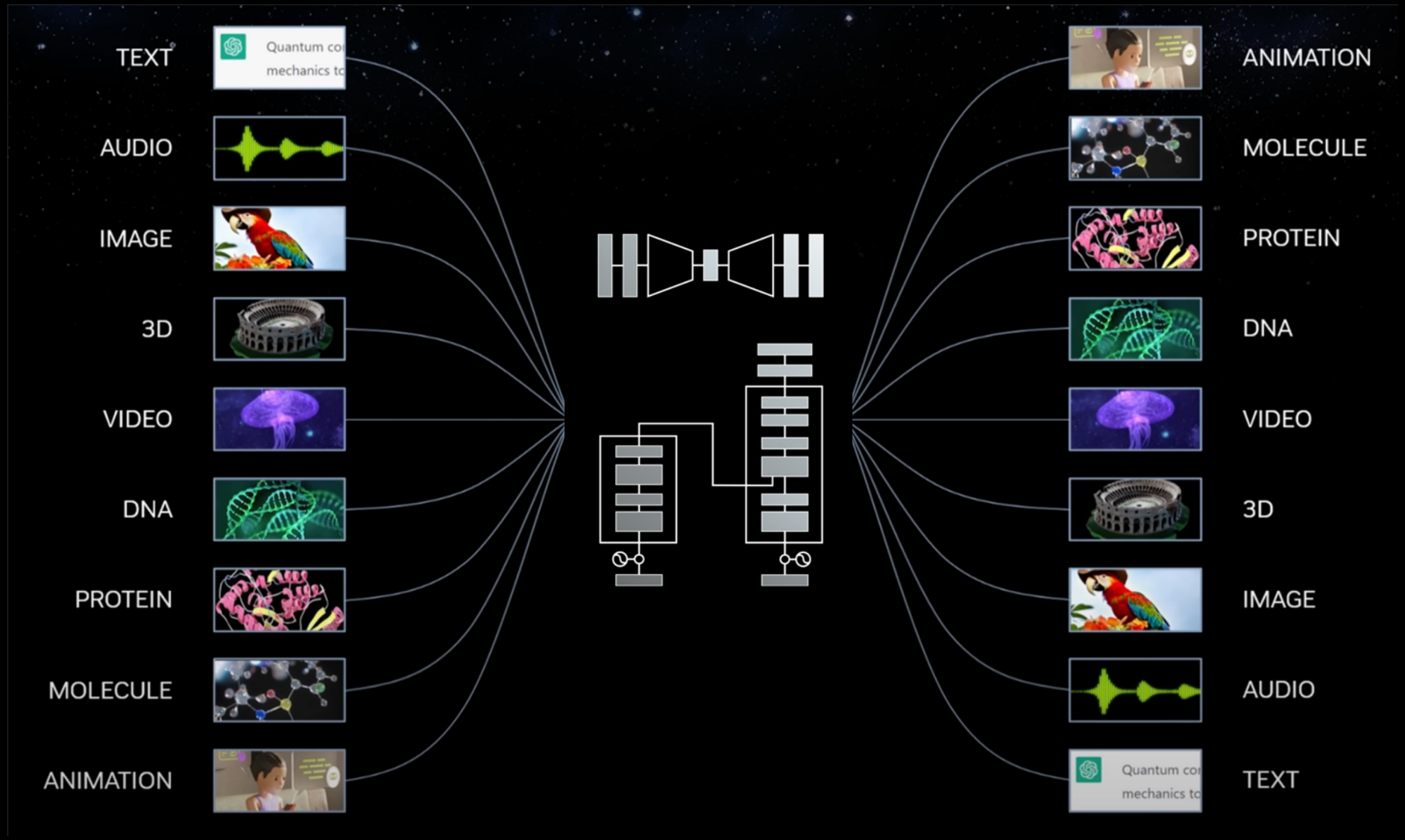
AI Generated Content (AIGC)



Source: Yihan Cao, Siyu Li, Yixin Liu, Zhiling Yan, Yutong Dai, Philip S. Yu, and Lichao Sun (2023). "A Comprehensive Survey of AI-Generated Content (AIGC): A History of Generative AI from GAN to ChatGPT." arXiv preprint arXiv:2303.04226.

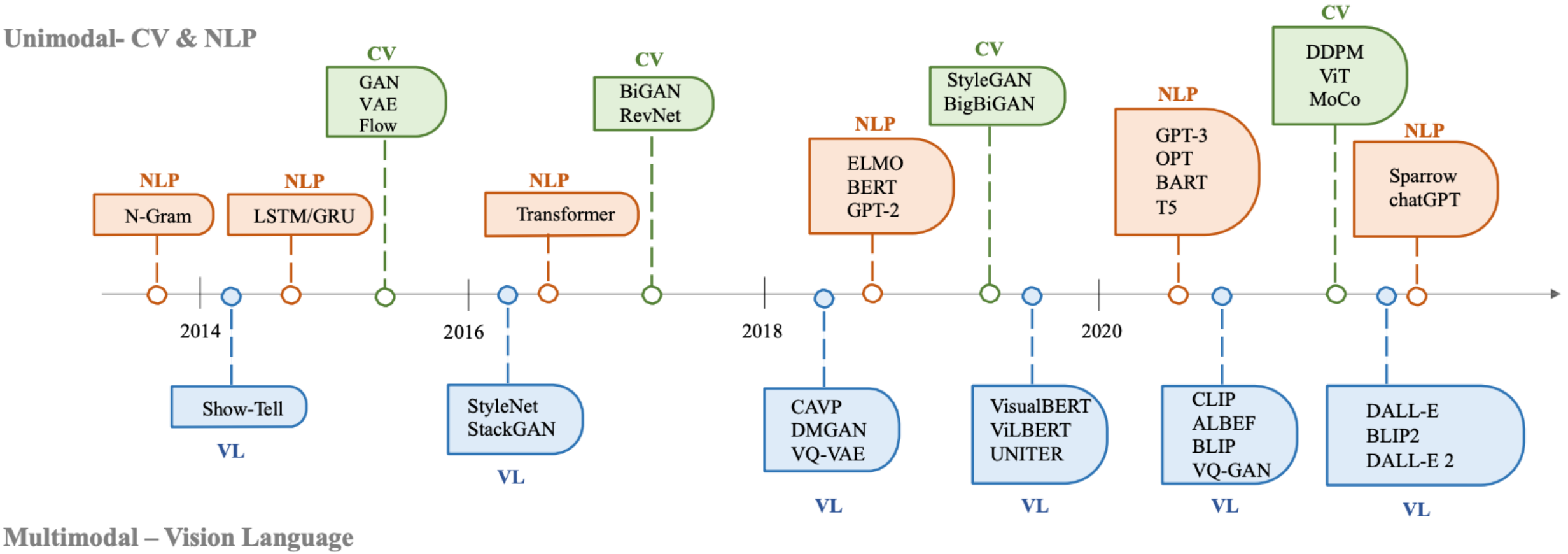
Modular Modalities

Where Can The Transformer Fit?



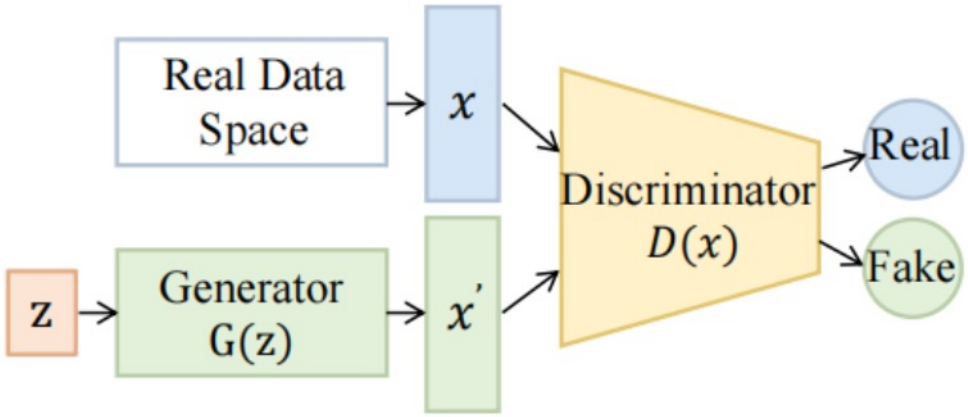
Source: NVIDIA DLI (2025), Rapid Application Development with Large Language Models (LLMs), https://learn.nvidia.com/courses/course-detail?course_id=course-v1:DLI+S-FX-26+V1

The history of Generative AI in CV, NLP and VL

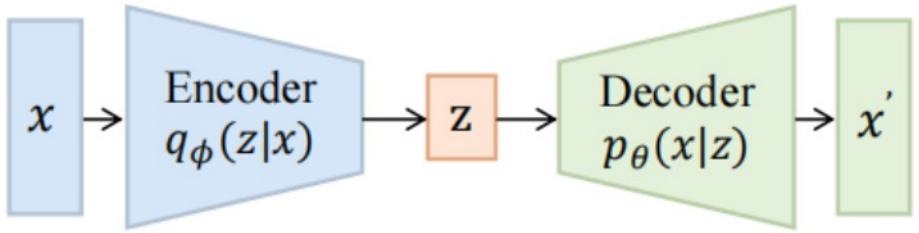


Source: Yihan Cao, Siyu Li, Yixin Liu, Zhiling Yan, Yutong Dai, Philip S. Yu, and Lichao Sun (2023). "A Comprehensive Survey of AI-Generated Content (AIGC): A History of Generative AI from GAN to ChatGPT." arXiv preprint arXiv:2303.04226.

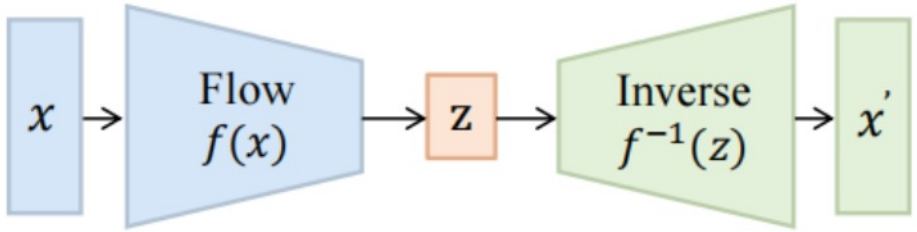
Categories of Vision Generative Models



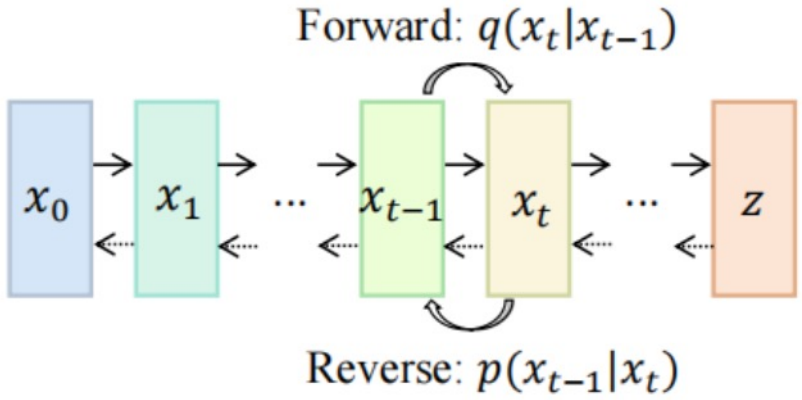
(1) Generative adversarial networks



(2) Variational autoencoders



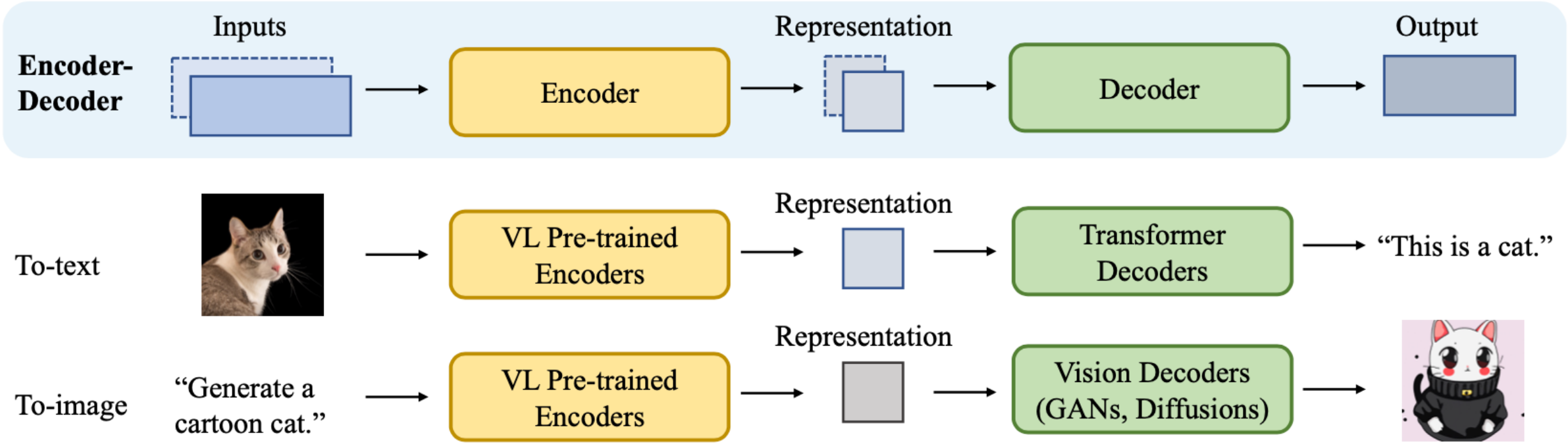
(3) Normalizing flows



(4) Diffusion models

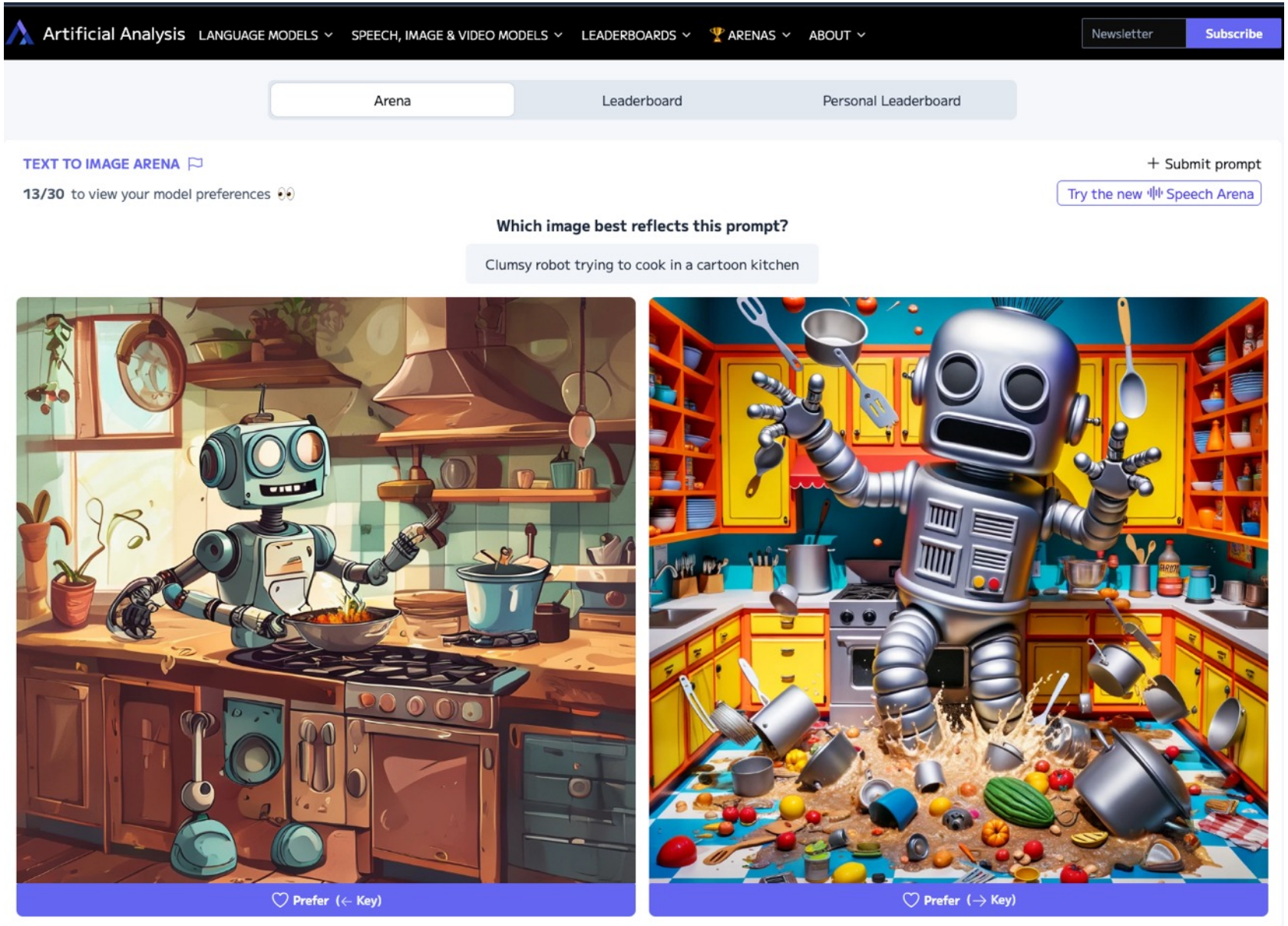
Source: Yihan Cao, Siyu Li, Yixin Liu, Zhiling Yan, Yutong Dai, Philip S. Yu, and Lichao Sun (2023). "A Comprehensive Survey of AI-Generated Content (AIGC): A History of Generative AI from GAN to ChatGPT." arXiv preprint arXiv:2303.04226.

The General Structure of Generative Vision Language



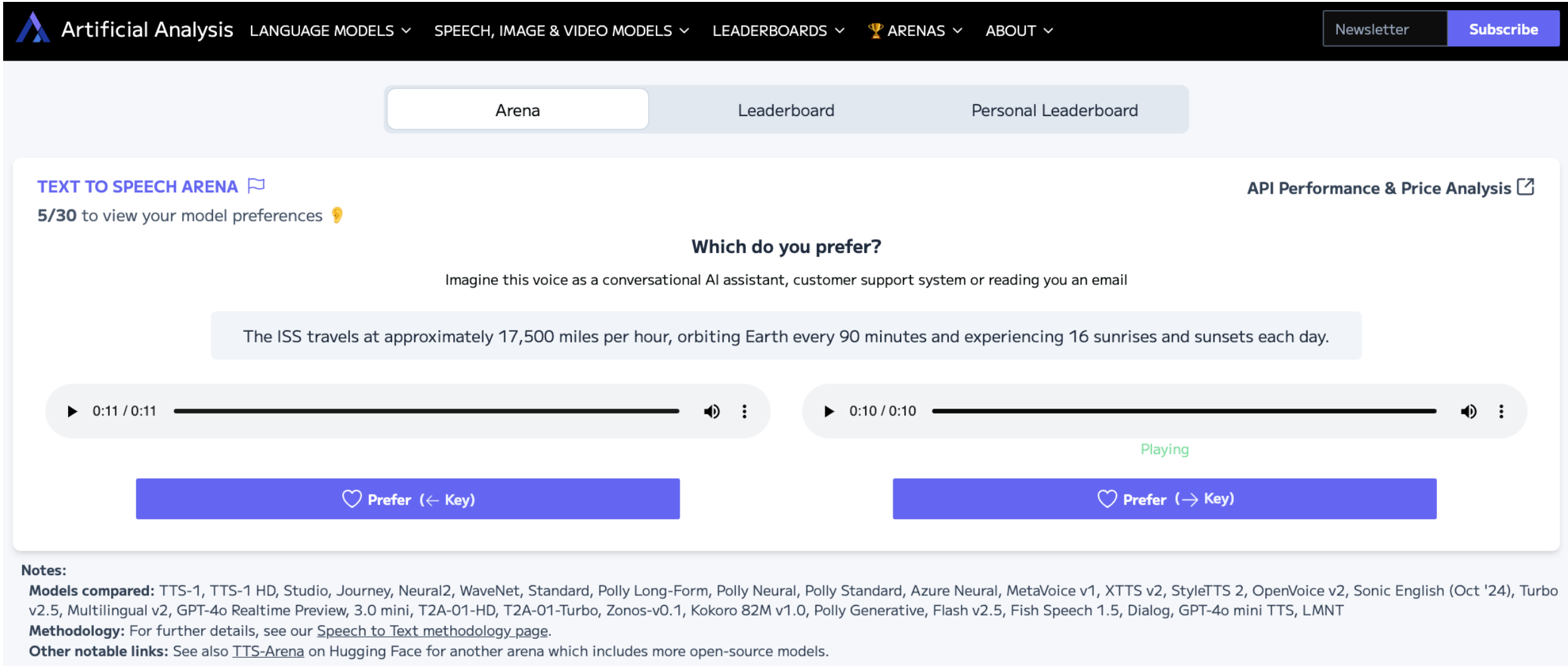
Source: Yihan Cao, Siyu Li, Yixin Liu, Zhiling Yan, Yutong Dai, Philip S. Yu, and Lichao Sun (2023). "A Comprehensive Survey of AI-Generated Content (AIGC): A History of Generative AI from GAN to ChatGPT." arXiv preprint arXiv:2303.04226.

Artificial Analysis Text to Image Arena



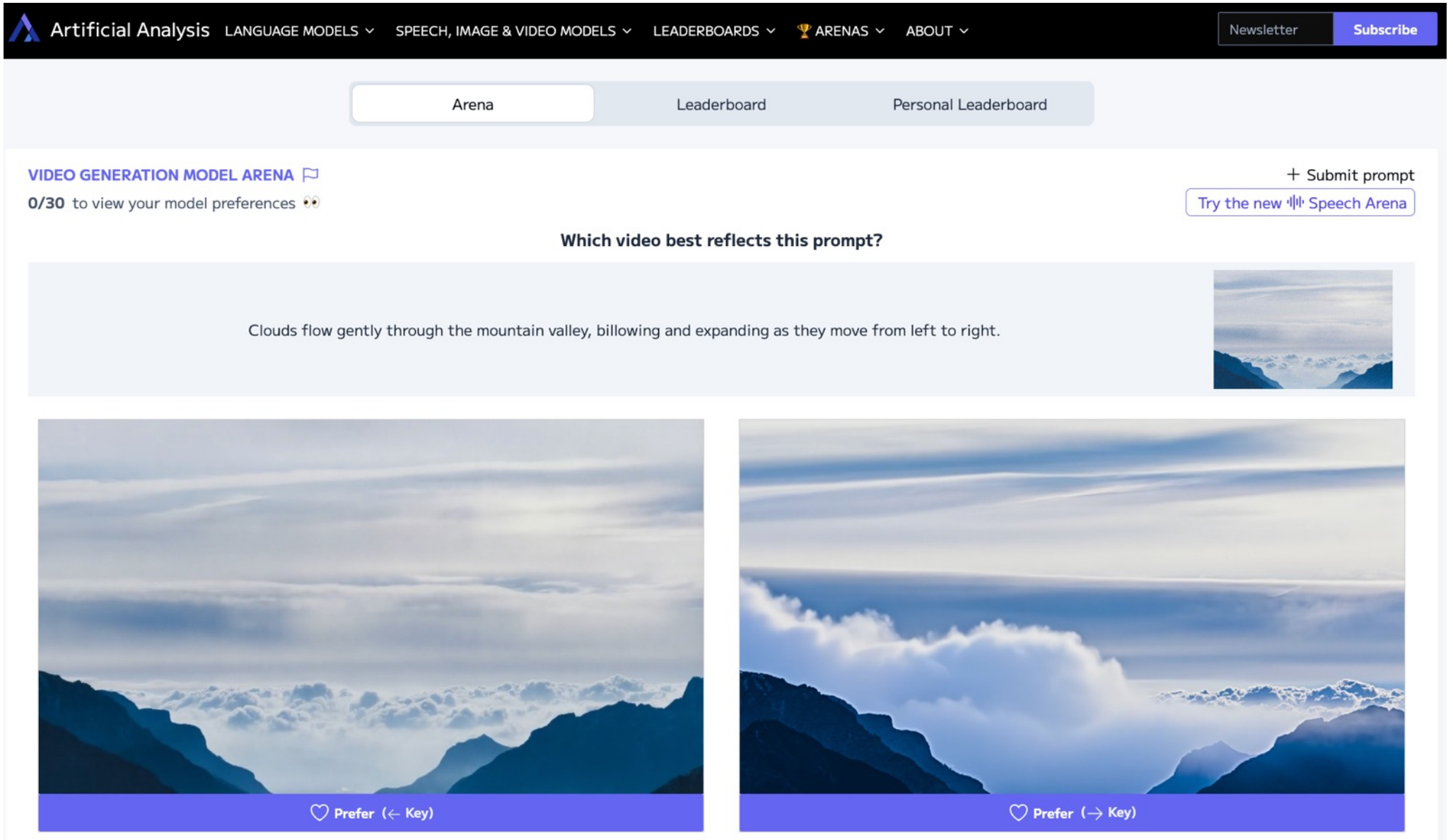
Source: https://artificialanalysis.ai/text-to-image/arena

Artificial Analysis Text to Speech Arena



Source: https://artificialanalysis.ai/text-to-speech/arena

Artificial Analysis Video Generation Model Arena



Source: https://artificialanalysis.ai/text-to-video/arena

Artificial Analysis Text to Image Leaderboard

Text to Image AI Model & Provider Leaderboard

Analysis and comparison of Text to Image generation models & API providers. Artificial Analysis has analyzed text to image models and hosting providers across quality, generation time, and price. For further details, see our methodology page.

Image Arena

Contribute to the Quality ELO score and see your personal model ranking

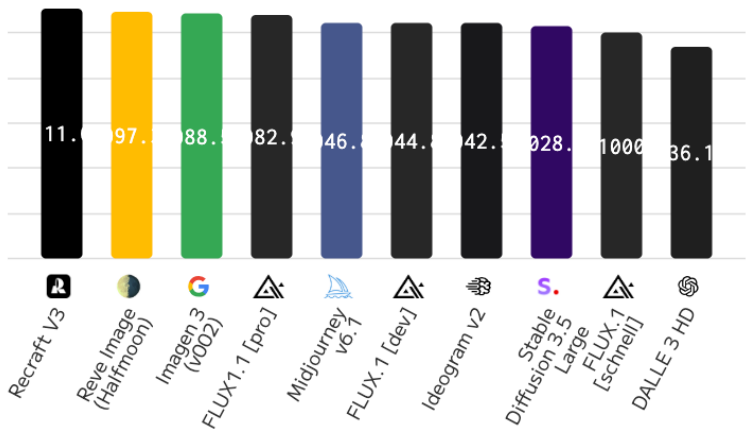
Image Arena

Text to image models & providers compared: Phoenix 0.9 Ultra, Playground v2.5, Stable Diffusion 3 Medium, Stable Diffusion XL 1.0, SDXL Lightning, Stable Diffusion 1.5, Stable Diffusion 2.1, Amazon Titan G1 (Standard), DALLE 2, DALLE 3 HD, DALLE 3, Midjourney v6, Stable Diffusion 1.6, Stable Diffusion 3 Large Turbo, Stable Diffusion 3 Large, Midjourney v6.1, Amazon Titan G1 v2 (Standard), Playground v3 (beta), Ideogram v2, FLUX.1 [pro], FLUX.1 [dev], Stable Diffusion 3.5 Medium, Ideogram v2 Turbo, Ideogram v1, FLUX1.1 [pro], Recraft 20B, FLUX.1 [schnell], Stable Diffusion 3.5 Large, Stable Diffusion 3.5 Large Turbo, Recraft V3, Luma Photon Flash, Adobe Firefly 3, GPT-4o, Janus Pro, Luma Photon, Lumina Image v2, Phoenix 1.0 Fast, Phoenix 1.0 Ultra, Image-01, Gemini 2.0 Flash Experimental, Reve Image (Halfmoon), Ideogram v2a, Ideogram v2a Turbo, Imagen 3 (v002), Ideogram 3.0, Midjourney v7 Alpha, Sana Sprint 1.6B, HiDream-I1-Dev, and Grok 2.

Highlights

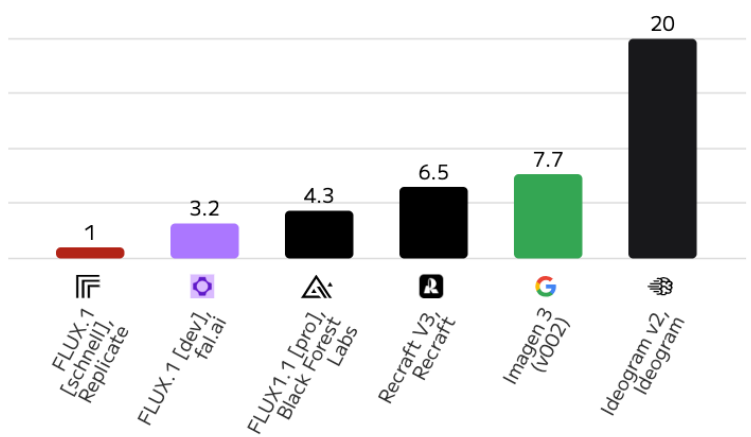
QUALITY ELO

ELO score in Artificial Analysis Image Arena (relative metric of image generation quality), Higher is better



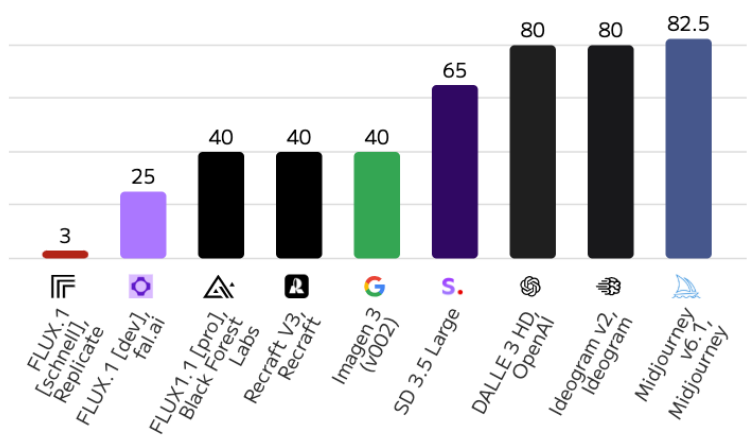
GENERATION TIME

Generation time: Seconds to generate 1 image, Lower is better



PRICE

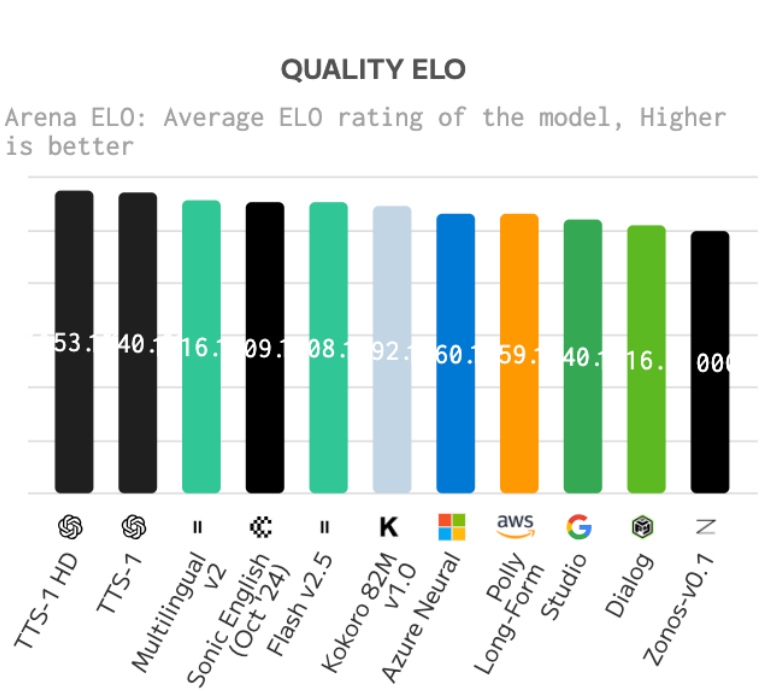
Price: USD per 1000 image generations, Lower is better

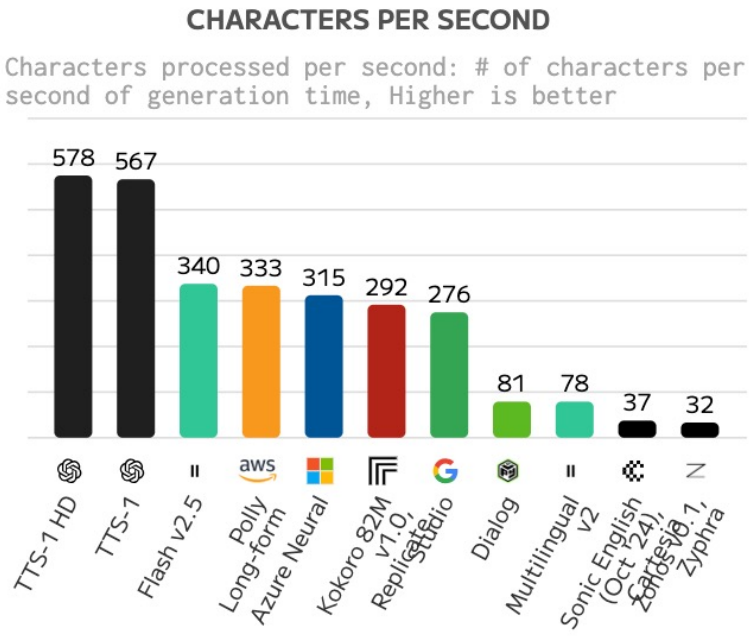


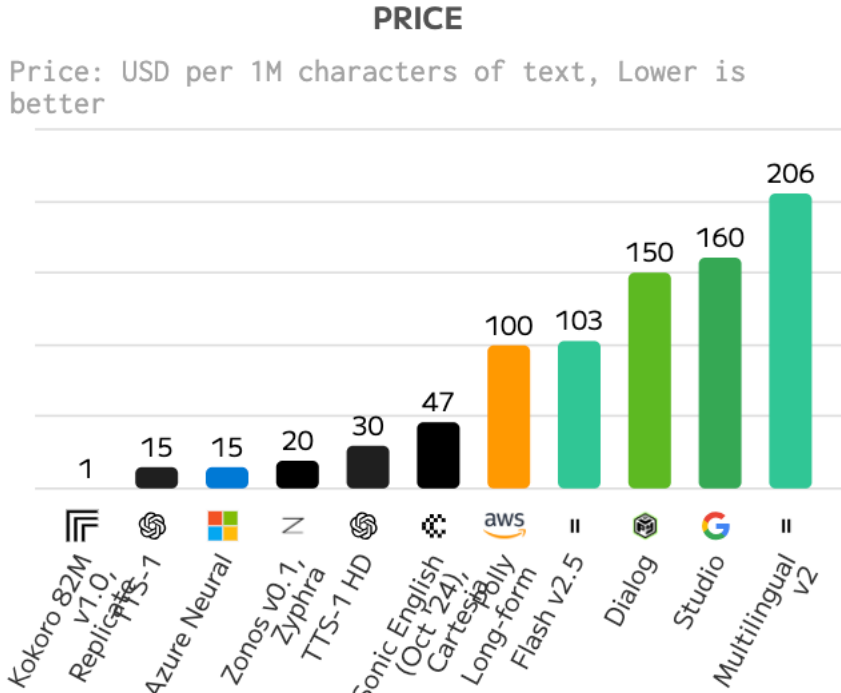
Source: https://artificialanalysis.ai/text-to-image

Text to Speech (TTS) AI Model & Provider Leaderboard

Text to speech models & providers compared: TTS-1, TTS-1 HD, Studio, Journey, Neural2, WaveNet, Standard, Polly Long-Form, Polly Neural, Polly Standard, Azure Neural, MetaVoice v1, XTTS v2, StyleTTS 2, OpenVoice v2, Sonic English (Oct '24), 3.0 mini, Turbo v2.5, Multilingual v2, T2A-01-HD, T2A-01-Turbo, Zonos-v0.1, Kokoro 82M v1.0, Polly Generative, Flash v2.5, Dialog, Murf Speech Gen 2, and Step TTS Mini.

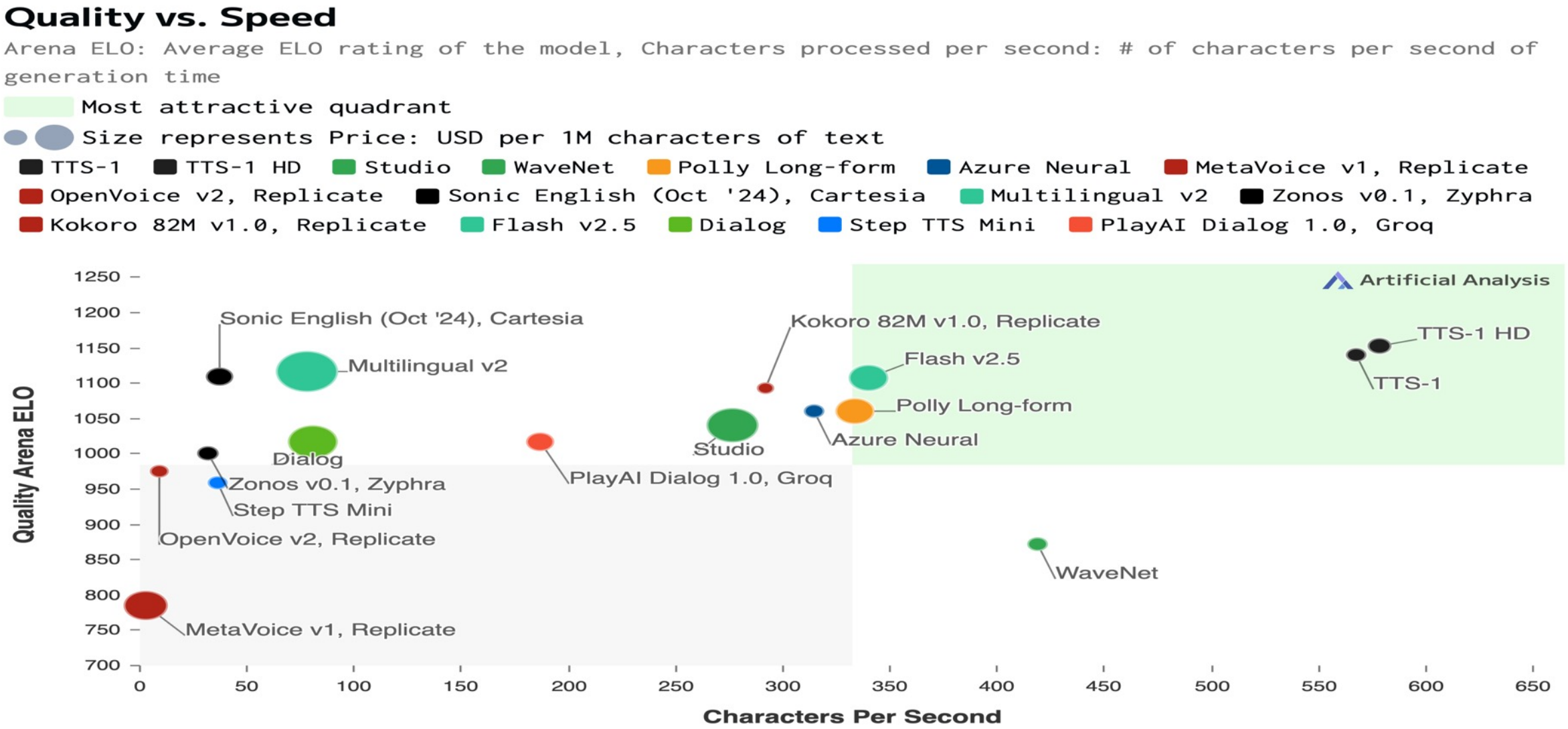






Source: https://artificialanalysis.ai/text-to-speech

Text to Speech (TTS) AI Model & Provider Leaderboard

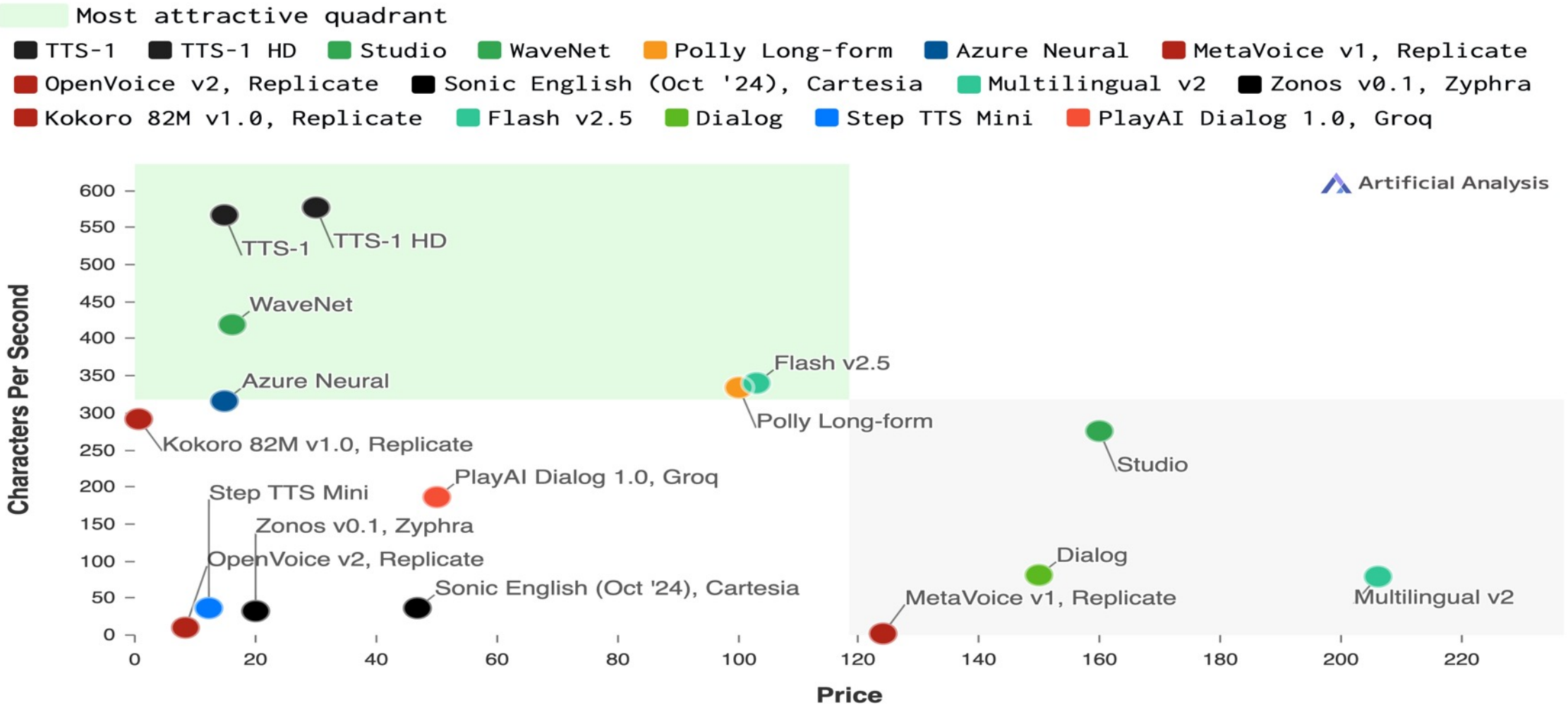


Source: https://artificialanalysis.ai/text-to-speech

Text to Speech (TTS) AI Model & Provider Leaderboard

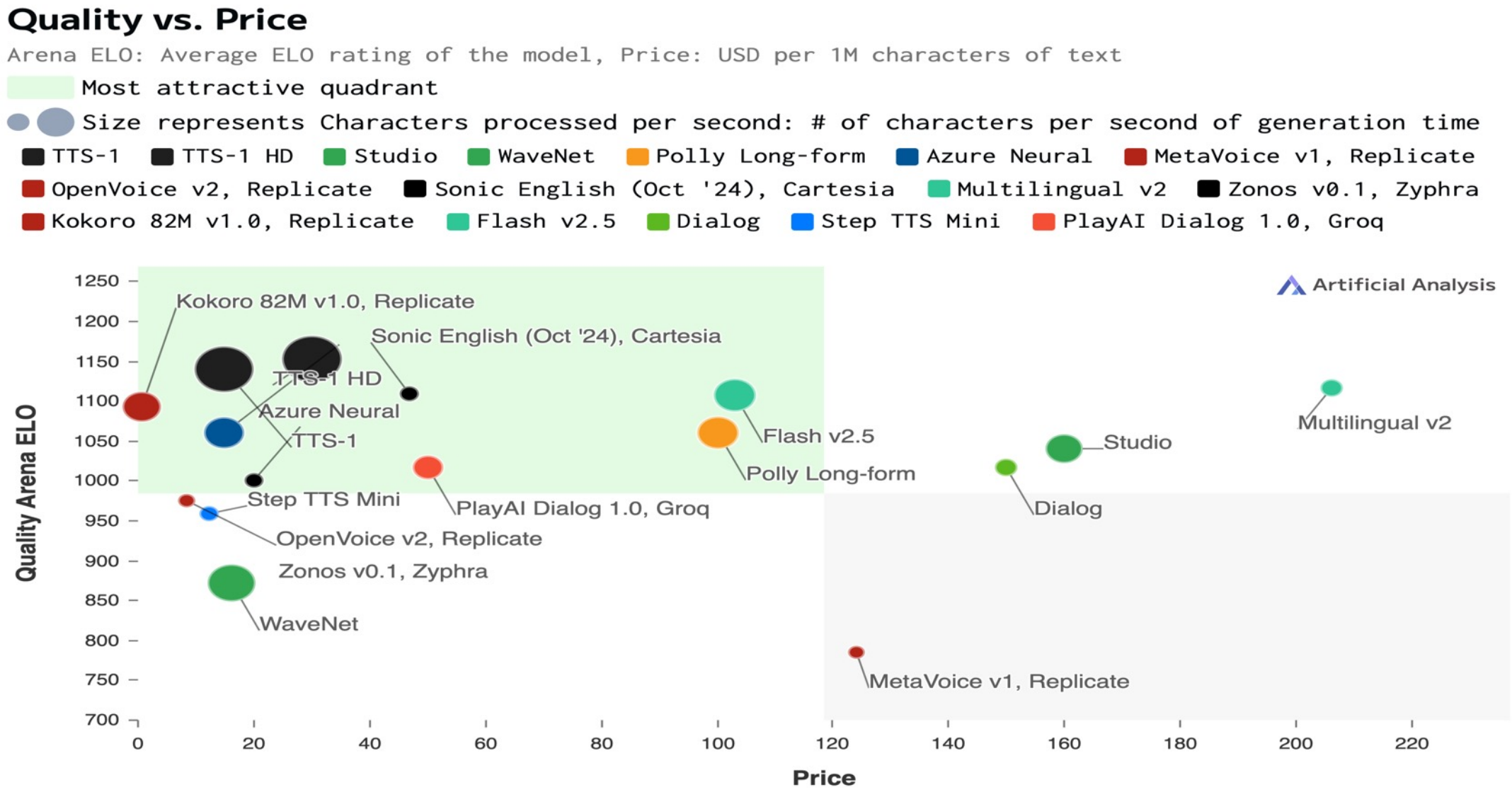
Speed vs. Price

Characters processed per second: # of characters per second of generation time, Price: USD per 1M characters of text



Source: https://artificialanalysis.ai/text-to-speech

Text to Speech (TTS) AI Model & Provider Leaderboard

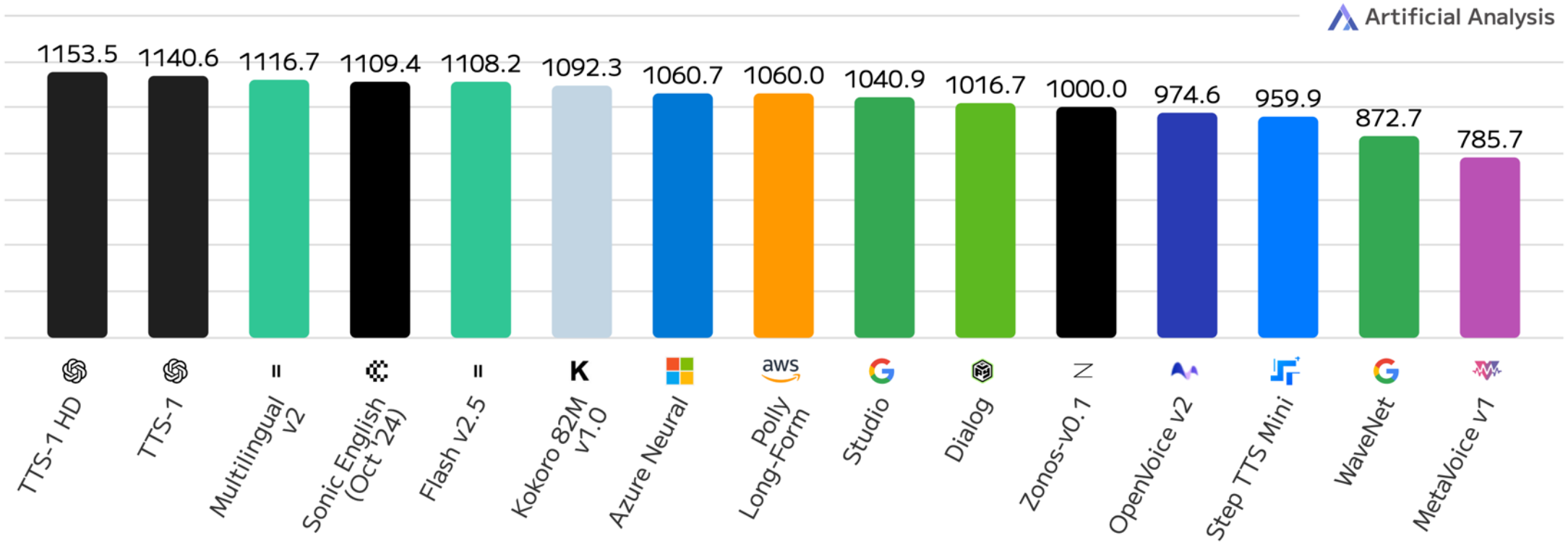


Source: https://artificialanalysis.ai/text-to-speech

Text to Speech (TTS) AI Model & Provider Leaderboard

Quality Arena ELO (Text to Speech Arena)

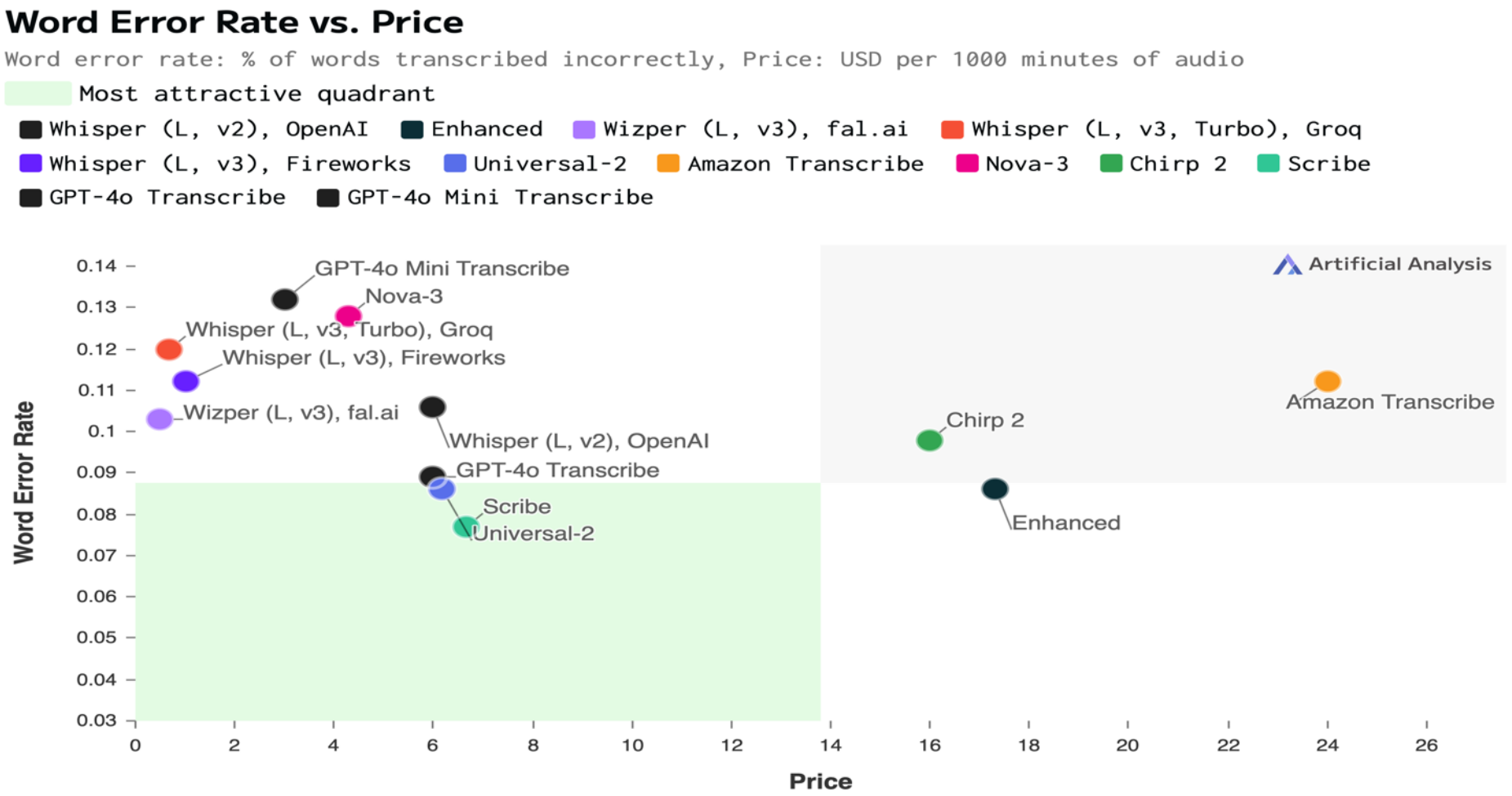
Arena ELO: Average ELO rating of the model, Higher is better



Source: https://artificialanalysis.ai/text-to-speech

Speech to Text (STT) AI Model & Provider Leaderboard

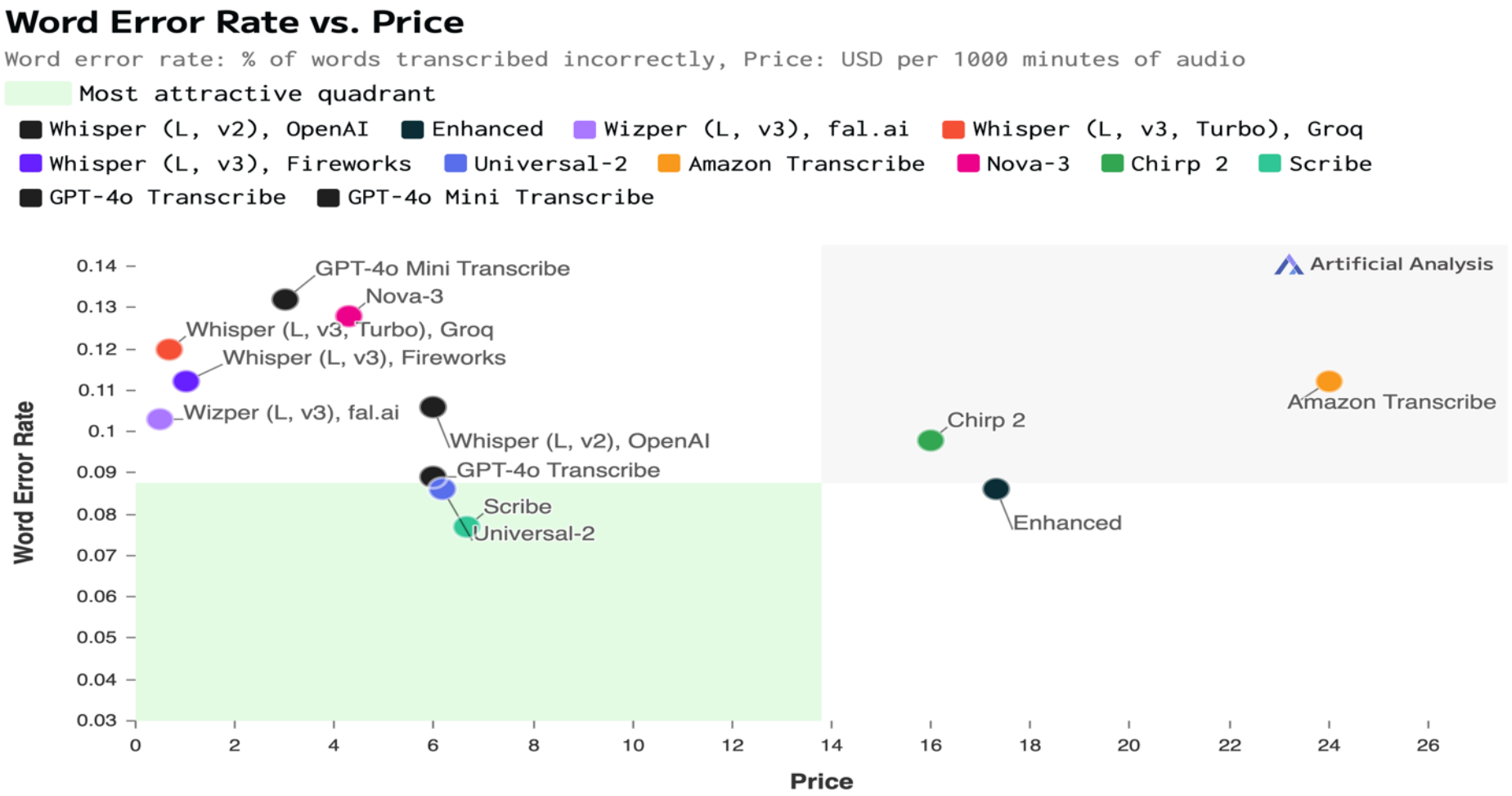
Speech-to-text models & providers compared: Whisper (L, v2), OpenAI, Universal-1, Standard, Whisper (L, v2), Azure, Enhanced, Nano, Wizper (L, v3), fal.ai, Incredibly Fast Whisper, Replicate, Nova-2, Whisper (L, v2), Replicate, Whisper (L, v3), Replicate, Base, WhisperX, Replicate, Whisper (L v2), Deepgram, Gladia, Whisper (L, v3), Groq, Distil-Whisper, Groq, Whisper (L, v3), fal.ai, Whisper (L, v3), Deepinfra, Whisper (L, v3, Turbo), Groq, Whisper (L, v3), Fireworks, Whisper (L, v3, Turbo), Fireworks, Universal-2, Amazon Transcribe, Fish Speech to Text, Nova-3, Chirp, Chirp 2, Scribe, GPT-4o Transcribe, and GPT-4o Mini Transcribe.



Source: https://artificialanalysis.ai/speech-to-text

Speech to Text (STT) AI Model & Provider Leaderboard

Speech-to-text models & providers compared: Whisper (L, v2), OpenAI, Universal-1, Standard, Whisper (L, v2), Azure, Enhanced, Nano, Wizper (L, v3), fal.ai, Incredibly Fast Whisper, Replicate, Nova-2, Whisper (L, v2), Replicate, Whisper (L, v3), Replicate, Base, WhisperX, Replicate, Whisper (L v2), Deepgram, Gladia, Whisper (L, v3), Groq, Distil-Whisper, Groq, Whisper (L, v3), fal.ai, Whisper (L, v3), Deepinfra, Whisper (L, v3, Turbo), Groq, Whisper (L, v3), Fireworks, Whisper (L, v3, Turbo), Fireworks, Universal-2, Amazon Transcribe, Fish Speech to Text, Nova-3, Chirp, Chirp 2, Scribe, GPT-4o Transcribe, and GPT-4o Mini Transcribe.



Source: https://artificialanalysis.ai/speech-to-text

Artificial Analysis Text to Video Leaderboard

Text to Video | Image to Video

CREATOR	NAME	ARENA ELO	95% CI	# APPEARANCES
Google	**Veo 2**	1124	-10/+10	6,452
Kuaishou	**Kling 1.5 (Pro)**	1053	-6/+6	20,631
OpenAI	**OpenAI Sora**	1049	-5/+5	23,649
MiniMax	**T2V-01**	1039	-4/+4	43,450
Pika Art	**Pika 2.0**	1038	-6/+6	20,432
Kuaishou	**Kling 1.6 (Standard)**	1029	-7/+6	13,607
MiniMax	**T2V-01-Director**	1022	-9/+9	7,765

Source: https://artificialanalysis.ai/text-to-video/arena?tab=Leaderboard&leaderboard_tab=t2v

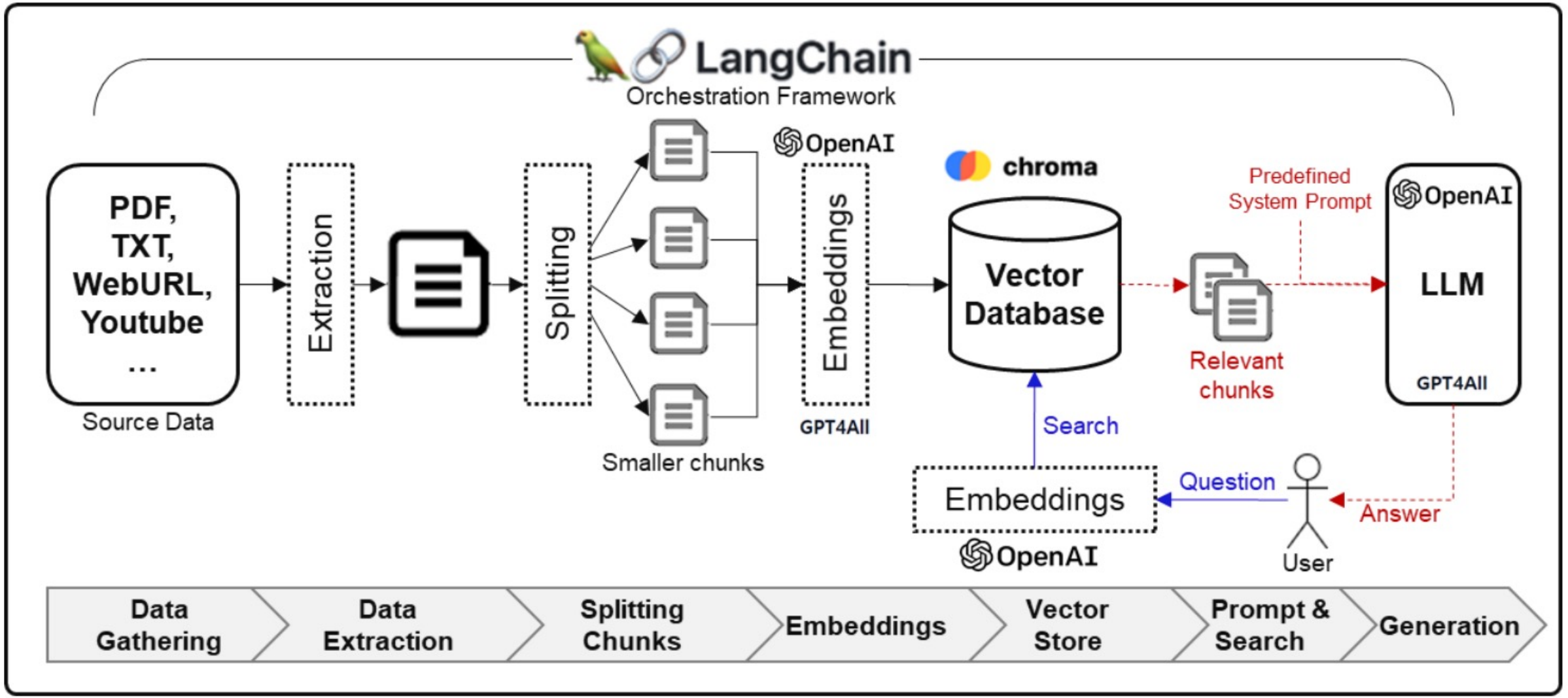
Artificial Analysis Image to Video Leaderboard

Text to Video | **Image to Video**

CREATOR	NAME	ARENA ELO	95% CI	# APPEARANCES
Kuaishou	**Kling 1.6 (Pro)**	1121	-17/+18	2,748
Runway	**Runway Gen 4**	1115	-14/+15	7,314
Google	**Veo 2**	1113	-18/+17	2,770
MiniMax	**I2V-01-Director**	1031	-15/+15	7,407
Pika Art	**Pika 2.2**	1001	-19/+17	2,740
Alibaba	**Wan 2.1 14B**	1000	+0/+0	2,700
Runway	**Runway Gen 3 Alpha Turbo**	992	-15/+14	7,420
Runway	**Runway Gen 3 Alpha**	971	-18/+16	2,558
OpenAI	**OpenAI Sora**	960	-19/+18	2,552
Tencent 腾讯 Tencent	**Hunyuan Video**	922	-18/+17	2,535

Source: https://artificialanalysis.ai/text-to-video/arena?tab=Leaderboard&leaderboard_tab=t2v

Framework for Implementing Generative AI Services using RAG Model



Source: Jeong, Cheonsu. "A Study on the Implementation of Generative AI Services Using an Enterprise Data-Based LLM Application Architecture." arXiv preprint arXiv:2309.01105 (2023).

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Spring 2025

Generative AI Innovative Applications

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University Ambassador

This certificate acknowledges that

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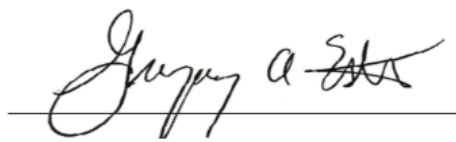

Greg Estes

Vice President, NVIDIA

Issue Date: : March 7, 2025

Ambassador Certification ID: cCFh1ZWWTvqKTq7dcKkEWw

https://learn.nvidia.com/certificates?id=cCFh1ZWWTvqKTq7dcKkEWw

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Certified Instructor

This certificate acknowledges that

Min-Yuh Day

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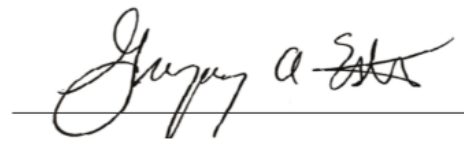
Building RAG Agents with LLMs



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Vice President, NVIDIA

Issue Date: : March 7, 2025

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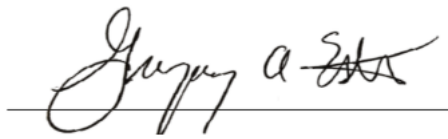

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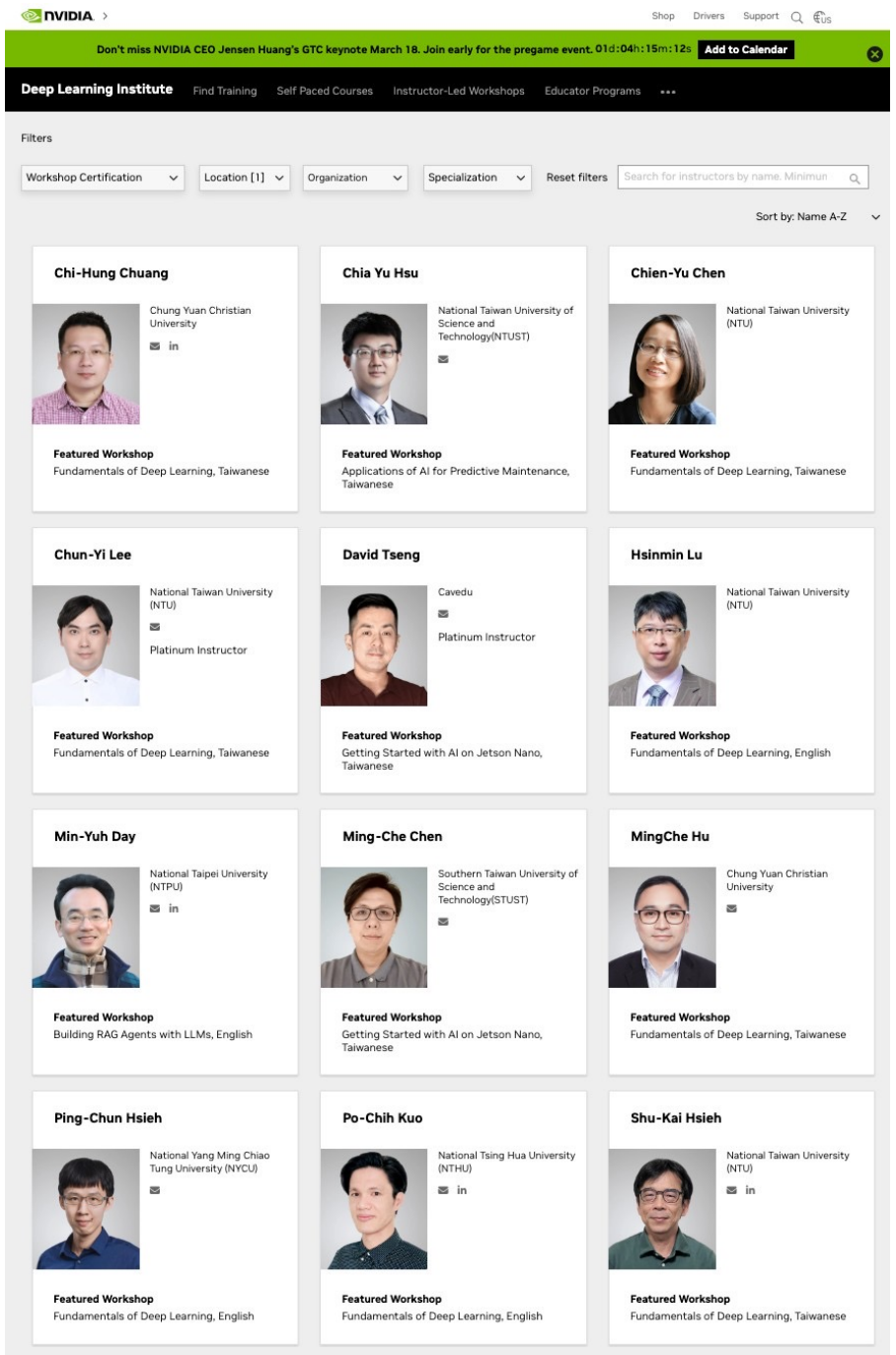
(12 from Taiwan)



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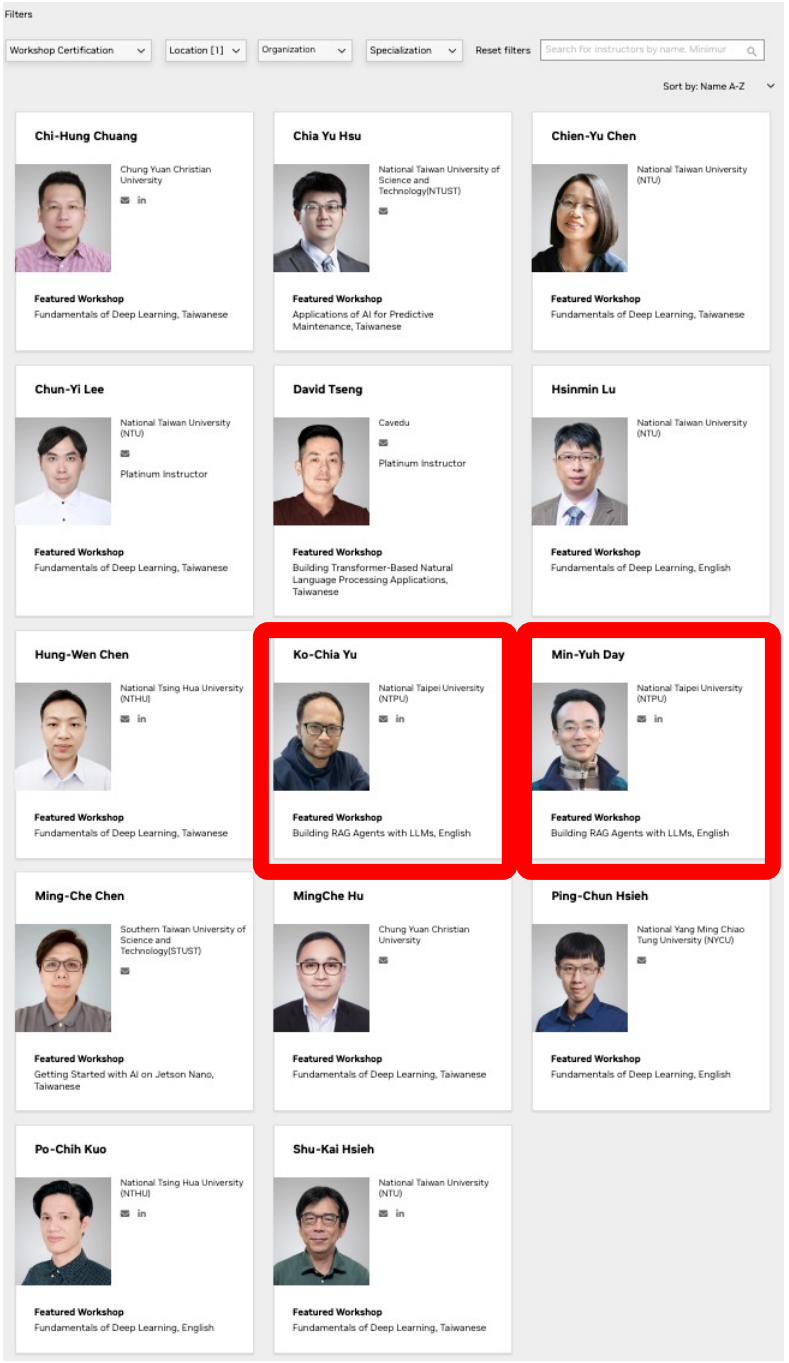
(14 from Taiwan)

(2 from NTPU)(April 2025)



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- **Step 3. Enroll "Generative AI with Diffusion Models"**
  Self-Paced Course ($90)
  https://learn.nvidia.com/courses/course-detail?course_id=course-v1:DLI+S-FX-14+V1

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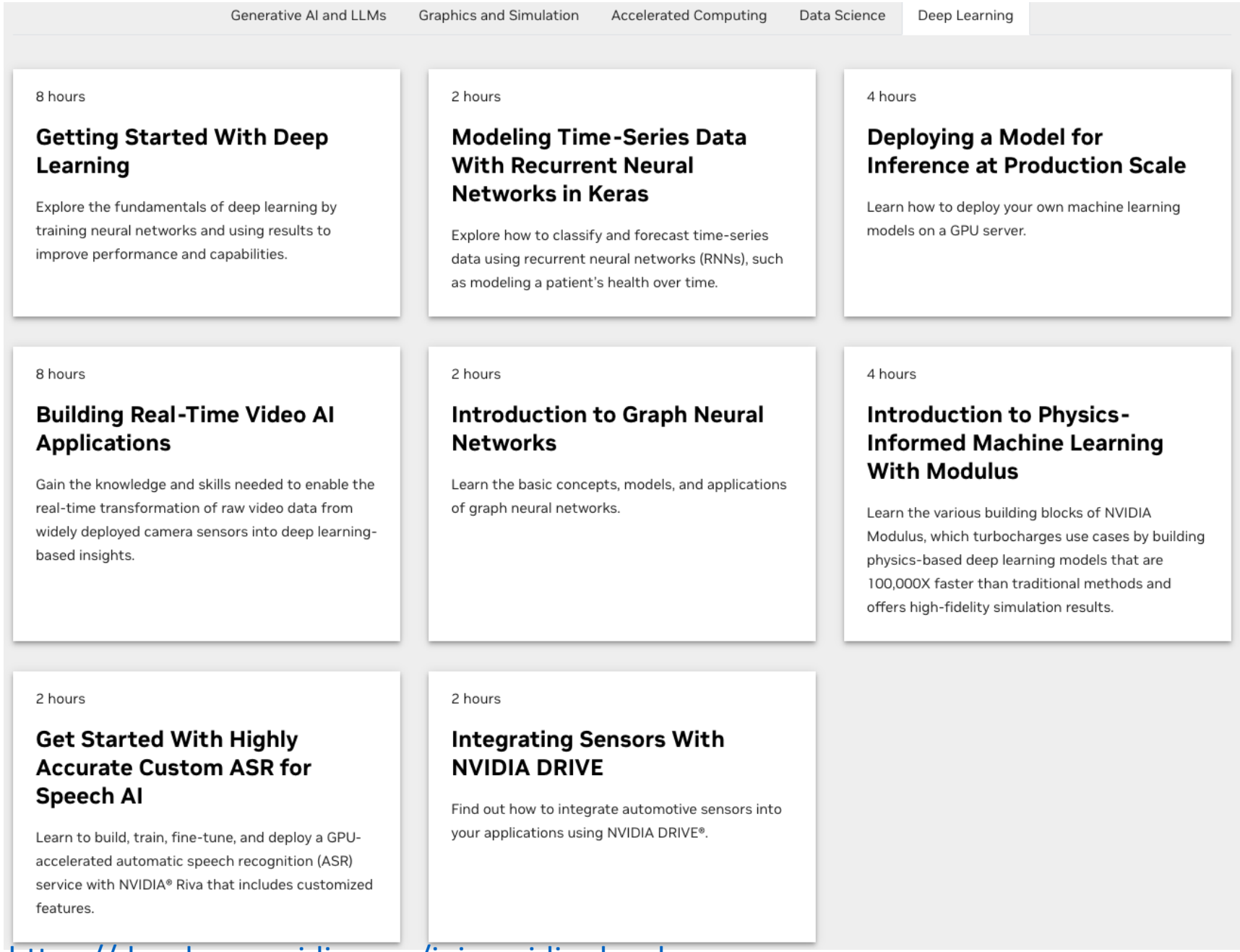

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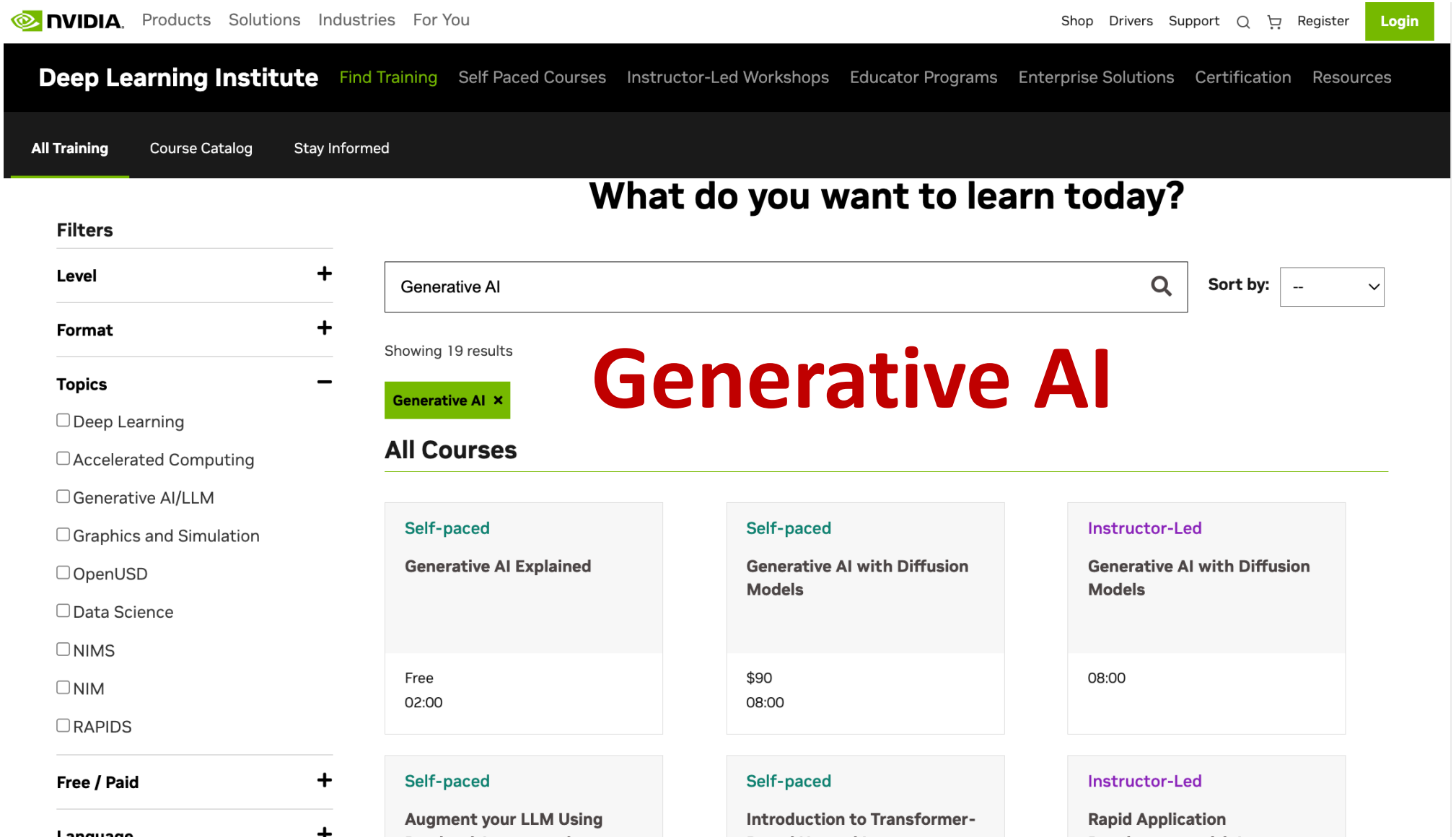
NVIDIA Deep Learning Institute (DLI)

Self-Paced Course **Generative AI Explained** Free 2 hours	Self-Paced Course **Getting Started With Deep Learning** Certificate available $90 8 hours	Instructor-Led Workshop **Fundamentals of Deep Learning** Certificate available $500 8 hours	Self-Paced Course **Introduction to Transformer-Based Natural Language Processing** Certificate available $30 6 hours
Self-Paced Course **Building RAG Agents With LLMs** Certificate available Free 8 hours	Instructor-Led Workshop **Building RAG Agents With LLMs** Certificate available $500 8 hours	Self-Paced Course **Generative AI with Diffusion Models** Certificate available $90 8 hours	Instructor-Led Workshop **Generative AI with Diffusion Models** Certificate available $500 8 hours

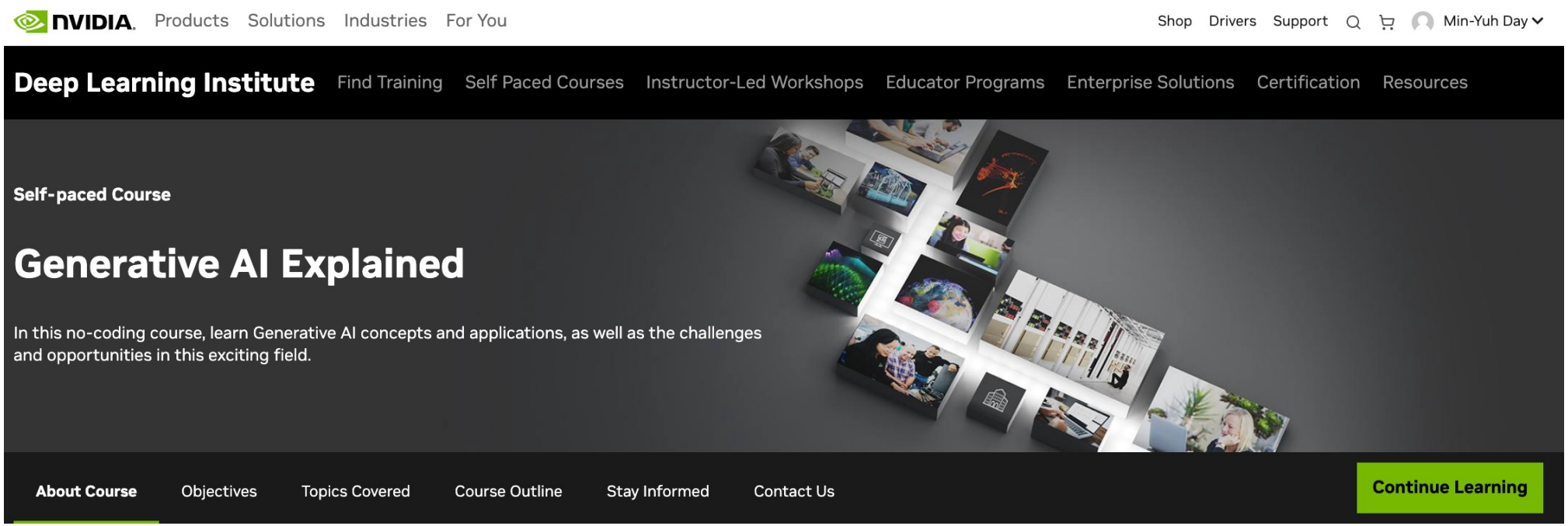
https://www.nvidia.com/en-us/learn/learning-path/generative-ai-llm/

NVIDIA Deep Learning Institute (DLI)



https://learn.nvidia.com/en-us/training/find-training?q=Generative+AI

Generative AI Explained



About this Course

Generative AI describes technologies that are used to generate new content based on a variety of inputs. In recent time, Generative AI involves the use of neural networks to identify patterns and structures within existing data to generate new content. In this course, you will learn Generative AI concepts, applications, as well as the challenges and opportunities in this exciting field.

Learning Objectives

Upon completion, you will have a basic understanding of Generative AI and be able to more effectively use the various tools built on this

Course Details

Duration: 02:00

Price: Free

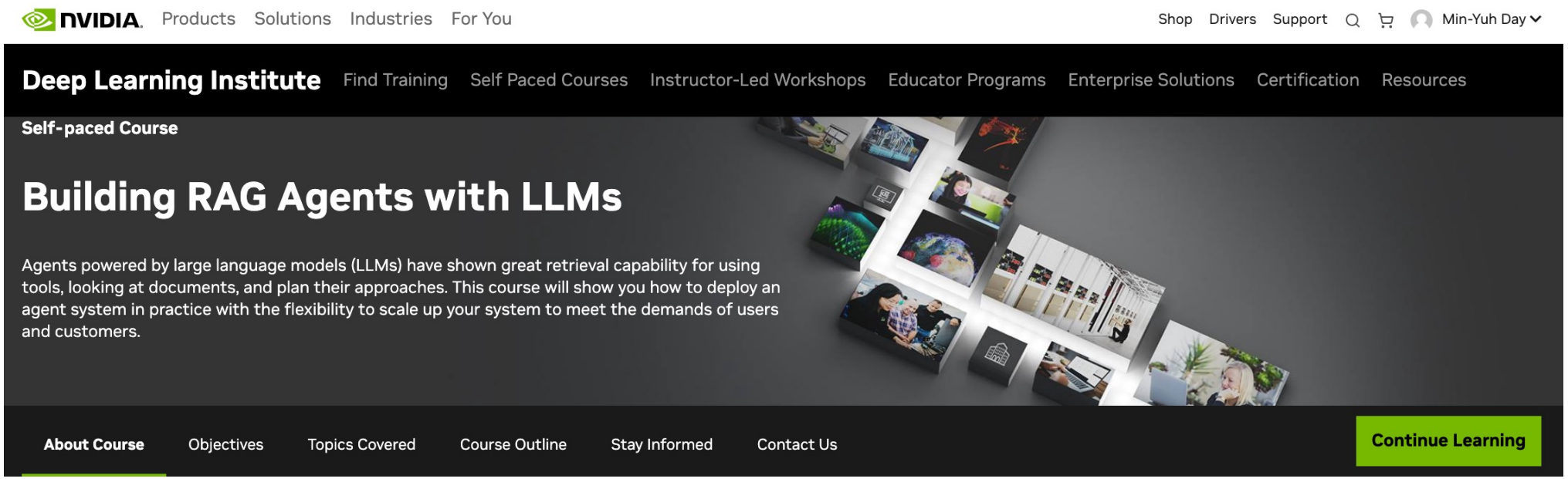
Level: Technical - Beginner

Subject: Generative AI/LLM

Language: English

https://learn.nvidia.com/courses/course-detail?course_id=course-v1:DLI+S-FX-15+V1

Building RAG Agents with LLMs



About this Course

This course is free for a limited time.

The evolution and adoption of large language models (LLMs) have been nothing short of revolutionary, with retrieval-based systems at the forefront of this technological leap. These models are not just tools for automation; they are partners in enhancing productivity, capable of holding informed conversations by interacting with a vast array of tools and documents. This course is designed for those eager to explore the potential of these systems, focusing on practical deployment and the efficient implementation required to manage the considerable demands of both users and deep learning models. As we delve into the intricacies of LLMs, participants will gain insights into advanced orchestration techniques that include internal reasoning, dialog management, and effective tooling strategies.

Course Details

Duration: 08:00

Price: Free

Level: Technical - Intermediate

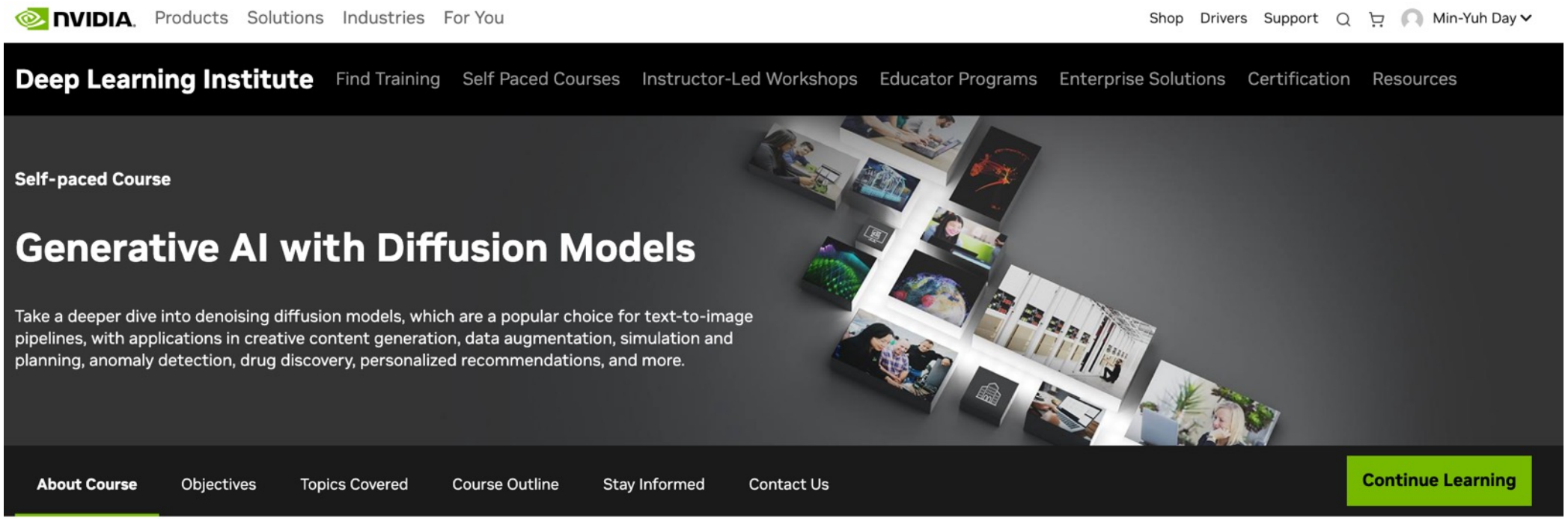
Subject: Generative AI/LLM

Language: English

Course Prerequisites:
Introductory deep learning knowledge, with comfort

https://learn.nvidia.com/courses/course-detail?course_id=course-v1:DLI+S-FX-15+V1

Generative AI with Diffusion Models



About this Course

Thanks to improvements in computing power and scientific theory, generative AI is more accessible than ever before. Generative AI plays a significant role across industries due to its numerous applications, such as creative content generation, data augmentation, simulation and planning, anomaly detection, drug discovery, personalized recommendations, and more. In this course, learners will take a deeper dive into denoising diffusion models, which are a popular choice for text-to-image pipelines.

Course Details

Duration: 08:00

Price: $90

Subject: Generative AI/LLM

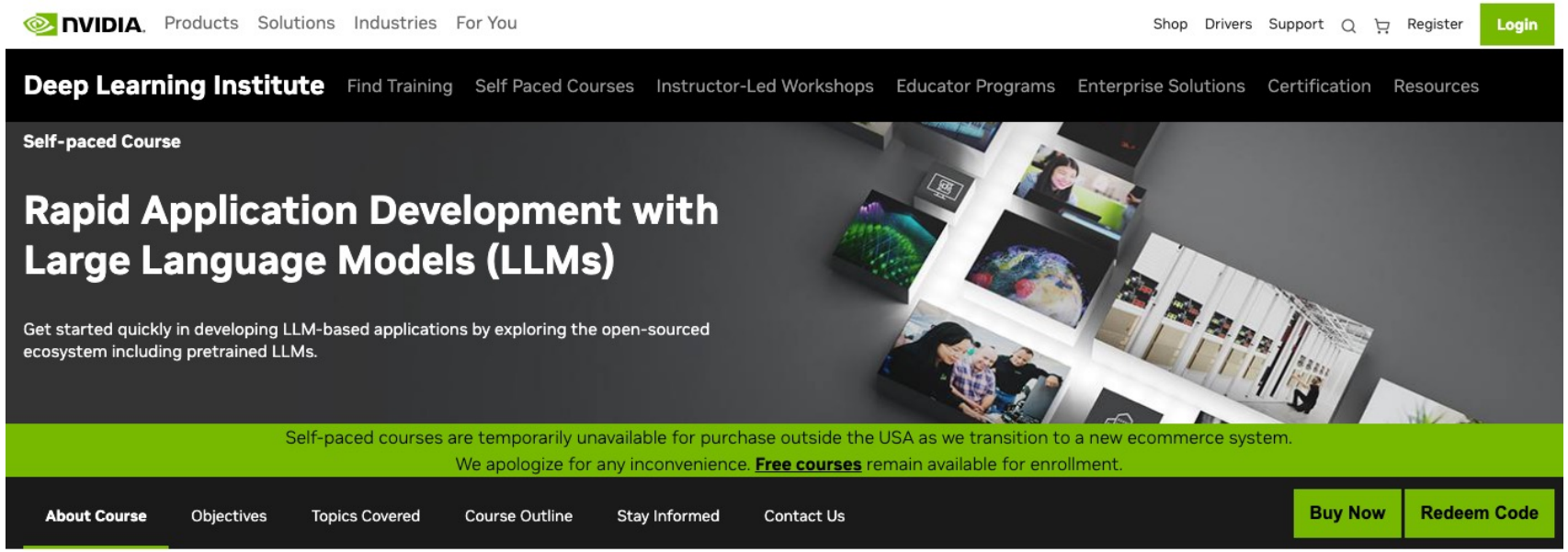
Language: English

Course Prerequisites:
A basic understanding of Deep Learning Concepts.

Learning Objectives

https://learn.nvidia.com/courses/course-detail?course_id=course-v1:DLI+S-FX-14+V1

Rapid Application Development with Large Language Models (LLMs)



About this Course

Recent advancements in both the techniques and accessibility of large language models (LLMs) have opened up unprecedented opportunities to help businesses streamline their operations, decrease expenses, and increase productivity at scale. Additionally, enterprises can use LLM-powered apps to provide innovative and improved services to clients or strengthen customer relationships. For example, enterprises could provide customer support via AI companions or use sentiment analysis apps to extract valuable customer insights. In this course you will gain a strong understanding and practical knowledge of LLM application development by exploring the open-sourced ecosystem including pretrained LLMs, enabling you to get started quickly in developing LLM-based applications.

Learning Objectives

By participating in this course, you will:

- Find, pull in, and experiment with the HuggingFace model repository and Transformers API.
- Use encoder models for tasks like semantic analysis, embedding, question-answering, and zero-shot classification.
- Work with conditioned decoder-style models to take in and generate interesting data formats, styles, and modalities.
- Kickstart and guide generative AI solutions for safe, effective, and scalable natural data tasks.
- Explore the use of LangChain for orchestrating data pipelines and environment-enabled agents.

Course Details

Duration: 08:00

Price: $90

Level: Technical - Beginner

Subject: Generative AI/LLM

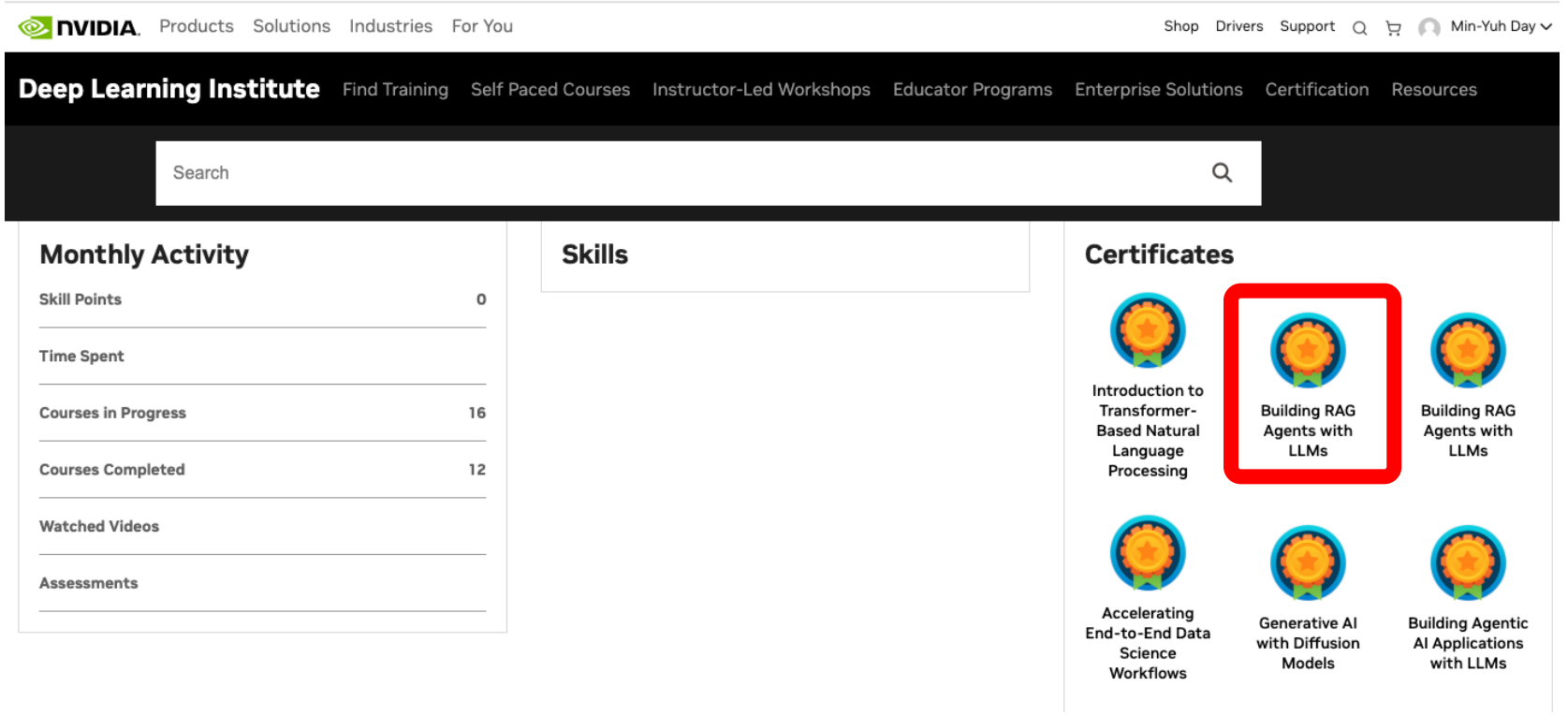
Language: English

Course Prerequisites:
Introductory deep learning, with comfort with PyTorch and transfer learning preferred. Content covered by DLI's Getting Started with Deep Learning or Fundamentals of Deep Learning courses, or similar experience is sufficient.

Intermediate Python experience, including object-oriented programming and libraries. Content covered by

https://learn.nvidia.com/courses/course-detail?course_id=course-v1:DLI+S-FX-26+V1

Deep Learning Institute (DLI)



Completed Courses

View more

Self-paced	Self-paced	Self-paced	Self-paced	Self-paced
Sizing LLM Inference Systems	Augment your LLM Using Retrieval Augmented Generation	Building RAG Agents with LLMs	Generative AI Explained	Introduction to Transform Based Natural Language Processing
100% Completed 03:00	100% Completed 01:00	100% Completed 08:00	100% Completed 02:00	100% Completed 06:00

https://learn.nvidia.com/my-learning

NVIDIA

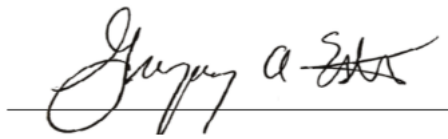
Certificate of Completion

This certificate is awarded to

Min-Yuh Day

for successfully completing

Building RAG Agents with LLMs



Greg Estes

Vice President, NVIDIA

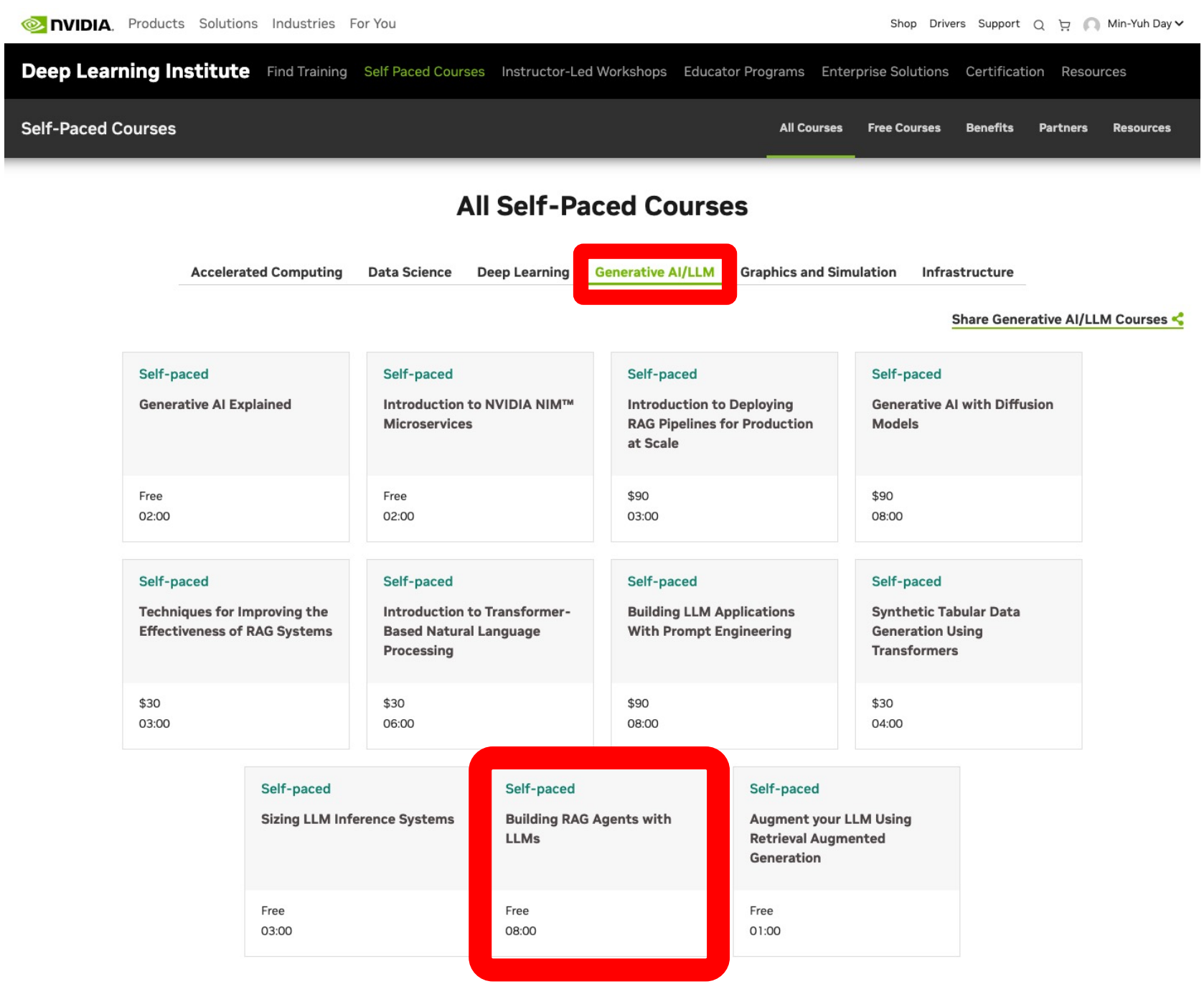
Issue Date: : December 8, 2024

Certification ID: ed-qOCIMQaatzU8SNUNxgw |

https://learn.nvidia.com/certificates?id=ed-qOCIMQaatzU8SNUNxgw/courses/course?course_id=course-v1:DLI+S-FX-15+V1

https://learn.nvidia.com/certificates?id=ed-qOCIMQaatzU8SNUNxgw

NVIDIA Deep Learning Institute (DLI)



https://learn.nvidia.com/en-us/training/self-paced-courses

Building RAG Agents with LLMs

NVIDIA Products Solutions Industries For You Shop Drivers Support Min-Yuh Day

Deep Learning Institute Find Training Self Paced Courses Instructor-Led Workshops Educator Programs Enterprise Solutions Certification Resources

Building RAG Agents with LLMs

Course Progress Bookmarks Updates

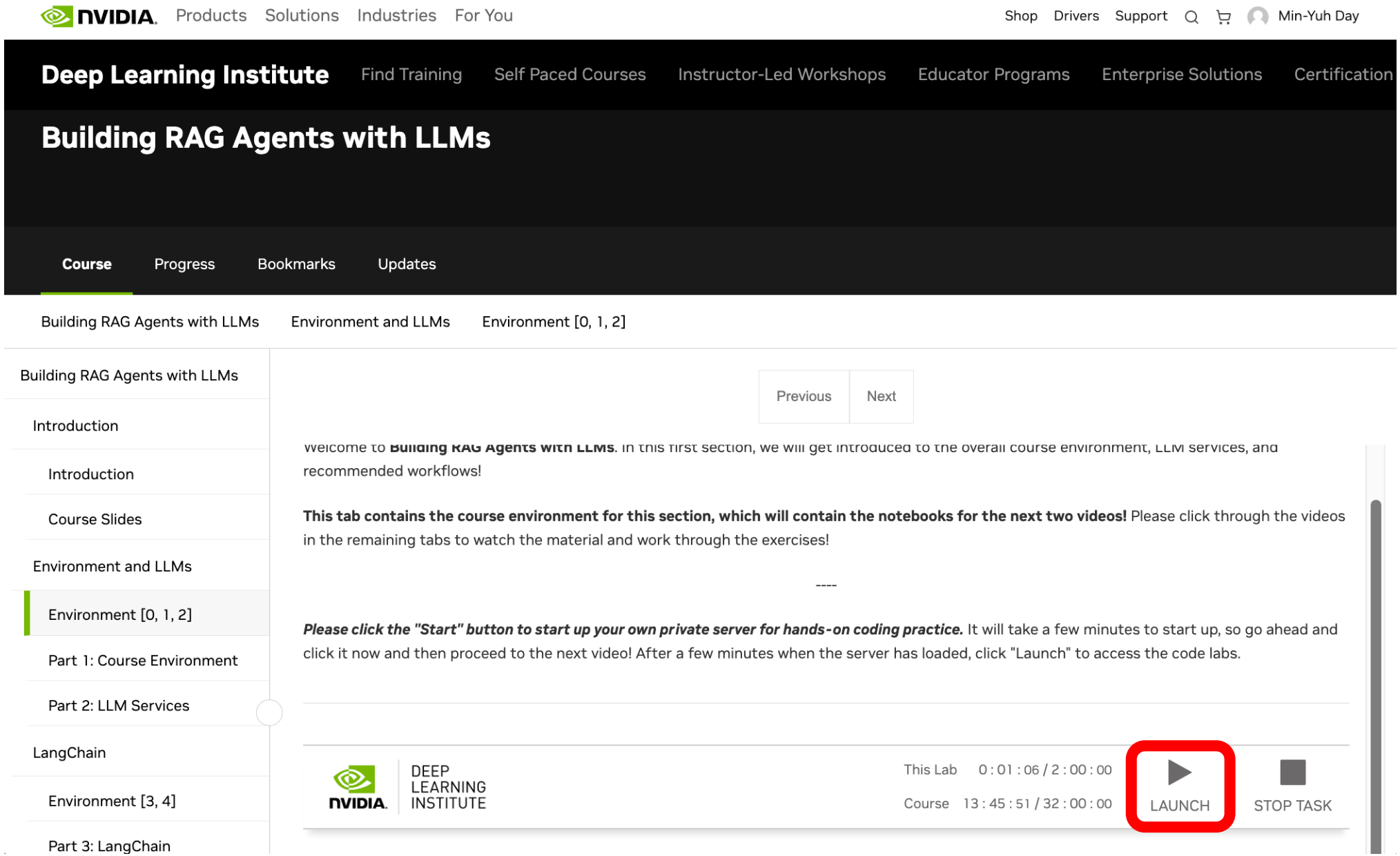
Building RAG Agents with LLMs Introduction Introduction

- Building RAG Agents with LLMs
- Introduction
- Environment and LLMs
- LangChain
- Documents and Embeddings
- Retrieval-Augmented Generation
- Next Steps
- Feedback

Previous Next

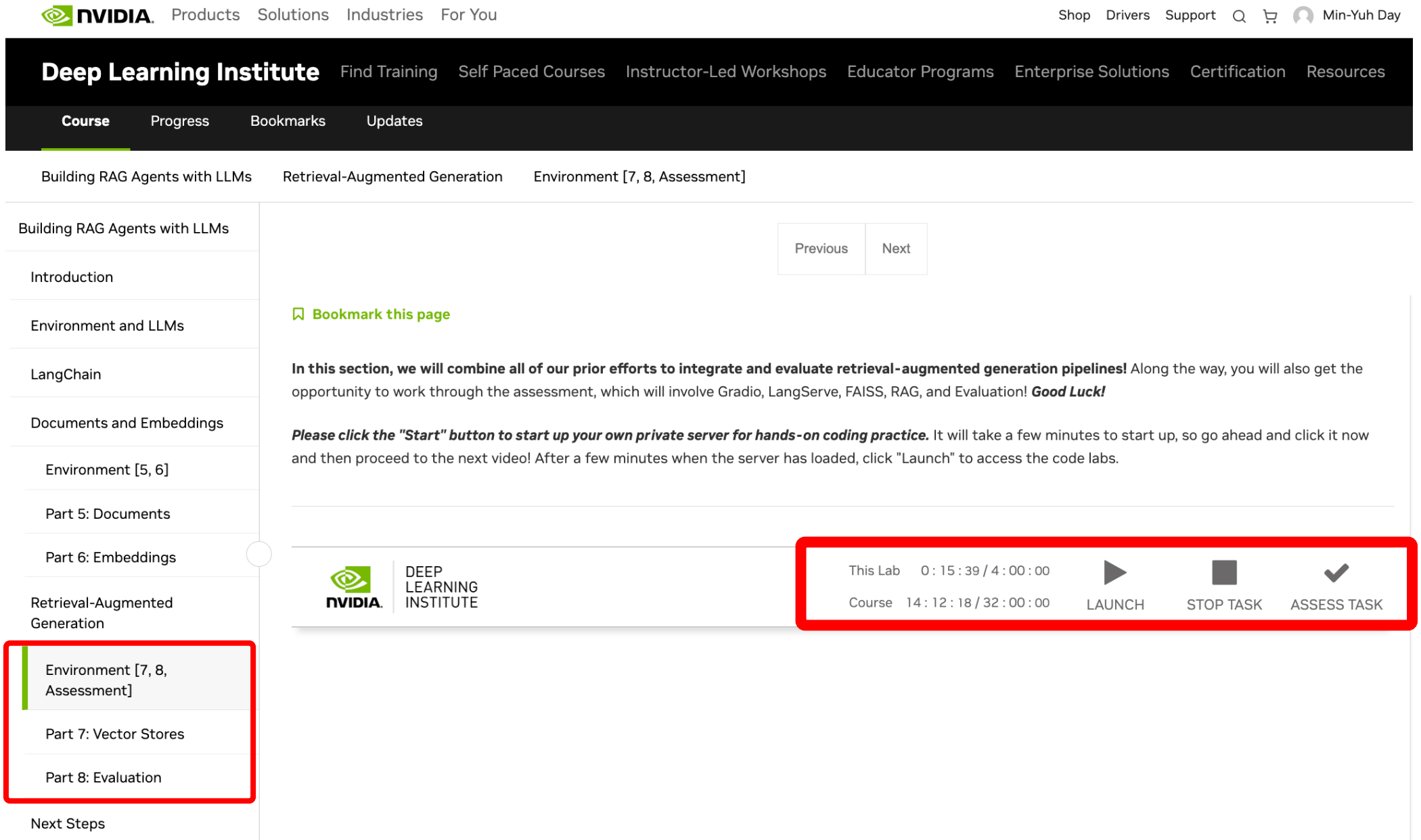
Source: NVIDIA DLI (2024), Building RAG Agents with LLMs, https://learn.nvidia.com/courses/course-detail?course_id=course-v1:DLI+S-FX-15+V1

Building RAG Agents with LLMs



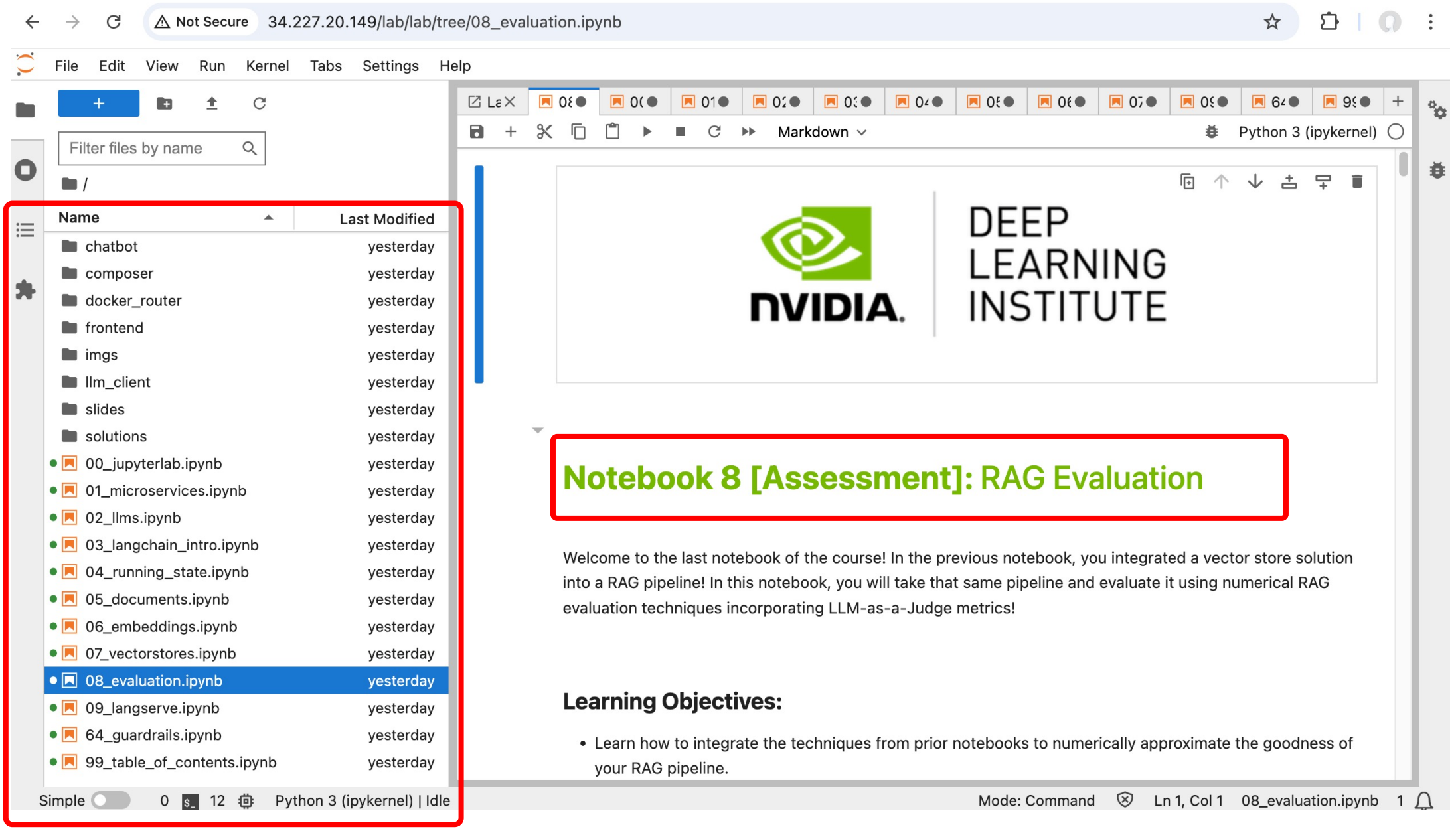
https://learn.nvidia.com/courses/course?course_id=course-v1:DLI+S-FX-15+V1

Building RAG Agents with LLMs



https://learn.nvidia.com/courses/course?course_id=course-v1:DLI+S-FX-15+V1

Building RAG Agents with LLMs



https://learn.nvidia.com/courses/course?course_id=course-v1:DLI+S-FX-15+V1

Digital Sustainability Transformation ESG Data Analytics

ESG:

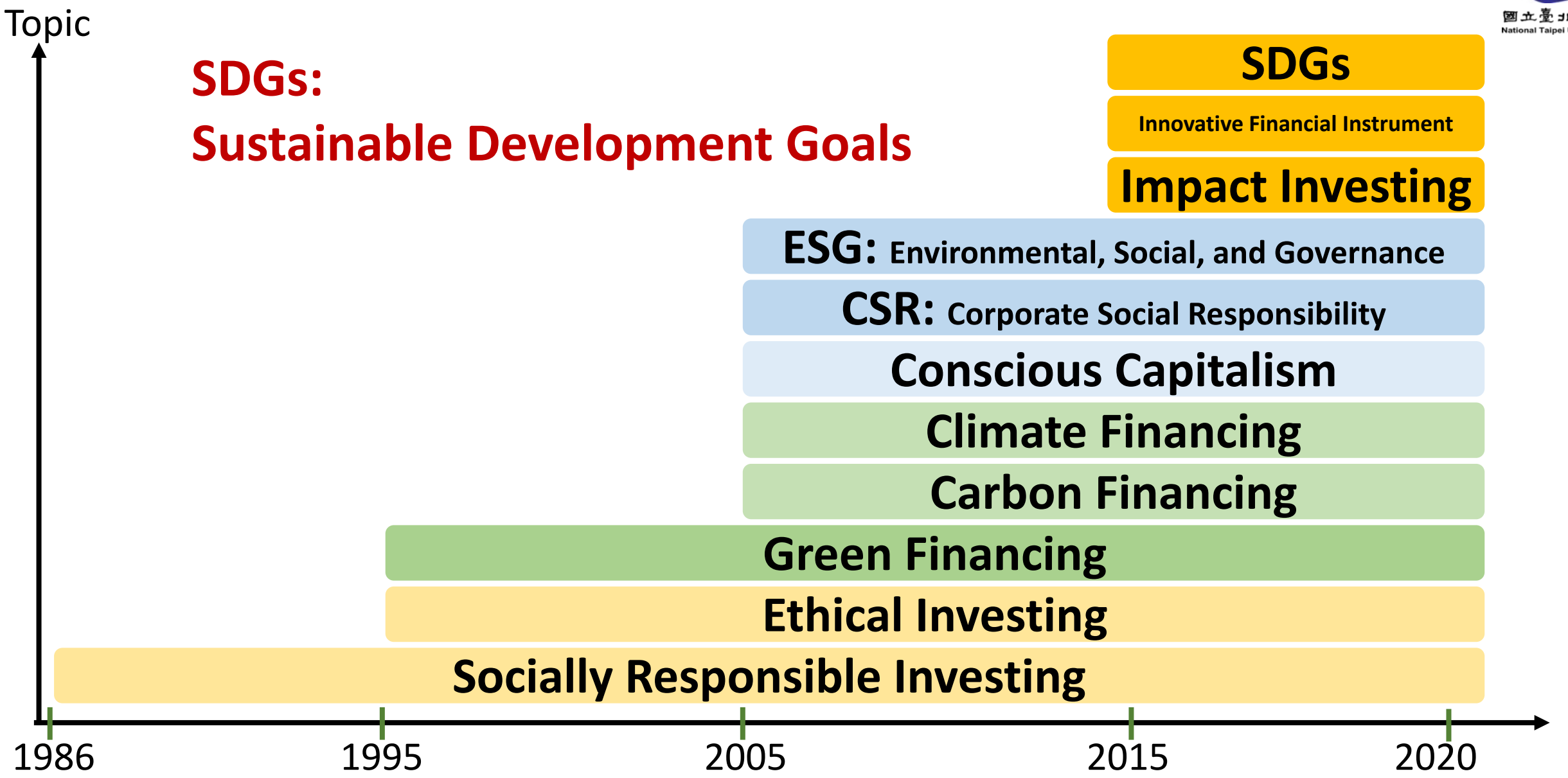
Environmental

Social

Governance

CSR: Corporate Social Responsibility

Evolution of Sustainable Finance Research



Source: Kumar, S., Sharma, D., Rao, S., Lim, W. M., & Mangla, S. K. (2022). Past, present, and future of sustainable finance: Insights from big data analytics through machine learning of scholarly research. Annals of Operations Research, 1-44.

Sustainable Development Goals (SDGs)

Source: https://sdgs.un.org/goals

Sustainable Development Goals (SDGs) and 5P

Partnership

Peace

Prosperity

People

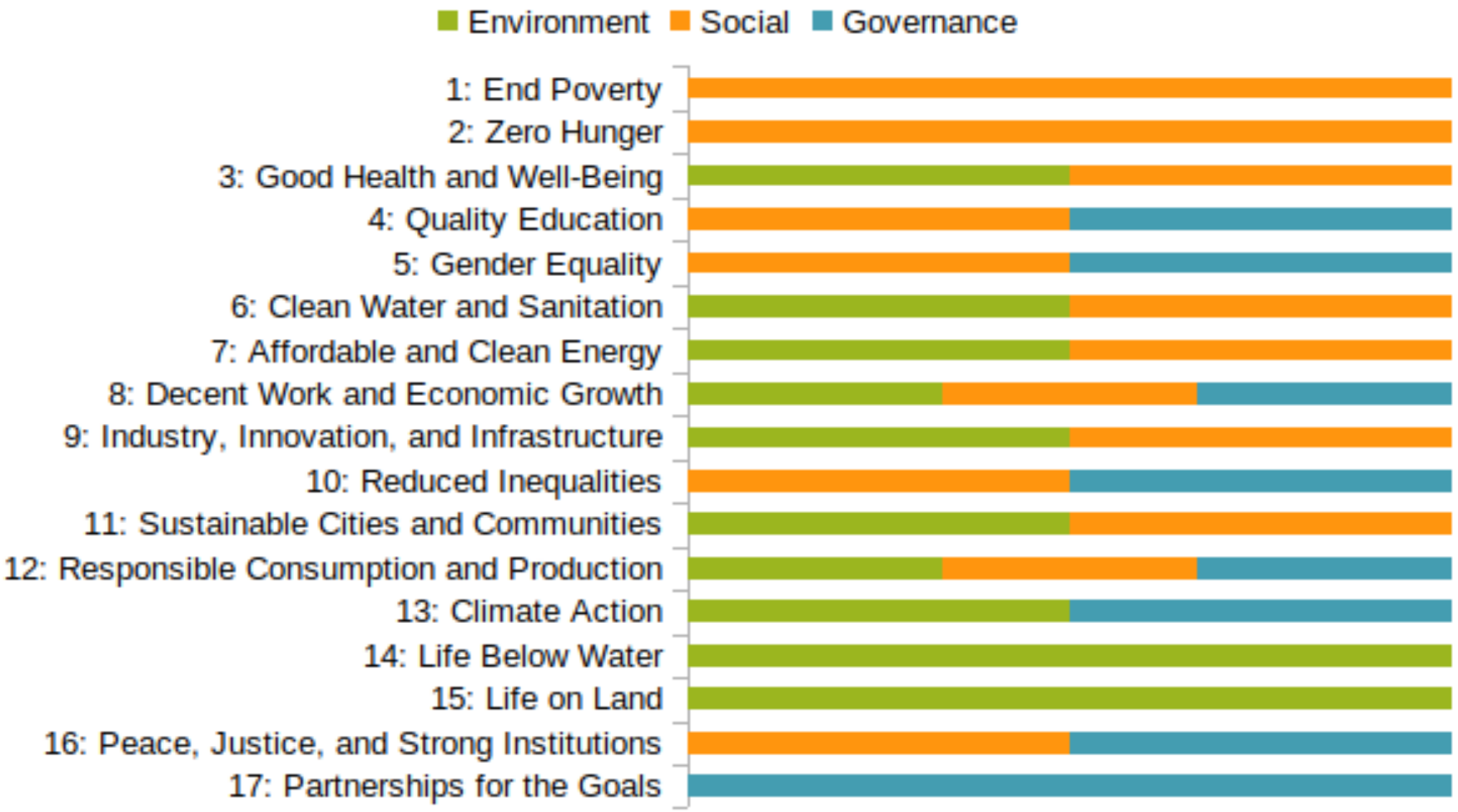
Planet

Source: Folke, Carl, Reinette Biggs, Albert V. Norström, Belinda Reyers, and Johan Rockström. "Social-ecological resilience and biosphere-based sustainability science."Ecology and Society 21, no. 3 (2016).

ESG to 17 SDGs

Source: Henrik Skaug Sætra (2021) "A Framework for Evaluating and Disclosing the ESG Related Impacts of AI with the SDGs." Sustainability 13, no. 15 (2021): 8503.

ESG to 17 SDGs



Source: https://sustainometric.com/esg-to-sdgs-connected-paths-to-a-sustainable-future/

Net-Zero Transformation

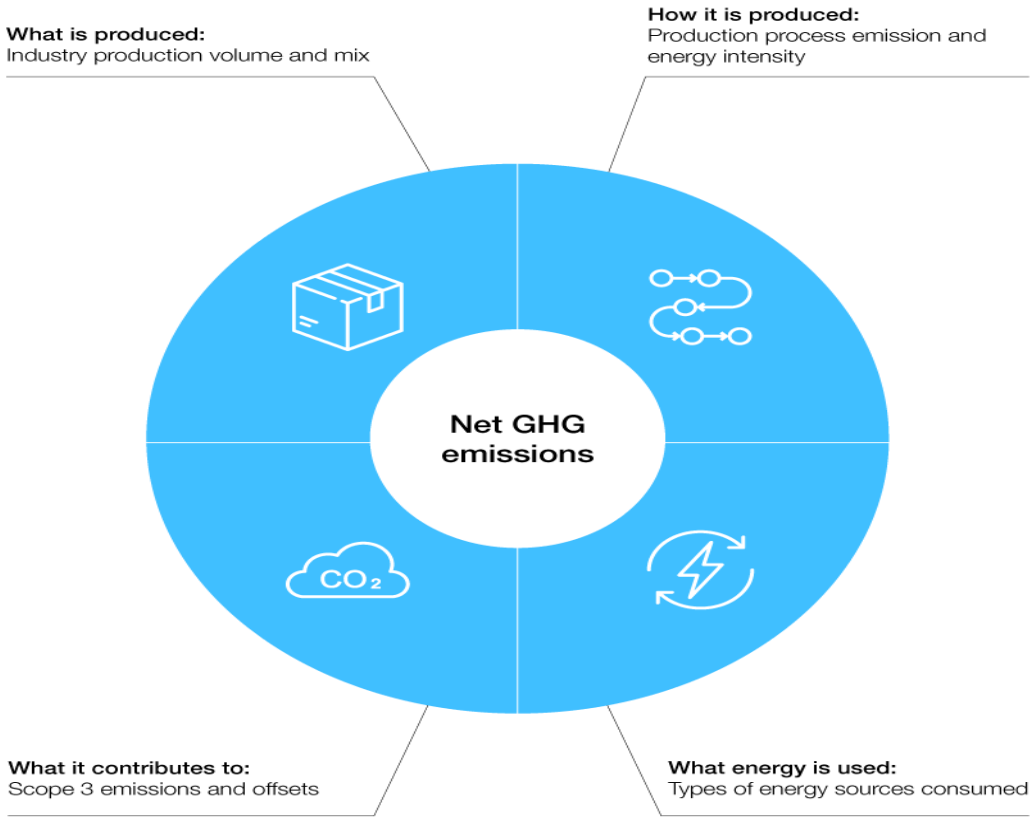
- **Ambition**
  - Aligned to achieving global net zero by no later than 2050 & to limit warming to 1.5°C
- **Governance**
  - Accountability driven from the top
- **Strategy**
  - Embedded and aligned net zero into company strategy
- **Enterprise**
  - Key operating model changes in support of transformation
- **Supply chains**
  - Transformed net zero supply chains
- **Innovation**
  - Developed innovation and technologies to deliver net zero
- **Finance**
  - Financing the net zero transformation
- **Transparency**
  - Communicating action
- **Engagement**
  - Enhancing the pace and scale of net zero action

Source: https://www.pwc.com/us/en/services/esg/library/building-blocks-for-net-zero-transformation.html

Net-Zero Transformation Enablers

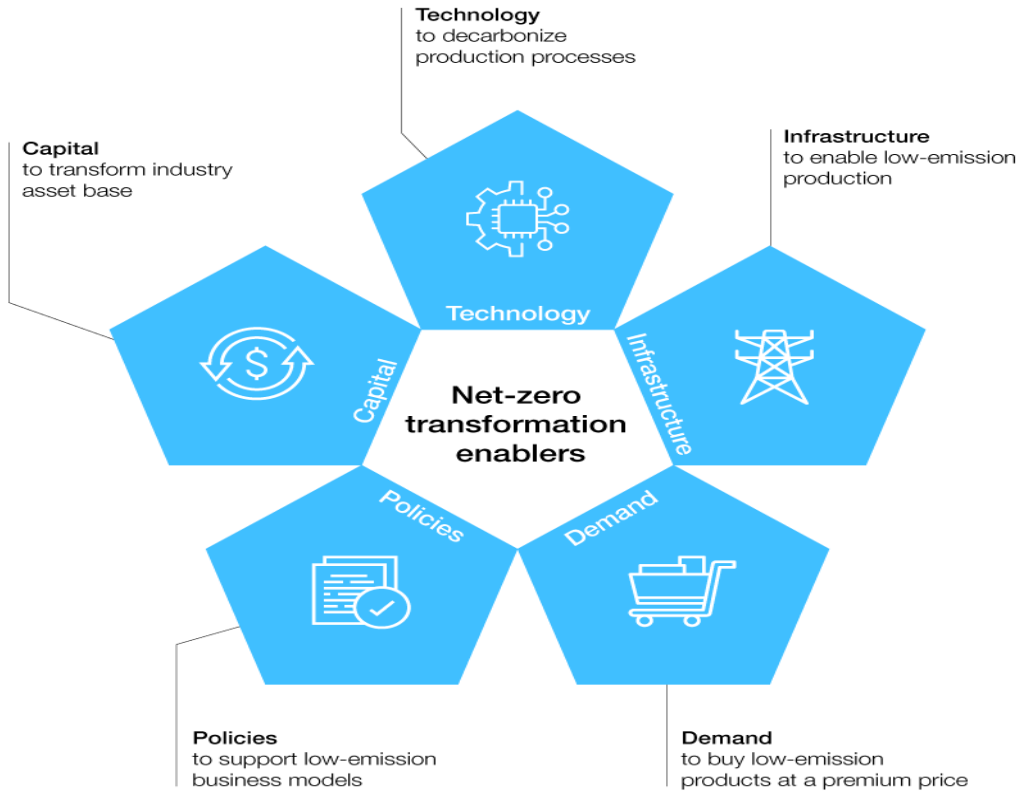
Net-zero industry performance

The four drivers of industry net greenhouse gas (GHG) emissions:



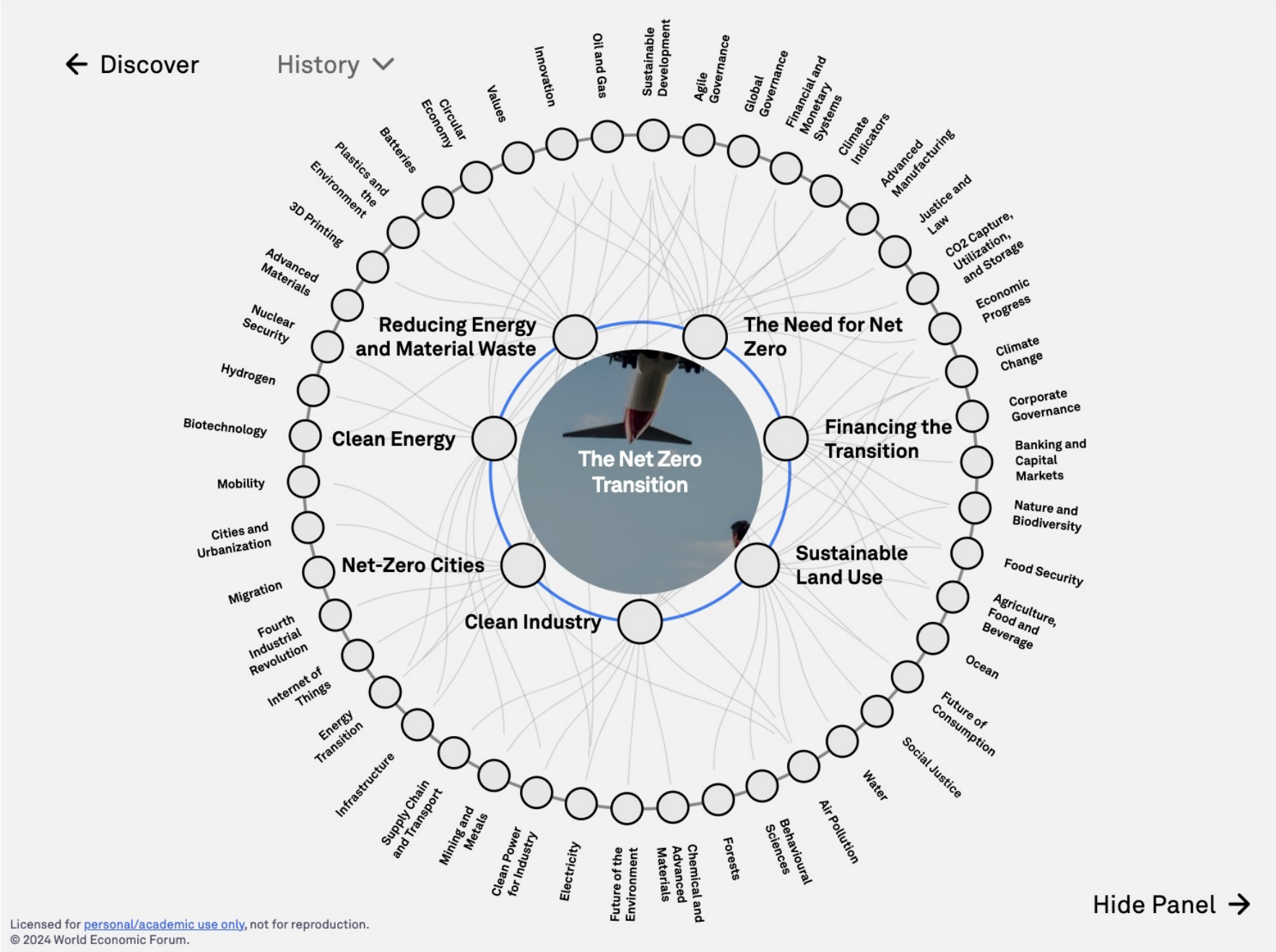
Net-zero industry readiness

The five enabling dimensions of industry net-zero transformation:



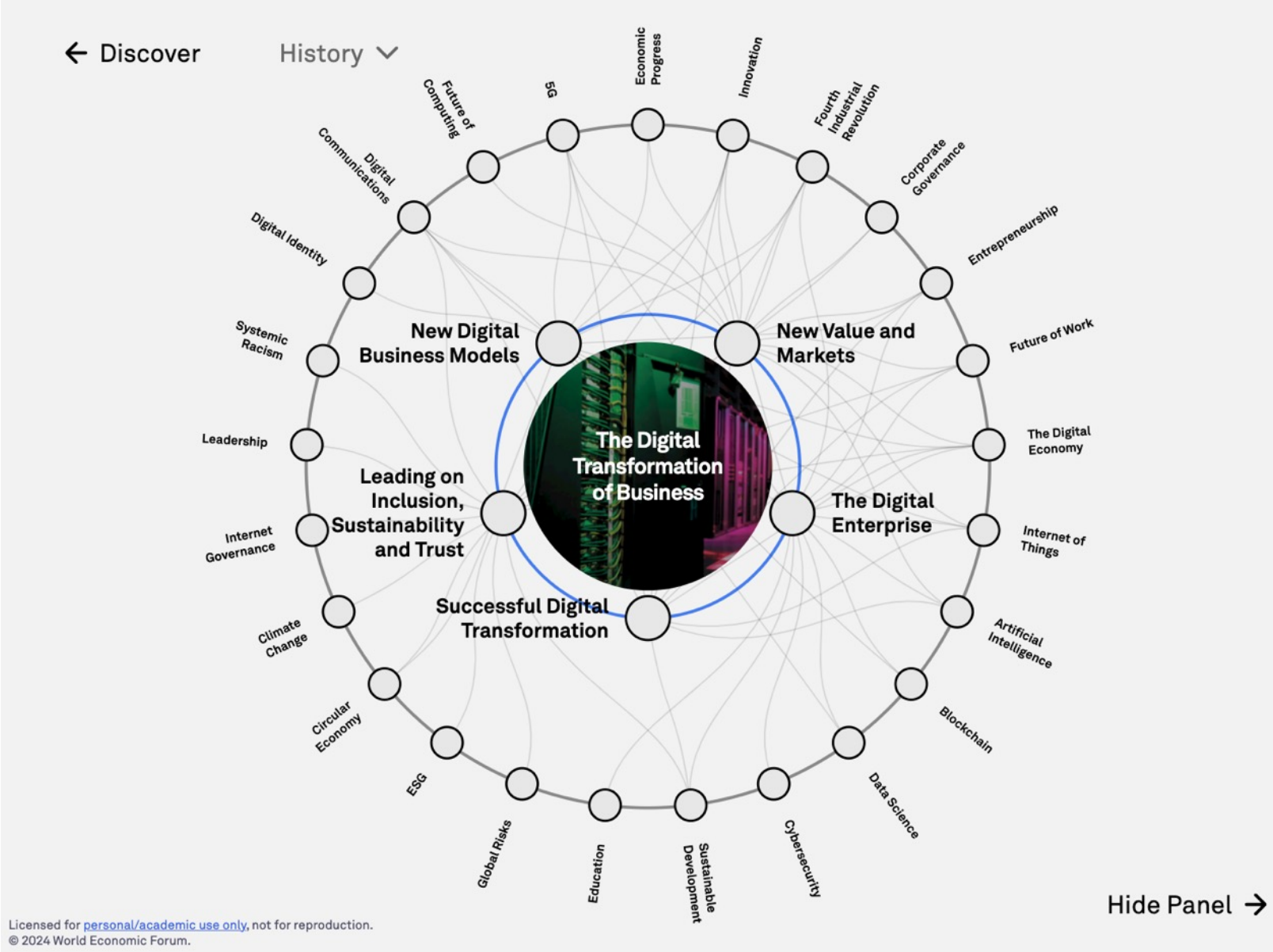
Source: https://www.weforum.org/agenda/2022/07/net-zero-tracker/

The Net Zero Transition



Source: https://intelligence.weforum.org/topics/a1G680000004C93EAE

The Digital Transformation of Business



Source: https://intelligence.weforum.org/topics/a1G0X000006DIDZUA4

Digital Transformation

Dimensions	Categories
A. BUSINESS MODELS	Business Process Innovation Business Strategy
B. DIGITAL BUSINESS	Digital Culture, Literacy and Skills Digital Economy Innovation and Socio-technical Shared Values
C. TECHNOLOGIES	Technology and Innovation Management Artificial Intelligence Big Data Internet of Things Industry 4.0
D. SUSTAINABILITY	Sustainable Business Sustainable Competitive Advantage Sustainable Development Sustainable Innovation
E. HUMAN RESOURCES	Employee Experience Career Dynamics
F. SMART CITIES	Sustainable Smart Manufacturing Digital Manufacturing

Source: Reis, João, and Nuno Melão (2023). "Digital transformation: A meta-review and guidelines for future research." Heliyon (2023).

ESG Challenges and Opportunities

- Challenges
  - Fragmented and unstructured ESG data.
  - Lack of standardization and transparency.
  - Timeliness of data availability.
- Opportunities
  - Rising demand for actionable ESG insights.
  - Innovation in sustainable solutions and policies.
  - Generative AI as a tool for transformation.

Sustainability and ESG Data Analytics

Generative AI for ESG Data Analytics

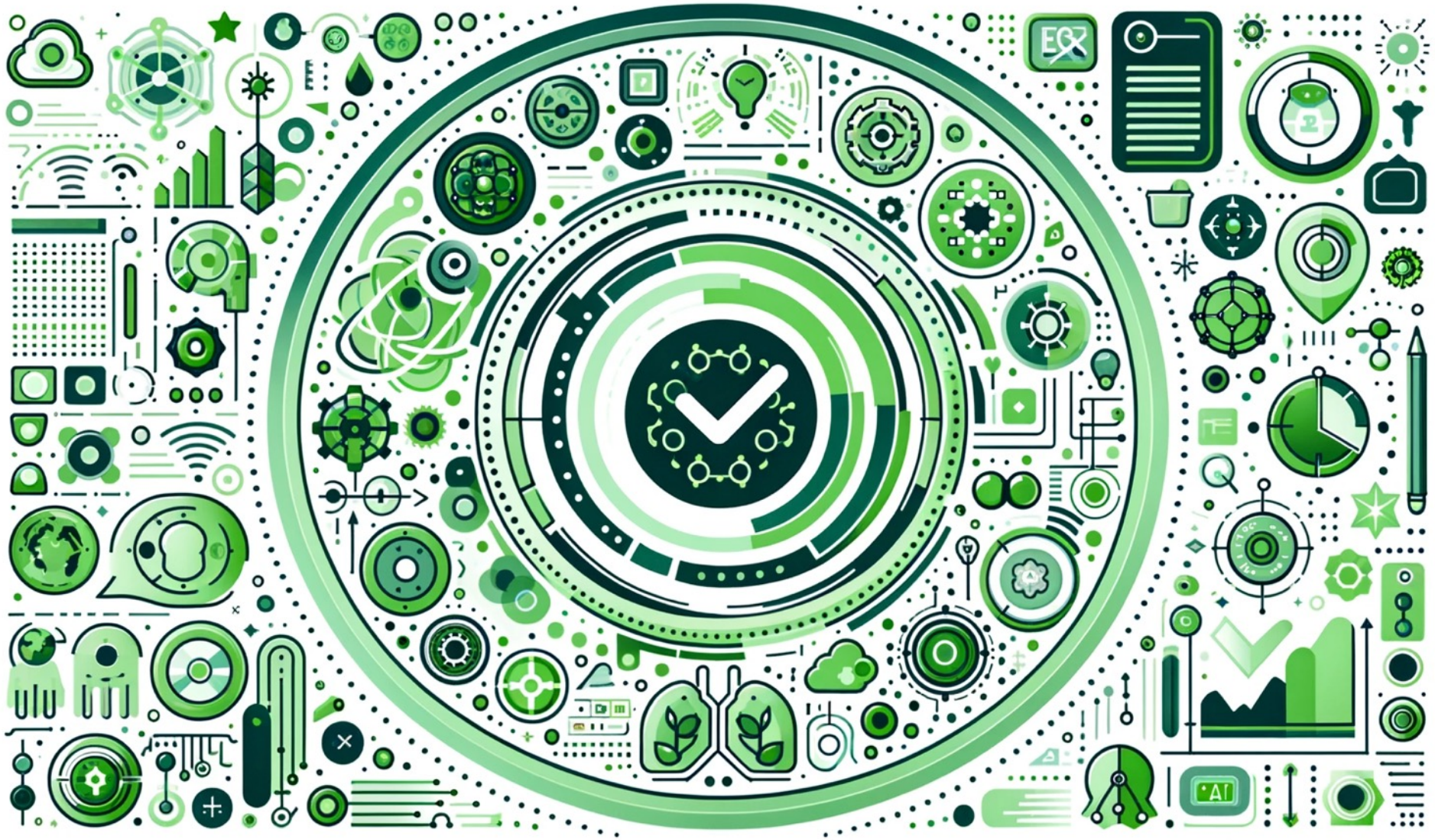
- Data Integration and Enrichment:
  - Synthesizing structured and unstructured ESG data.
- Automated Reporting and Insight Generation:
  - Tailored ESG reports and insights for stakeholders.
- Scenario Modeling and Forecasting:
  - Simulating potential risks and opportunities.
- Addressing Bias and Ensuring Accountability:
  - Transparent, fair, and ethical AI deployment.

Generative AI and LLMs for Sustainability and ESG Data Analytics

Sustainability Innovation with Generative AI

- Sustainable Product Design:
  - Eco-friendly designs minimizing waste and energy.
- Policy Formulation and Implementation:
  - AI-driven simulations for effective policies.
- Stakeholder Engagement and Awareness:
  - Communicating ESG strategies with compelling AI-driven visuals.

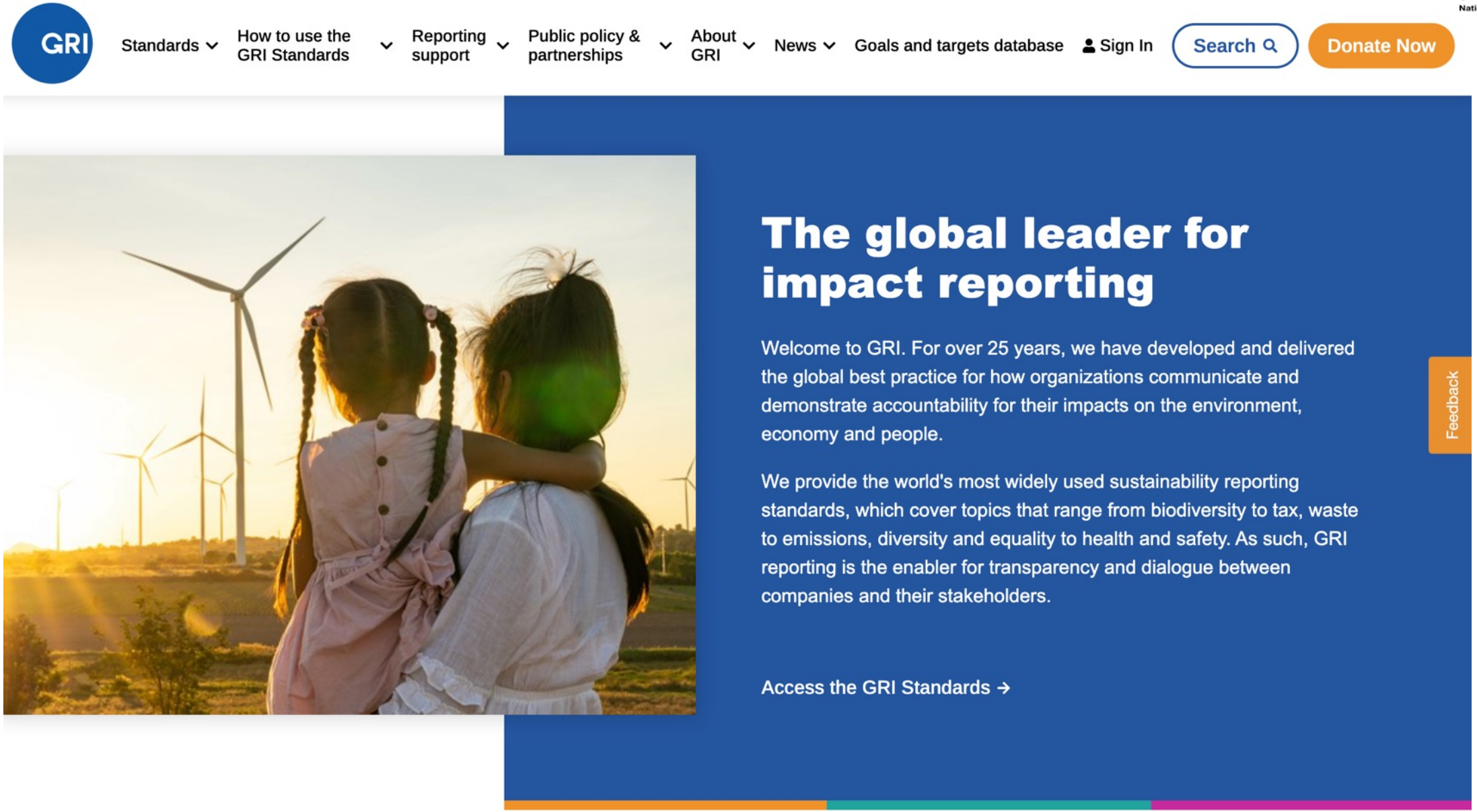
Generative AI for ESG Rating and Reporting Generation



Mapping the ESG Standards Landscape

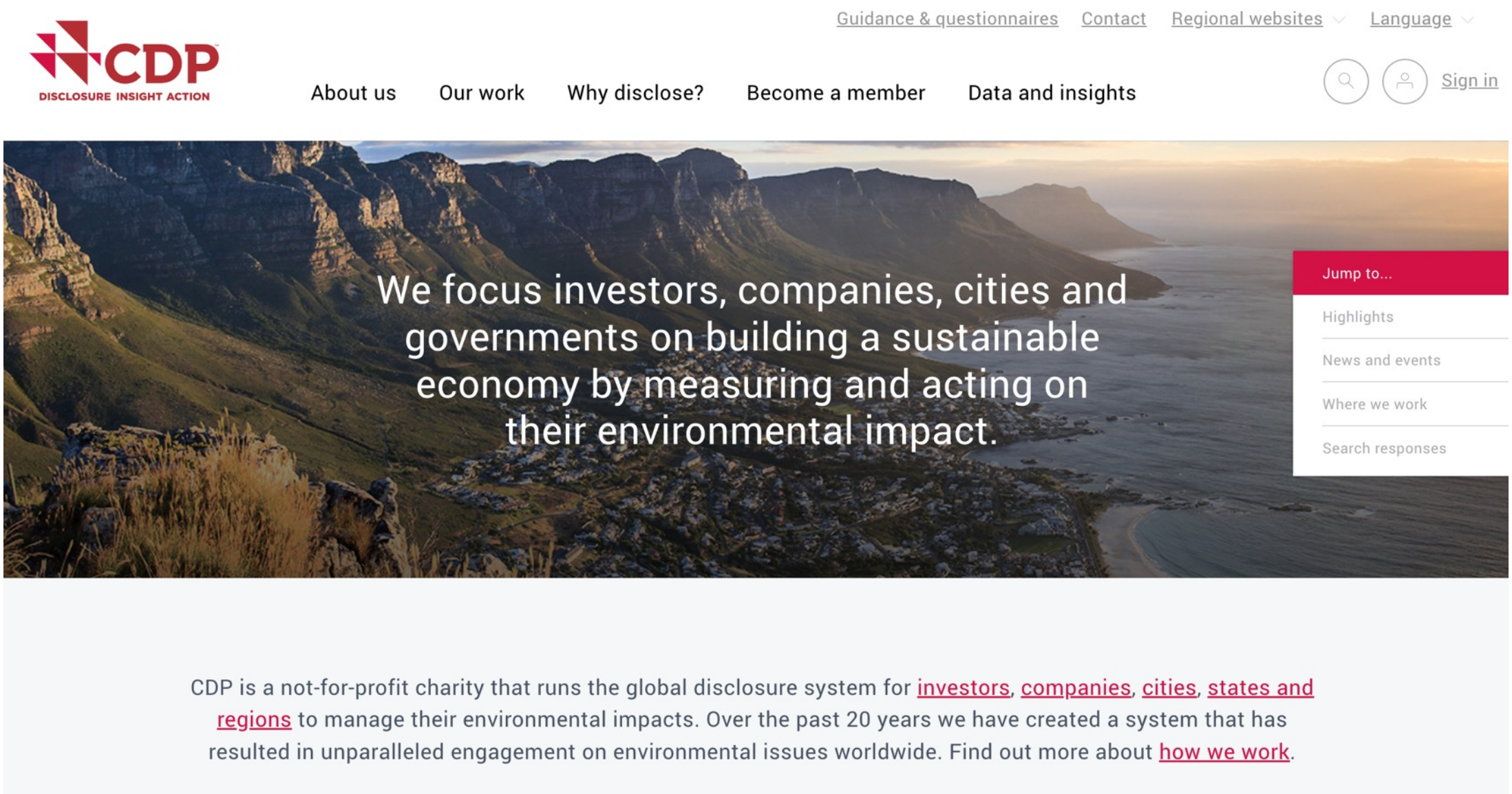
- The most prevalent ESG reporting frameworks
  - GRI (Global Report Initiative)
  - CDP (Carbon Disclosure Project)
  - SASB (Sustainability Accounting Standards Board
  - ISSB (International Sustainability Standards Board)
  - TCFD (Task Force on Climate-related Financial Disclosures
- How companies choose
  - Materiality, industry-specific standards, investor alignment

GRI (Global Report Initiative)



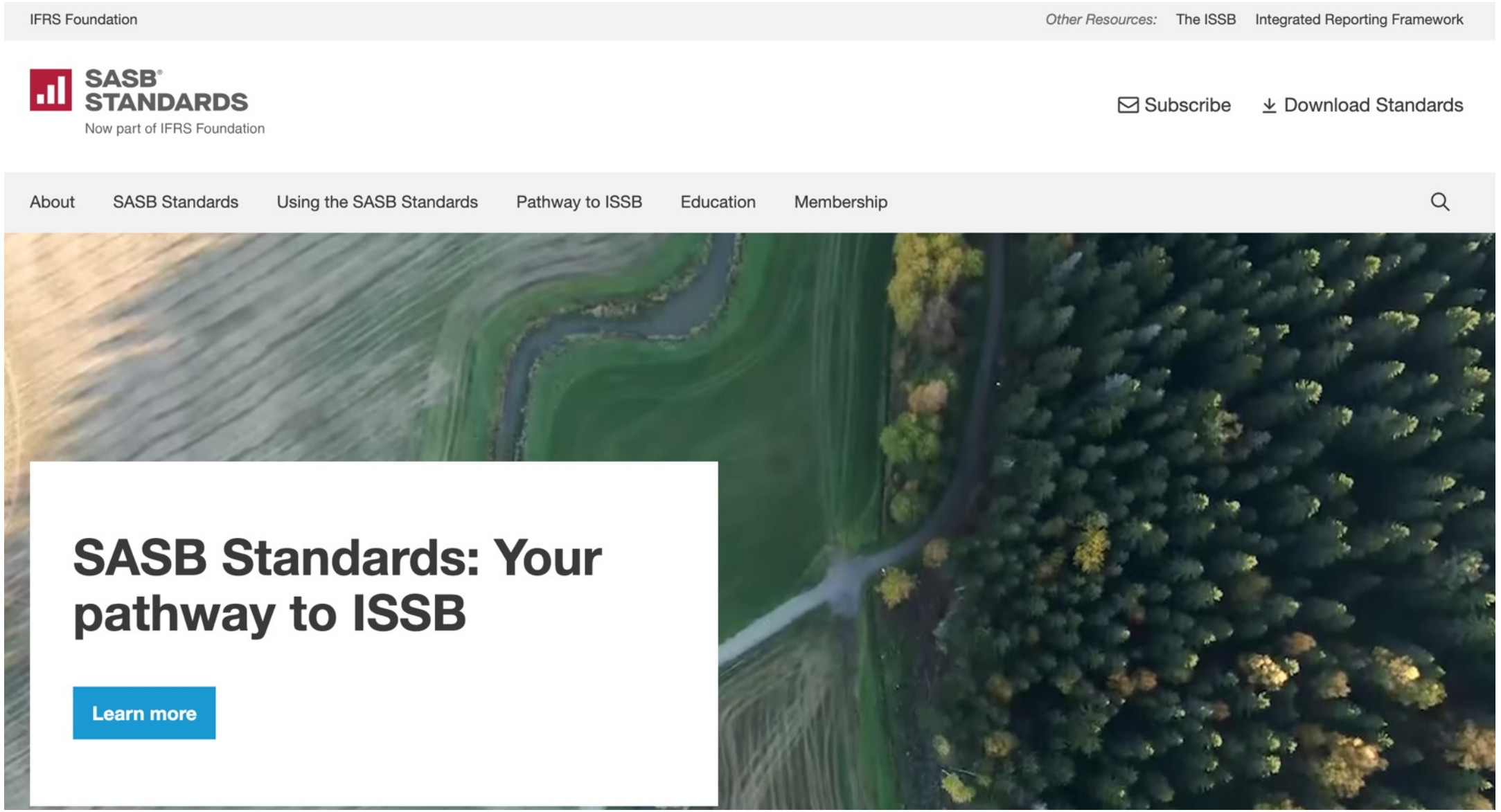
https://www.globalreporting.org/

CDP (Carbon Disclosure Project)



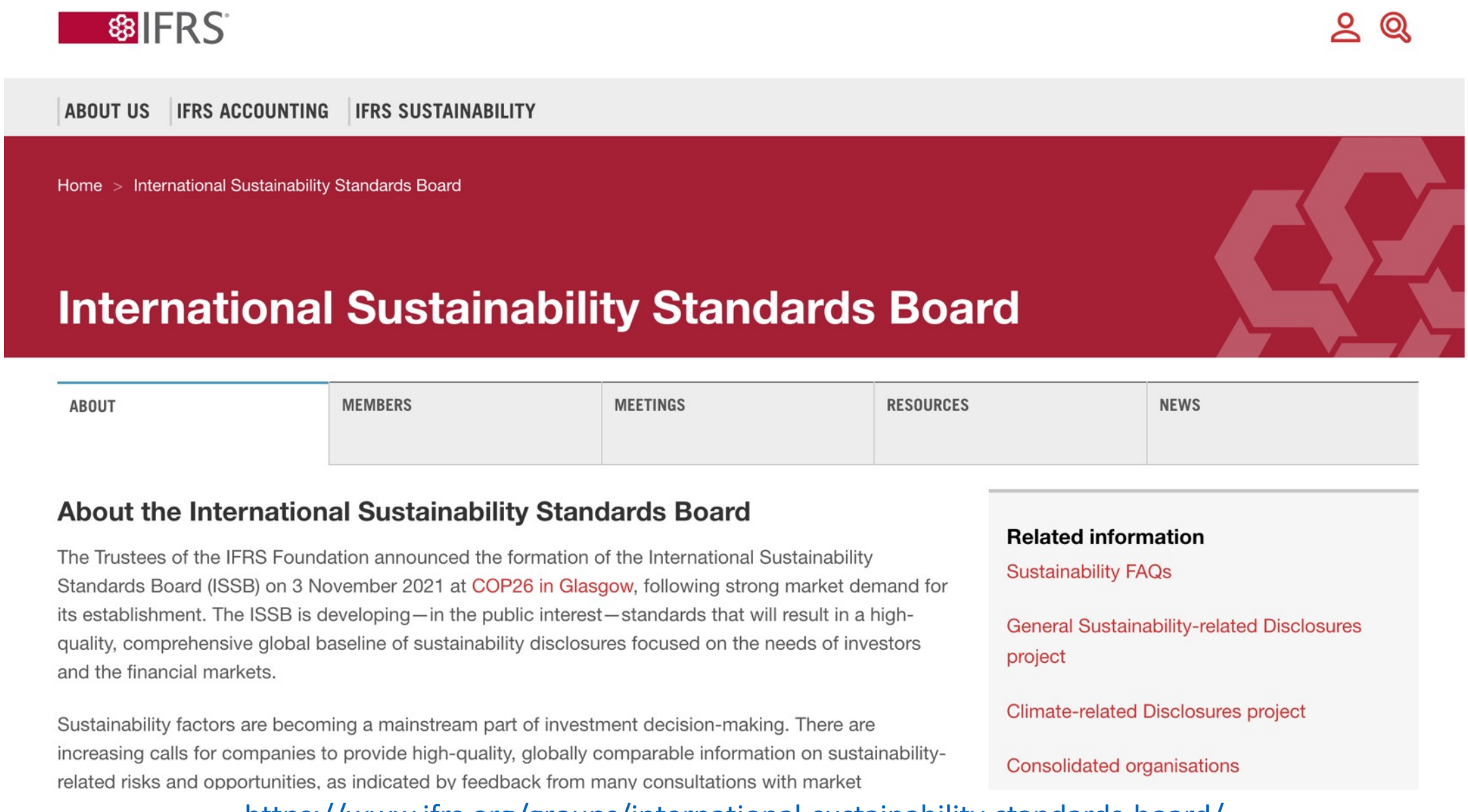
https://www.cdp.net/

SASB (Sustainability Accounting Standards Board)



https://sasb.org/

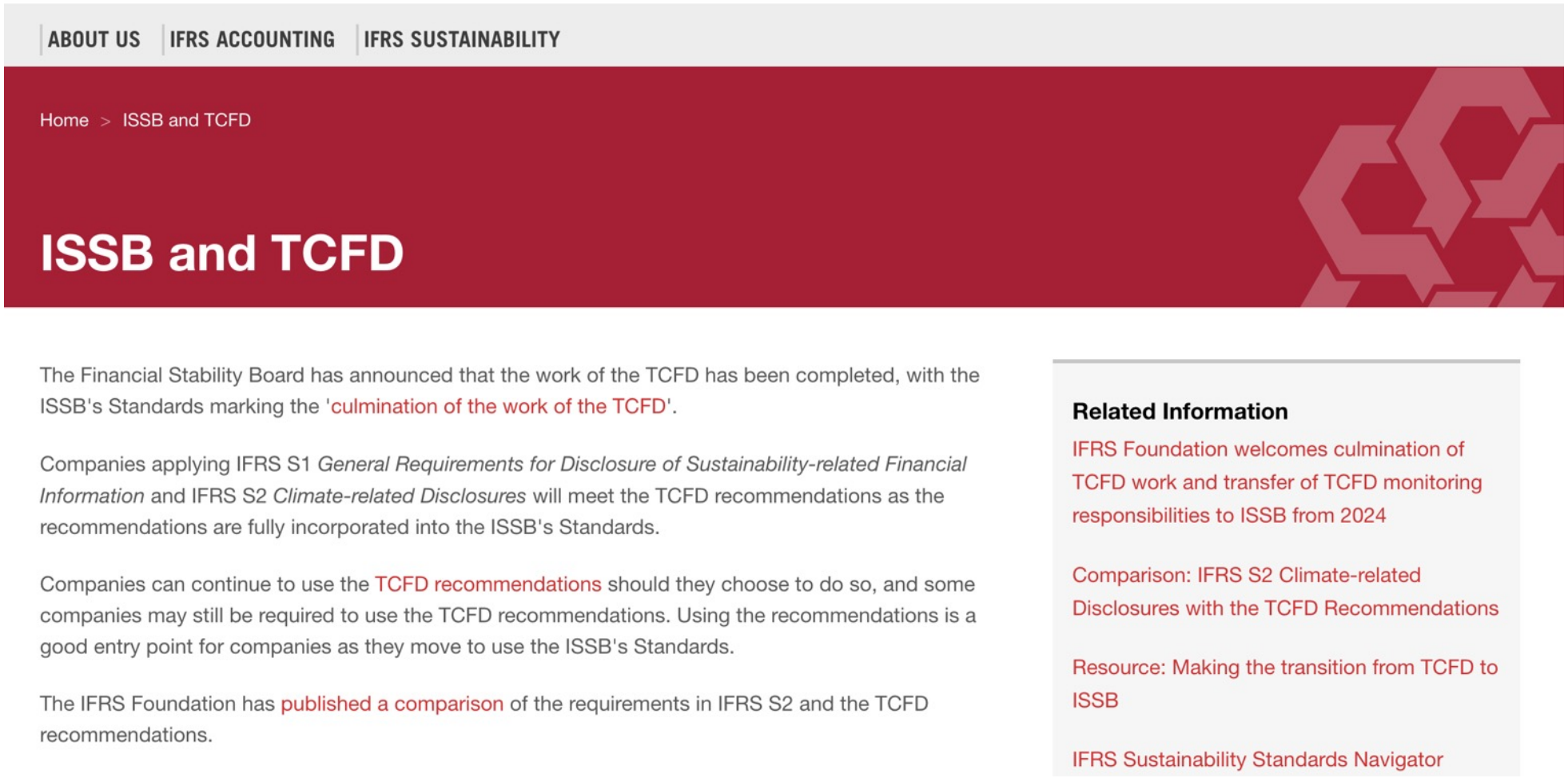
ISSB (International Sustainability Standards Board)



https://www.ifrs.org/groups/international-sustainability-standards-board/

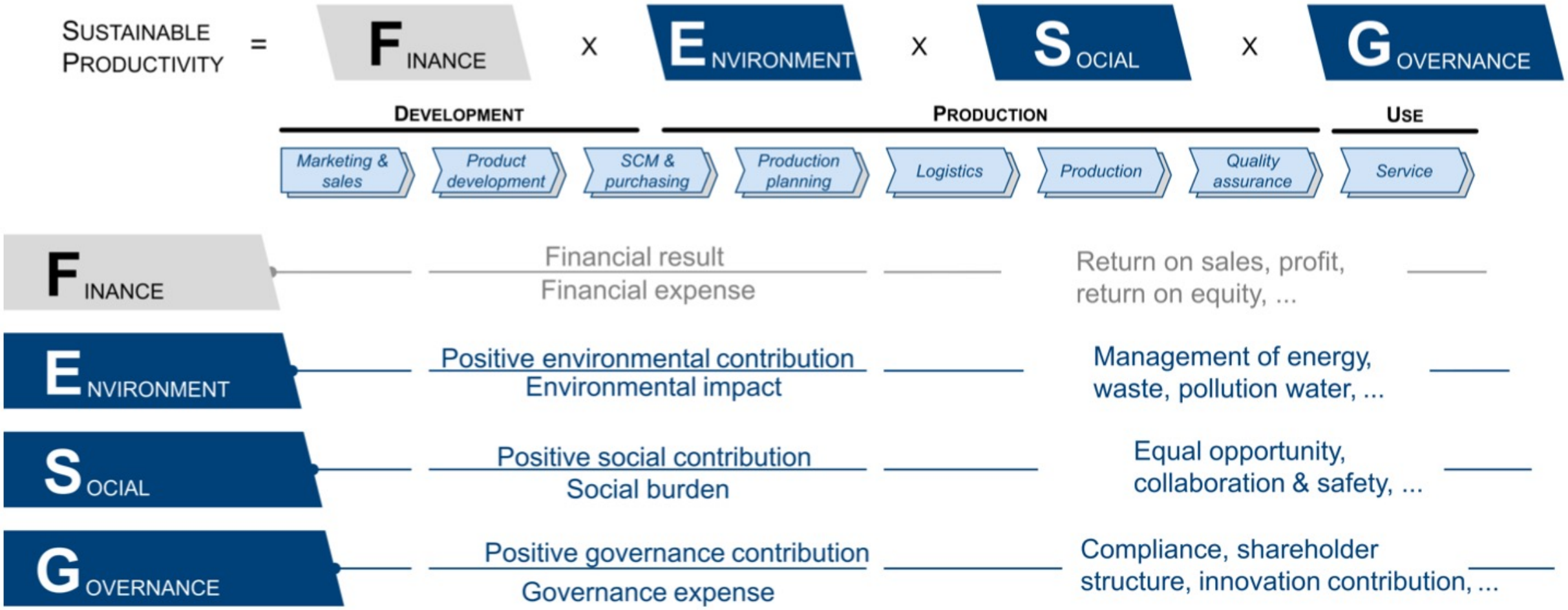
TCFD
(Task Force on Climate-related Financial Disclosures)

https://www.ifrs.org/sustainability/tcfd/



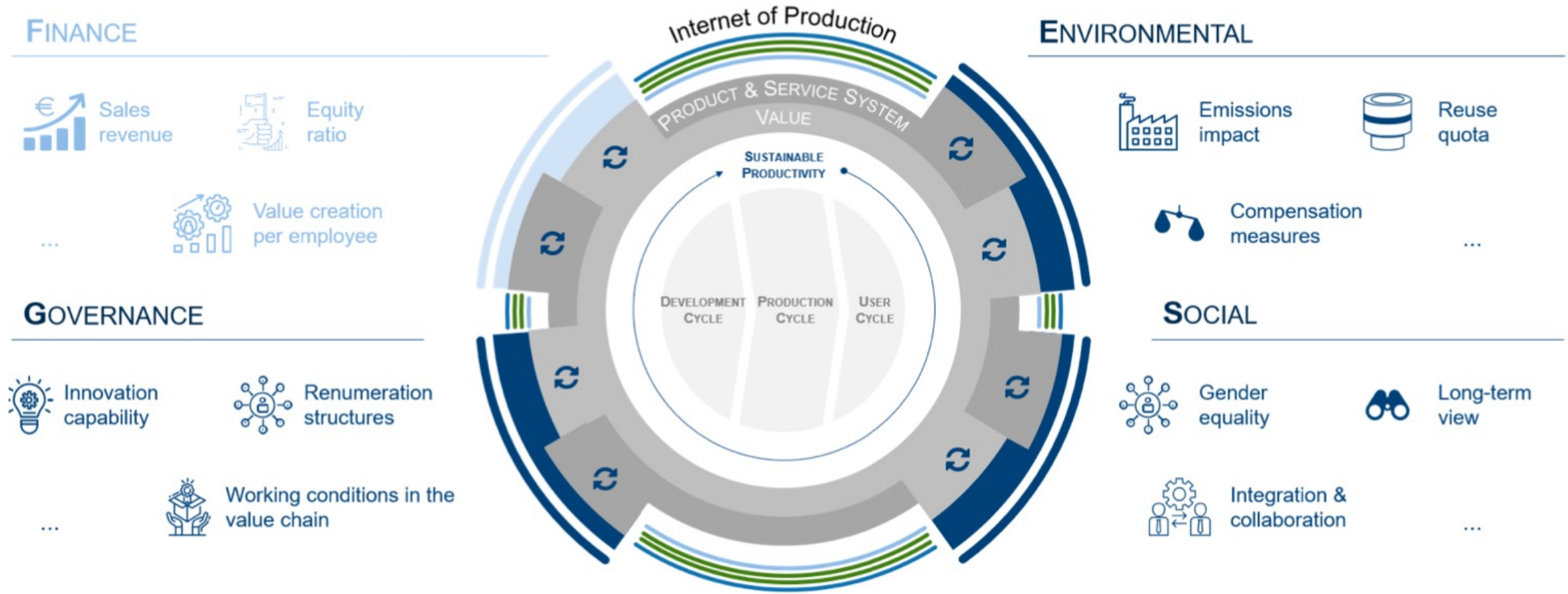
https://www.fsb-tcfd.org/

Sustainable Productivity: Finance ESG



Source: Huang, Ziqi, Yang Shen, Jiayi Li, Marcel Fey, and Christian Brecher (2021). "A survey on AI-driven digital twins in Industry 4.0: Smart manufacturing and advanced robotics." Sensors 21, no. 19: 6340.

Sustainable Resilient Manufacturing
ESG

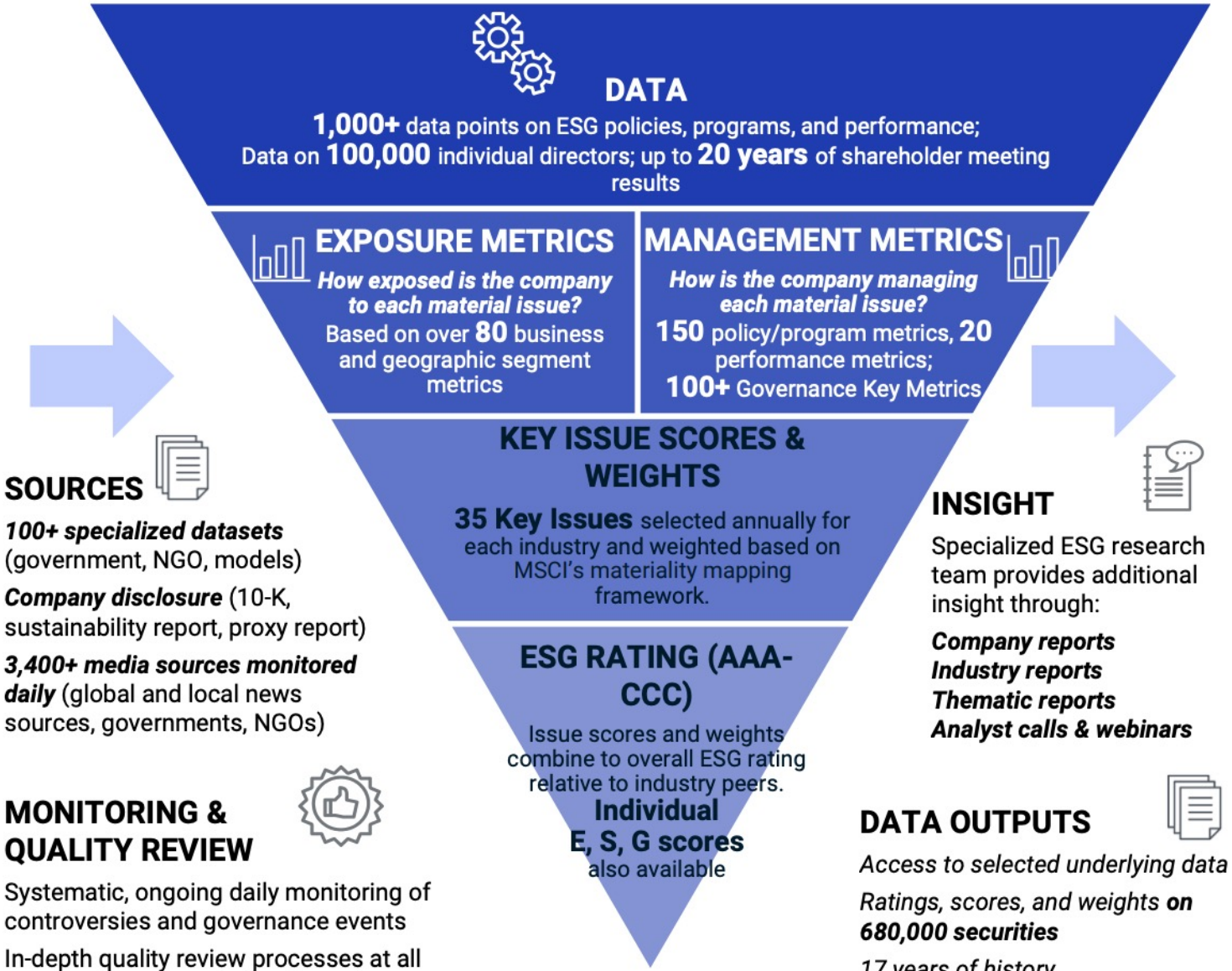


Source: Huang, Ziqi, Yang Shen, Jiayi Li, Marcel Fey, and Christian Brecher (2021). "A survey on AI-driven digital twins in Industry 4.0: Smart manufacturing and advanced robotics." Sensors 21, no. 19: 6340.

ESG Indexes

- MSCI ESG Index
- Dow Jones Sustainability Indices (DJSI)
- FTSE ESG Index

MSCI ESG Rating Framework



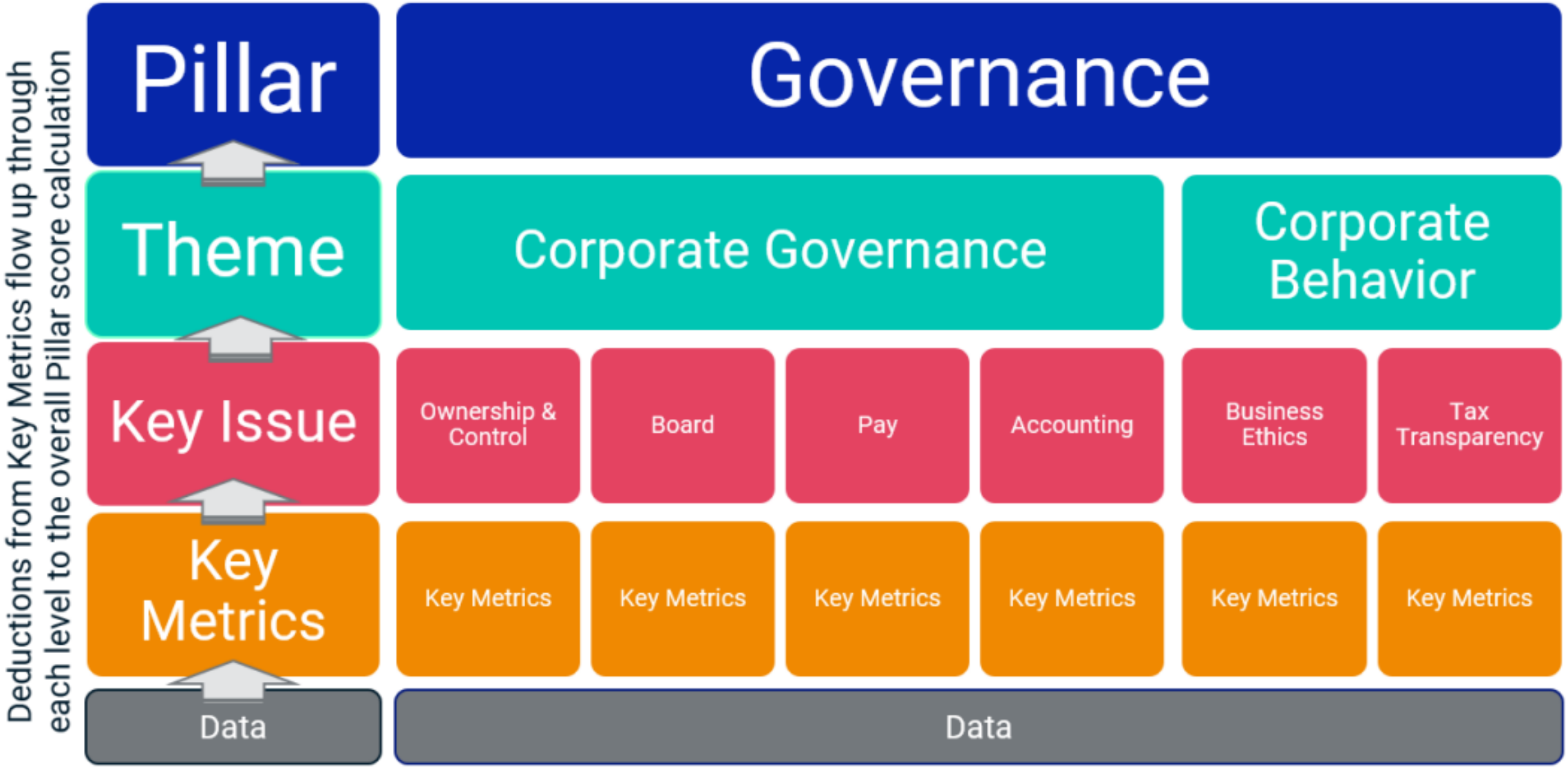
Source: https://www.msci.com/documents/1296102/21901542/ESG-Ratings-Methodology-Exec-Summary.pdf

MSCI ESG Key Issue Hierarchy

3 Pillars	10 Themes	35 ESG Key Issues	
Environment	**Climate Change**	Carbon Emissions	Financing Environmental Impact
		Product Carbon Footprint	Climate Change Vulnerability
	Natural Capital	Water Stress	Raw Material Sourcing
		Biodiversity & Land Use	
	Pollution & Waste	Toxic Emissions & Waste	Electronic Waste
		Packaging Material & Waste	
	Environmental Opportunities	Opportunities in Clean Tech	Opportunities in Renewable Energy
		Opportunities in Green Building	
Social	**Human Capital**	Labor Management	Human Capital Development
		Health & Safety	Supply Chain Labor Standards
	Product Liability	Product Safety & Quality	Privacy & Data Security
		Chemical Safety	Responsible Investment
		Consumer Financial Protection	Health & Demographic Risk
	Stakeholder Opposition	Controversial Sourcing	
		Community Relations	
	Social Opportunities	Access to Communications	Access to Health Care
		Access to Finance	Opportunities in Nutrition & Health
Governance	**Corporate Governance**	Ownership & Control	Pay
		Board	Accounting
	Corporate Behavior	Business Ethics	
		Tax Transparency	

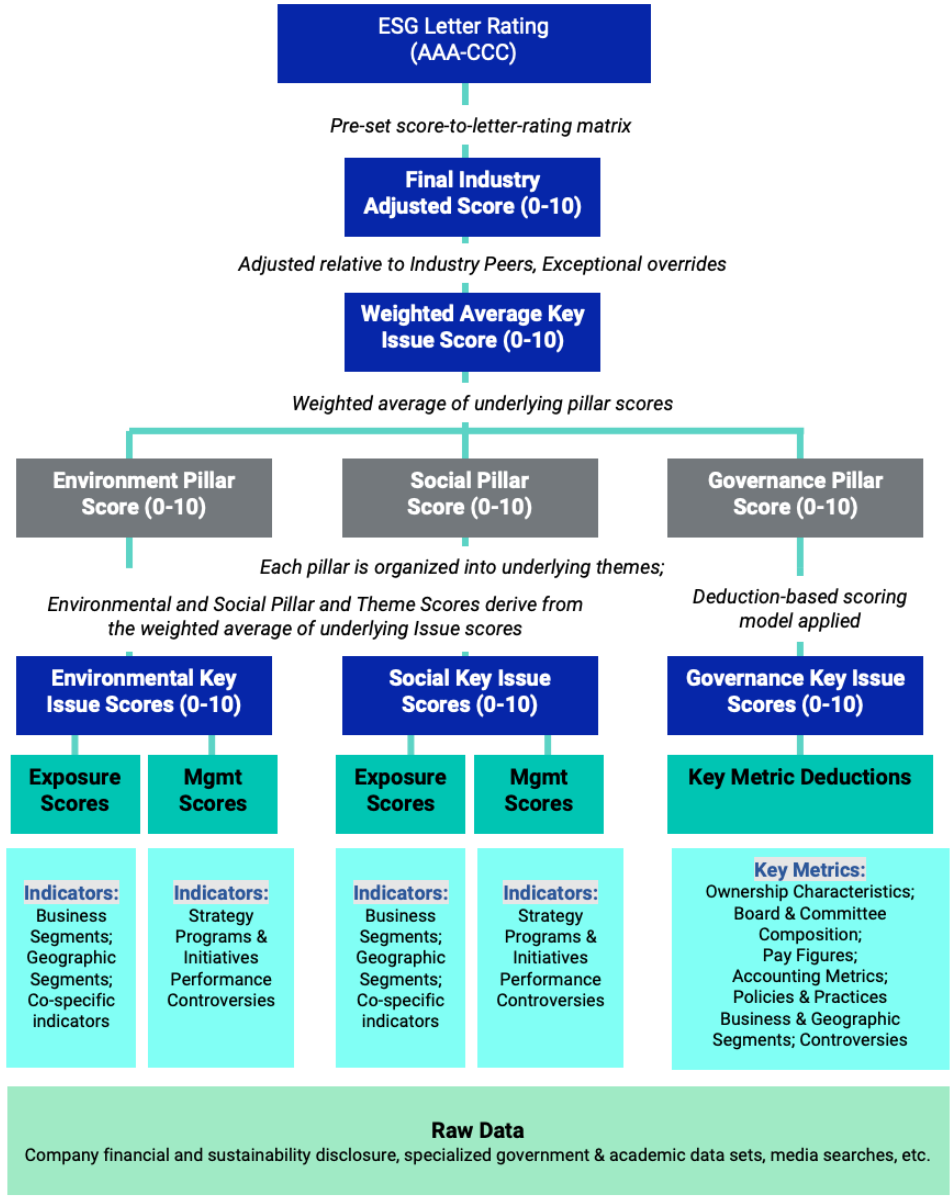
Source: https://www.msci.com/documents/1296102/21901542/ESG-Ratings-Methodology-Exec-Summary.pdf

MSCI Governance Model Structure



Source: https://www.msci.com/documents/1296102/21901542/ESG-Ratings-Methodology-Exec-Summary.pdf

MSCI Hierarchy of ESG Scores



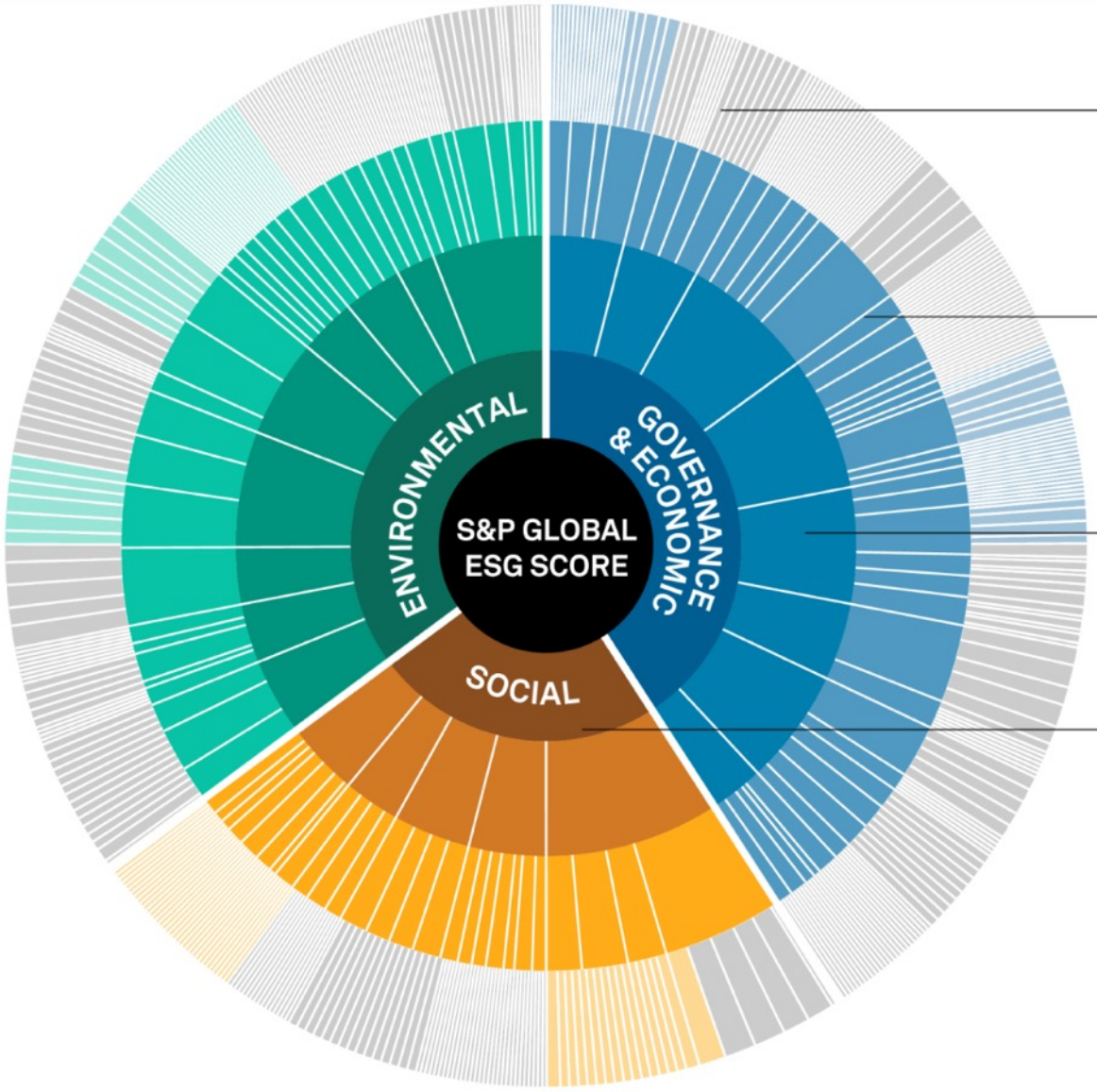
Source: https://www.msci.com/documents/1296102/21901542/ESG-Ratings-Methodology-Exec-Summary.pdf

DJSI S&P Global ESG Score

8,000
Companies

90%
Global market capitalization

340,000+
Current Research Universe and Active Securities



Approx.
1,000
Datapoints

Assessed values, text, checkboxes, documents
Sources: Web-based questionnaire and company documents

130+
Questions

Weighted data point scores
Up to 50% industry-specific

Ave.
30+
Criteria scores

Weighted question scores
61 industry specific approaches, with tailored questions, criteria and related weightings

3
Dimension scores

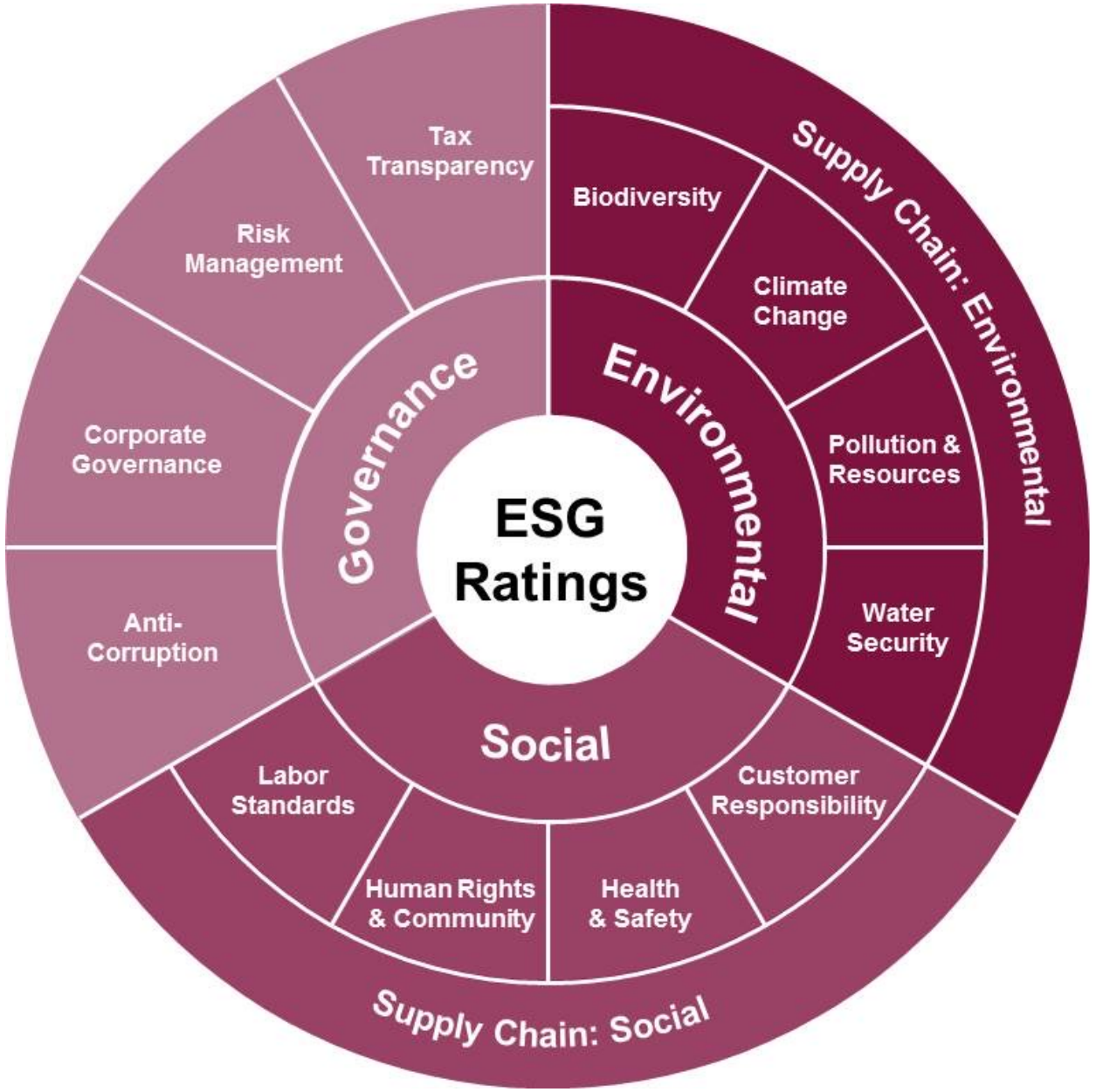
Weighted criteria scores
Adjusted for corporate ESG controversies where applicable

1
S&P Global ESG Score

Sum of weighted dimension scores

Source: DJSI, S&P Global Corporate Sustainability Assessment (CSA), https://www.spglobal.com/esg/solutions/data-intelligence-esg-scores

FTSE Russell ESG Ratings



Source: https://www.ftserussell.com/data/sustainability-and-esg-data/esg-ratings

Sustainalytics ESG Risk Ratings

Analyst-based approach

Sustainalytics' ESG Risk Ratings measure a company's exposure to industry-specific material ESG risks and how well a company is managing those risks.

Negligible	Low	Medium	High	Severe
0 - 10	10 - 20	20 - 30	30 - 40	40+

Source: https://www.sustainalytics.com/esg-data

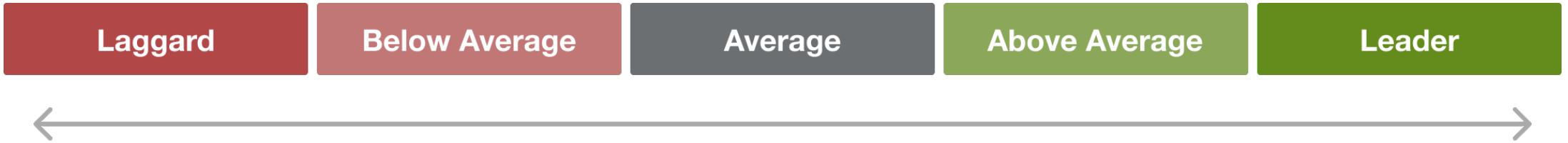
TruValue Labs

FACTSET

Machine-based approach

Truvalue ESG Ranks

- **Truvalue Labs applies AI to analyze over 100,000 sources and uncover ESG risks and opportunities hidden in unstructured text.**
- **The ESG Ranks data service produces an overall company rank based on industry percentile leveraging the 26 ESG categories defined by the Sustainability Accounting Standards Board (SASB).**
- **The data feed covers 20,000+ companies with more than 13 years of history.**



Source: :https://developer.truvaluelabs.com/data/esg-ranks

Analyst-driven vs. AI-driven ESG

Analyst-driven ESG research

Derives ratings in a structured data model

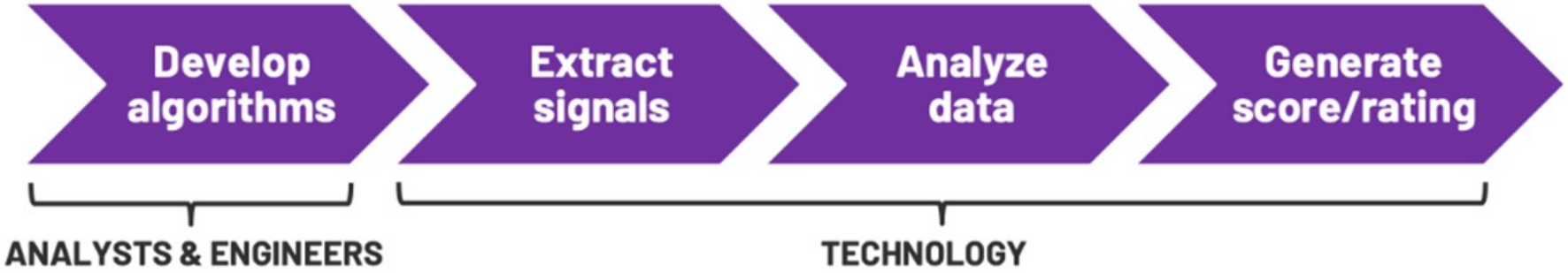
Sustainalytics

Analyst role at the end of the process allows subjectivity to color results

AI-driven ESG research

Derives signals from unstructured data

Truvalue Labs

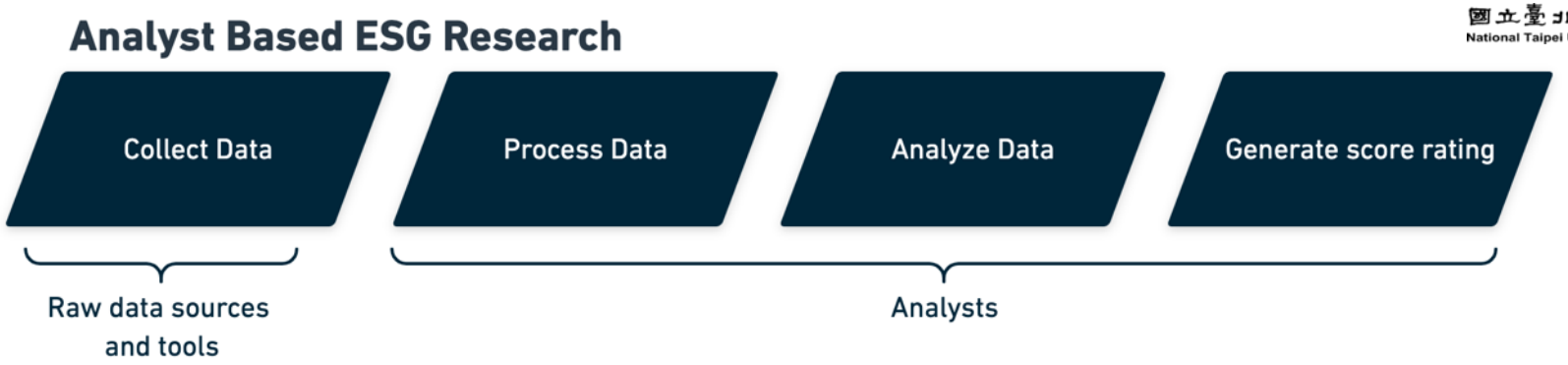


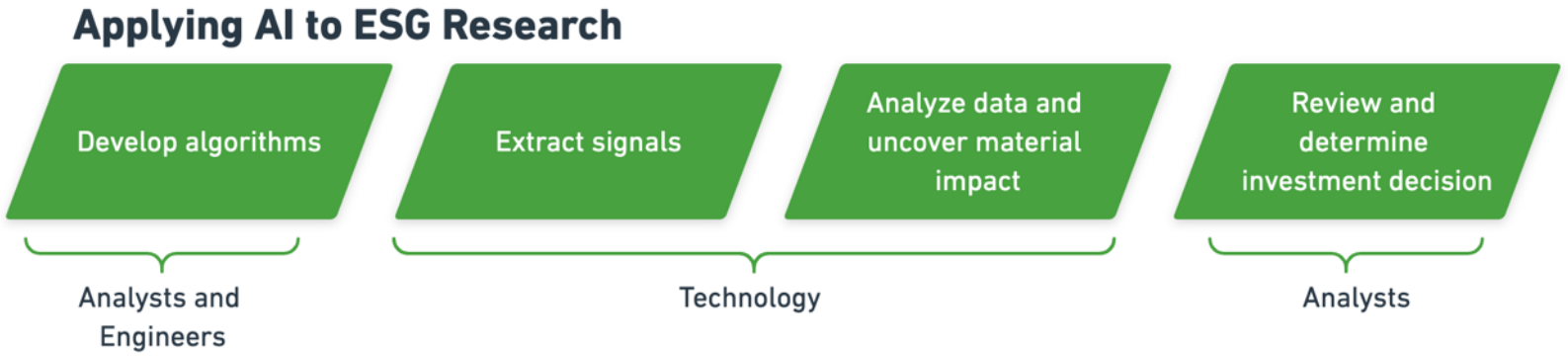
Analyst expertise at the beginning of the process produces consistent results

Source: Mark Tulay (2020), Man vs. machine: A tale of two sustainability ratings systems, GreenBiz, https://www.greenbiz.com/article/man-vs-machine-tale-two-sustainability-ratings-systems

Analyst based ESG Research

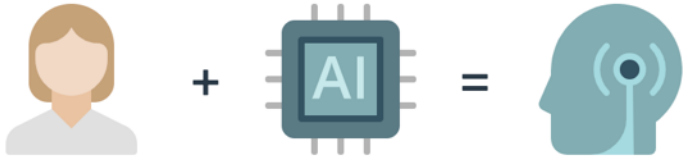
AI based ESG Research





It would take an analyst over 5 years to do what our AI can in 1 week

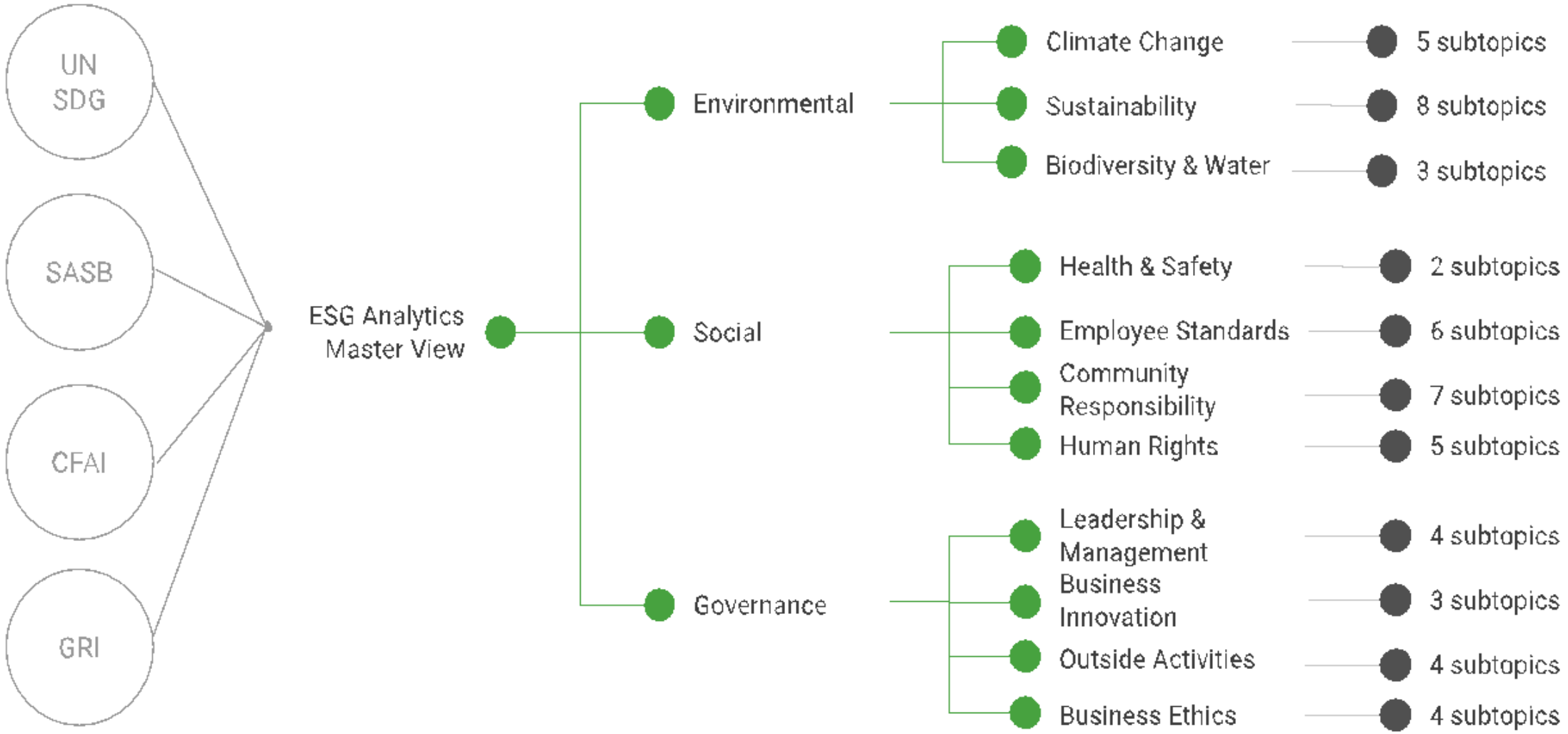
Combining analysts with AI creates gives you the full picture



ESG ANALYTICS
Invest where it matters.

Source: https://www.esganalytics.io/insights/how-data-is-accelerating-esg

ESG Analytics: NLP Taxonomy

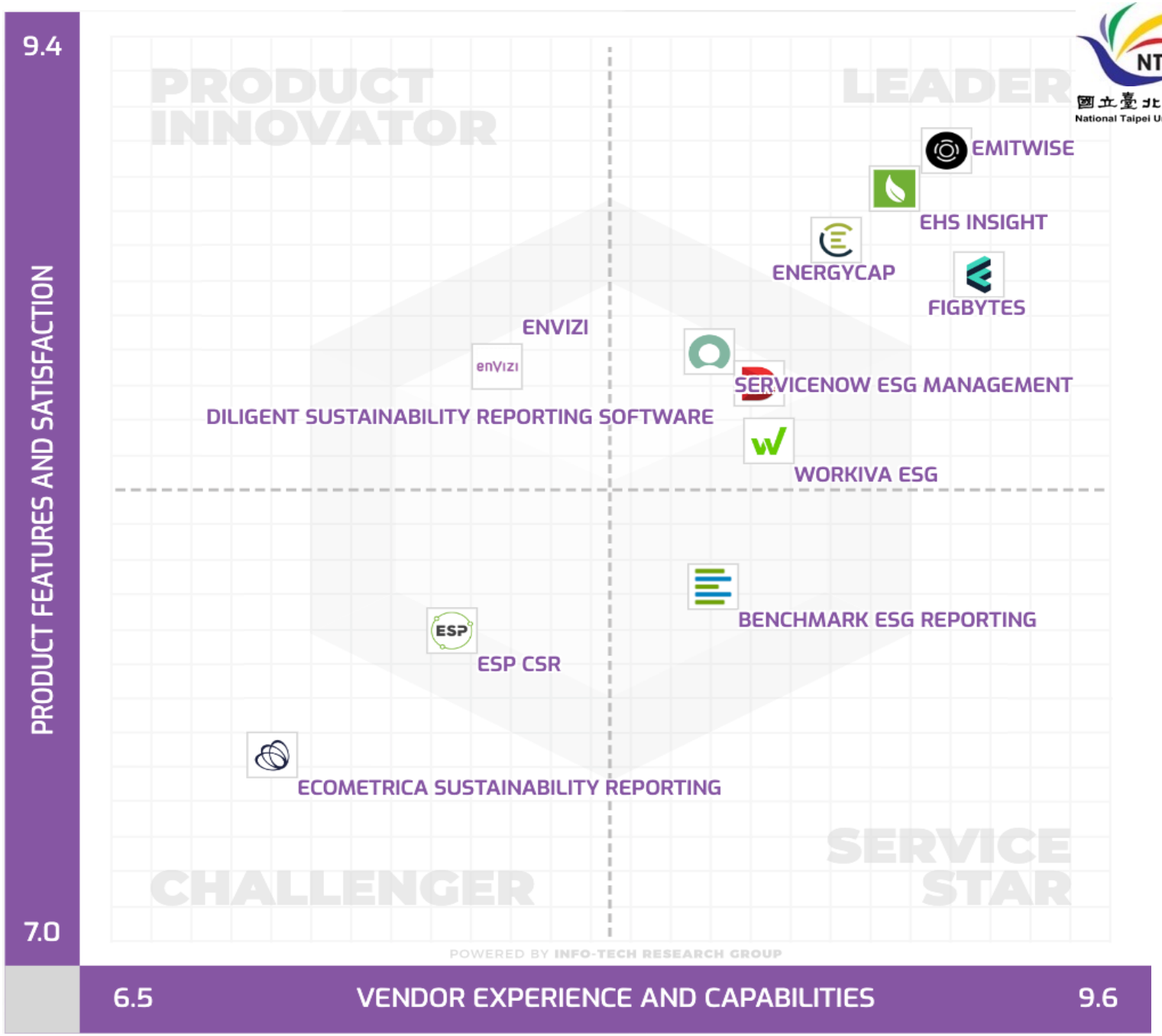


ESG ANALYTICS

Source: https://www.esganalytics.io/insights/how-data-is-accelerating-esg

Top ESG Reporting Software

Environmental, Social and Governance (ESG) Reporting software or **Sustainability software** helps organizations manage their operational data, evaluate their impact on the environment and provide reporting to perform audits.



Source: https://www.softwarereviews.com/categories/environmental-social-and-governance-reporting

Future Directions

- Integrating blockchain, IoT, and digital twins.
- Democratizing AI tools for all stakeholders.
- Promoting collaboration among experts and communities.

Conclusion

- Agentic AI is transforming ESG analytics and sustainability innovation.
- Collaboration among researchers, policymakers, and innovators is key.
- Agentic AI to build a sustainable future.

Summary

1. Agentic AI
2. ESG Data Analytics
3. Digital Sustainability Innovation

2022

IMNTPU at the NTCIR-16 FinNum-3 Task: Data Augmentation for Financial Numclaim Classification

[1] Information Management, National Taipei University, New Taipei City, Taiwan
[2] Zeals Co., Ltd. Tokyo, Japan





Yung-Wei Teng [1] Pei-Tz Chiu [1] Ting-Yun Hsiao [1] Mike Tian-Jian Jiang [2] Min-Yuh Day [1,*]

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2022

IMNTPU Dialogue System Evaluation at the NTCIR-16 DialEval-2 Dialogue Quality and Nugget Detection

[1] Information Management, National Taipei University, New Taipei City, Taiwan
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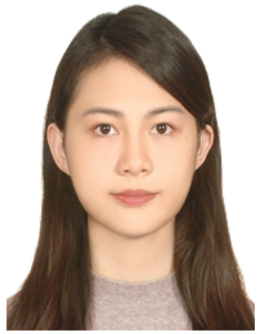
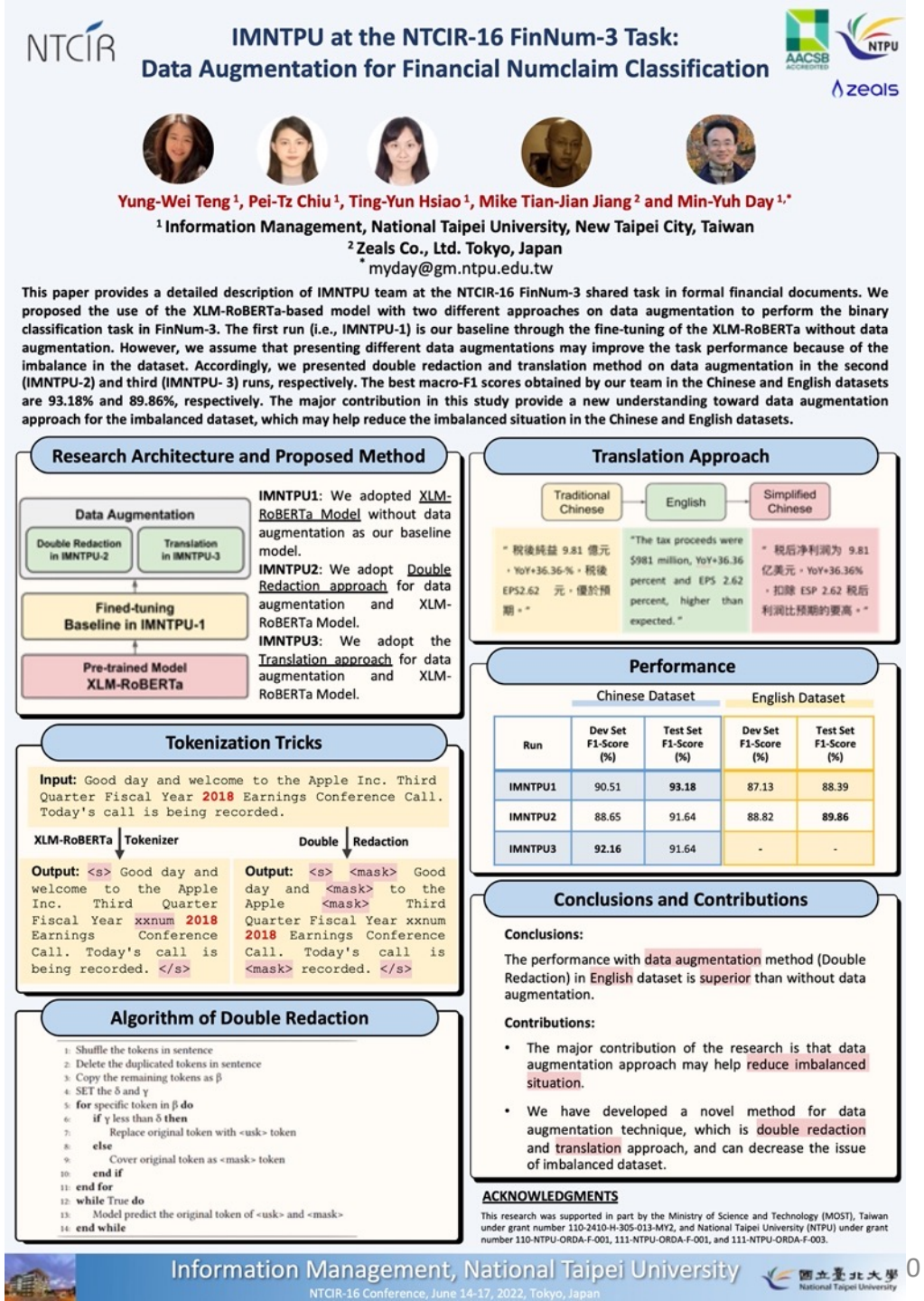


Ting-Yun Hsiao [1] Yung-Wei Teng [1] Pei-Tz Chiu [1] Mike Tian-Jian Jiang [2] Min-Yuh Day [1,*]

myday@gm.ntpu.edu.tw

NTCIR-16 FinNum-3

2022 NTCIR-16 Best Poster Presentation Award



NTCIR

IMNTPU at the NTCIR-16 FinNum-3 Task: Data Augmentation for Financial Numclaim Classification

Yung-Wei Teng [1], Pei-Tz Chiu [1], Ting-Yun Hsiao [1], Mike Tian-Jian Jiang [2] and Min-Yuh Day [1,*]

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This paper provides a detailed description of IMNTPU team at the NTCIR-16 FinNum-3 shared task in formal financial documents. We proposed the use of the XLM-RoBERTa-based model with two different approaches on data augmentation to perform the binary classification task in FinNum-3. The first run (i.e., IMNTPU-1) is our baseline through the fine-tuning of the XLM-RoBERTa without data augmentation. However, we assume that presenting different data augmentations may improve the task performance because of the imbalance in the dataset. Accordingly, we presented double redaction and translation method on data augmentation in the second (IMNTPU-2) and third (IMNTPU- 3) runs, respectively. The best macro-F1 scores obtained by our team in the Chinese and English datasets are 93.18% and 89.86%, respectively. The major contribution in this study provide a new understanding toward data augmentation approach for the imbalanced dataset, which may help reduce the imbalanced situation in the Chinese and English datasets.

Research Architecture and Proposed Method

Data Augmentation: Double Redaction in IMNTPU-2; Translation in IMNTPU-3

Fined-tuning Baseline in IMNTPU-1

Pre-trained Model XLM-RoBERTa

IMNTPU1: We adopted XLM-RoBERTa Model without data augmentation as our baseline model.

IMNTPU2: We adopt Double Redaction approach for data augmentation and XLM-RoBERTa Model.

IMNTPU3: We adopt the Translation approach for data augmentation and XLM-RoBERTa Model.

Translation Approach

Traditional Chinese → English → Simplified Chinese

"稅後純益 9.81 億元，YoY+36.36%，稅後 EPS2.62 元，優於預期。"

"The tax proceeds were $981 million, YoY+36.36 percent and EPS 2.62 percent, higher than expected."

"税后净利润为 9.81 亿美元，YoY+36.36%，扣除 ESP 2.62 税后利润比预期的要高。"

Performance

Run	Chinese Dataset Dev Set F1-Score (%)	Chinese Dataset Test Set F1-Score (%)	English Dataset Dev Set F1-Score (%)	English Dataset Test Set F1-Score (%)
IMNTPU1	90.51	**93.18**	87.13	88.39
IMNTPU2	88.65	91.64	88.82	**89.86**
IMNTPU3	**92.16**	91.64	-	-

Tokenization Tricks

Input: Good day and welcome to the Apple Inc. Third Quarter Fiscal Year **2018** Earnings Conference Call. Today's call is being recorded.

XLM-RoBERTa Tokenizer

Output: <s> Good day and welcome to the Apple Inc. Third Quarter Fiscal Year xxnum **2018** Earnings Conference Call. Today's call is being recorded. </s>

Double Redaction

Output: <s> <mask> Good day and <mask> to the Apple <mask> Third Quarter Fiscal Year xxnum **2018** Earnings Conference Call. Today's call is <mask> recorded. </s>

Algorithm of Double Redaction

1: Shuffle the tokens in sentence
2: Delete the duplicated tokens in sentence
3: Copy the remaining tokens as β
4: SET the δ and γ
5: **for** specific token in β **do**
6: **if** γ less than δ **then**
7: Replace original token with <usk> token
8: **else**
9: Cover original token as <mask> token
10: **end if**
11: **end for**
12: **while** True **do**
13: Model predict the original token of <usk> and <mask>
14: **end while**

Conclusions and Contributions

Conclusions:

The performance with data augmentation method (Double Redaction) in English dataset is superior than without data augmentation.

Contributions:

- The major contribution of the research is that data augmentation approach may help reduce imbalanced situation.
- We have developed a novel method for data augmentation technique, which is double redaction and translation approach, and can decrease the issue of imbalanced dataset.

ACKNOWLEDGMENTS

This research was supported in part by the Ministry of Science and Technology (MOST), Taiwan under grant number 110-2410-H-305-013-MY2, and National Taipei University (NTPU) under grant number 110-NTPU-ORDA-F-001, 111-NTPU-ORDA-F-001, and 111-NTPU-ORDA-F-003.

Information Management, National Taipei University

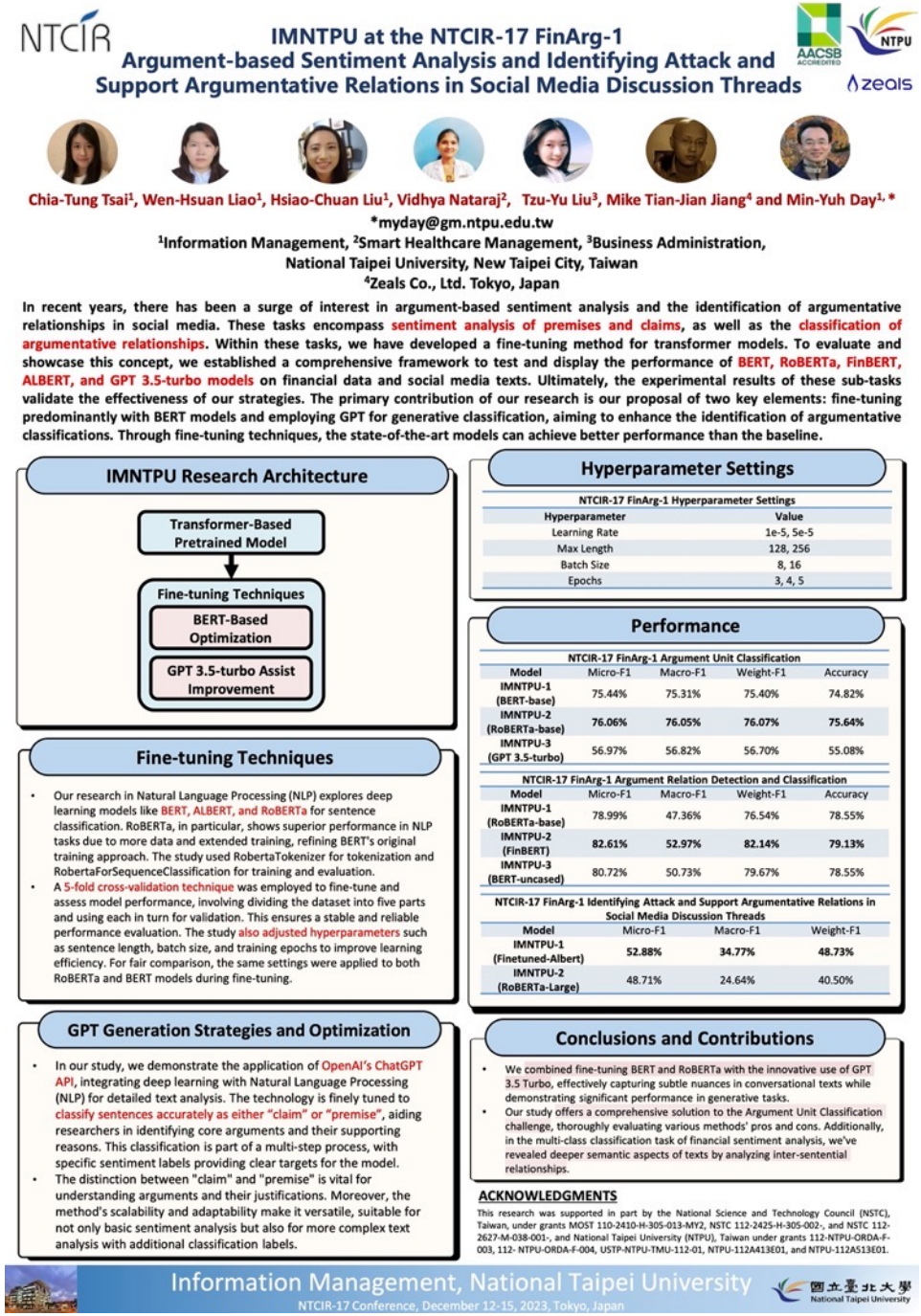
NTCIR-16 Conference, June 14-17, 2022, Tokyo, Japan

國立臺北大學 National Taipei University

NTCIR-17 FinArg-1

1

2023 NTCIR-17 Best Poster Presentation Award



IMNTPU at the NTCIR-17 FinArg-1 Argument-based Sentiment Analysis and Identifying Attack and Support Argumentative Relations in Social Media Discussion Threads

Chia-Tung Tsai[1], Wen-Hsuan Liao[1], Hsiao-Chuan Liu[1], Vidhya Nataraj[2], Tzu-Yu Liu[3], Mike Tian-Jian Jiang[4] and Min-Yuh Day[1,*]
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[1]Information Management, [2]Smart Healthcare Management, [3]Business Administration,
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In recent years, there has been a surge of interest in argument-based sentiment analysis and the identification of argumentative relationships in social media. These tasks encompass sentiment analysis of premises and claims, as well as the classification of argumentative relationships. Within these tasks, we have developed a fine-tuning method for transformer models. To evaluate and showcase this concept, we established a comprehensive framework to test and display the performance of BERT, RoBERTa, FinBERT, ALBERT, and GPT 3.5-turbo models on financial data and social media texts. Ultimately, the experimental results of these sub-tasks validate the effectiveness of our strategies. The primary contribution of our research is our proposal of two key elements: fine-tuning predominantly with BERT models and employing GPT for generative classification, aiming to enhance the identification of argumentative classifications. Through fine-tuning techniques, the state-of-the-art models can achieve better performance than the baseline.

IMNTPU Research Architecture

Transformer-Based Pretrained Model
Fine-tuning Techniques
BERT-Based Optimization
GPT 3.5-turbo Assist Improvement

Hyperparameter Settings

NTCIR-17 FinArg-1 Hyperparameter Settings

Hyperparameter	Value
Learning Rate	1e-5, 5e-5
Max Length	128, 256
Batch Size	8, 16
Epochs	3, 4, 5

Performance

NTCIR-17 FinArg-1 Argument Unit Classification

Model	Micro-F1	Macro-F1	Weight-F1	Accuracy
IMNTPU-1 (BERT-base)	75.44%	75.31%	75.40%	74.82%
IMNTPU-2 (RoBERTa-base)	**76.06%**	**76.05%**	**76.07%**	**75.64%**
IMNTPU-3 (GPT 3.5-turbo)	56.97%	56.82%	56.70%	55.08%

NTCIR-17 FinArg-1 Argument Relation Detection and Classification

Model	Micro-F1	Macro-F1	Weight-F1	Accuracy
IMNTPU-1 (RoBERTa-base)	78.99%	47.36%	76.54%	78.55%
IMNTPU-2 (FinBERT)	**82.61%**	**52.97%**	**82.14%**	**79.13%**
IMNTPU-3 (BERT-uncased)	80.72%	50.73%	79.67%	78.55%

NTCIR-17 FinArg-1 Identifying Attack and Support Argumentative Relations in Social Media Discussion Threads

Model	Micro-F1	Macro-F1	Weight-F1
IMNTPU-1 (Finetuned-Albert)	**52.88%**	**34.77%**	**48.73%**
IMNTPU-2 (RoBERTa-Large)	48.71%	24.64%	40.50%

Fine-tuning Techniques

- Our research in Natural Language Processing (NLP) explores deep learning models like BERT, ALBERT, and RoBERTa for sentence classification. RoBERTa, in particular, shows superior performance in NLP tasks due to more data and extended training, refining BERT's original training approach. The study used RobertaTokenizer for tokenization and RobertaForSequenceClassification for training and evaluation.
- A 5-fold cross-validation technique was employed to fine-tune and assess model performance, involving dividing the dataset into five parts and using each in turn for validation. This ensures a stable and reliable performance evaluation. The study also adjusted hyperparameters such as sentence length, batch size, and training epochs to improve learning efficiency. For fair comparison, the same settings were applied to both RoBERTa and BERT models during fine-tuning.

GPT Generation Strategies and Optimization

- In our study, we demonstrate the application of OpenAI's ChatGPT API, integrating deep learning with Natural Language Processing (NLP) for detailed text analysis. The technology is finely tuned to classify sentences accurately as either "claim" or "premise", aiding researchers in identifying core arguments and their supporting reasons. This classification is part of a multi-step process, with specific sentiment labels providing clear targets for the model.
- The distinction between "claim" and "premise" is vital for understanding arguments and their justifications. Moreover, the method's scalability and adaptability make it versatile, suitable for not only basic sentiment analysis but also for more complex text analysis with additional classification labels.

Conclusions and Contributions

- We combined fine-tuning BERT and RoBERTa with the innovative use of GPT 3.5 Turbo, effectively capturing subtle nuances in conversational texts while demonstrating significant performance in generative tasks.
- Our study offers a comprehensive solution to the Argument Unit Classification challenge, thoroughly evaluating various methods' pros and cons. Additionally, in the multi-class classification task of financial sentiment analysis, we've revealed deeper semantic aspects of texts by analyzing inter-sentential relationships.

ACKNOWLEDGMENTS
This research was supported in part by the National Science and Technology Council (NSTC), Taiwan, under grants MOST 110-2410-H-305-013-MY2, NSTC 112-2425-H-305-002-, and NSTC 112-2627-M-038-001-, and National Taipei University (NTPU), Taiwan under grants 112-NTPU-ORDA-F-003, 112- NTPU-ORDA-F-004, USTP-NTPU-TMU-112-01, NTPU-112A413E01, and NTPU-112AS13E01.

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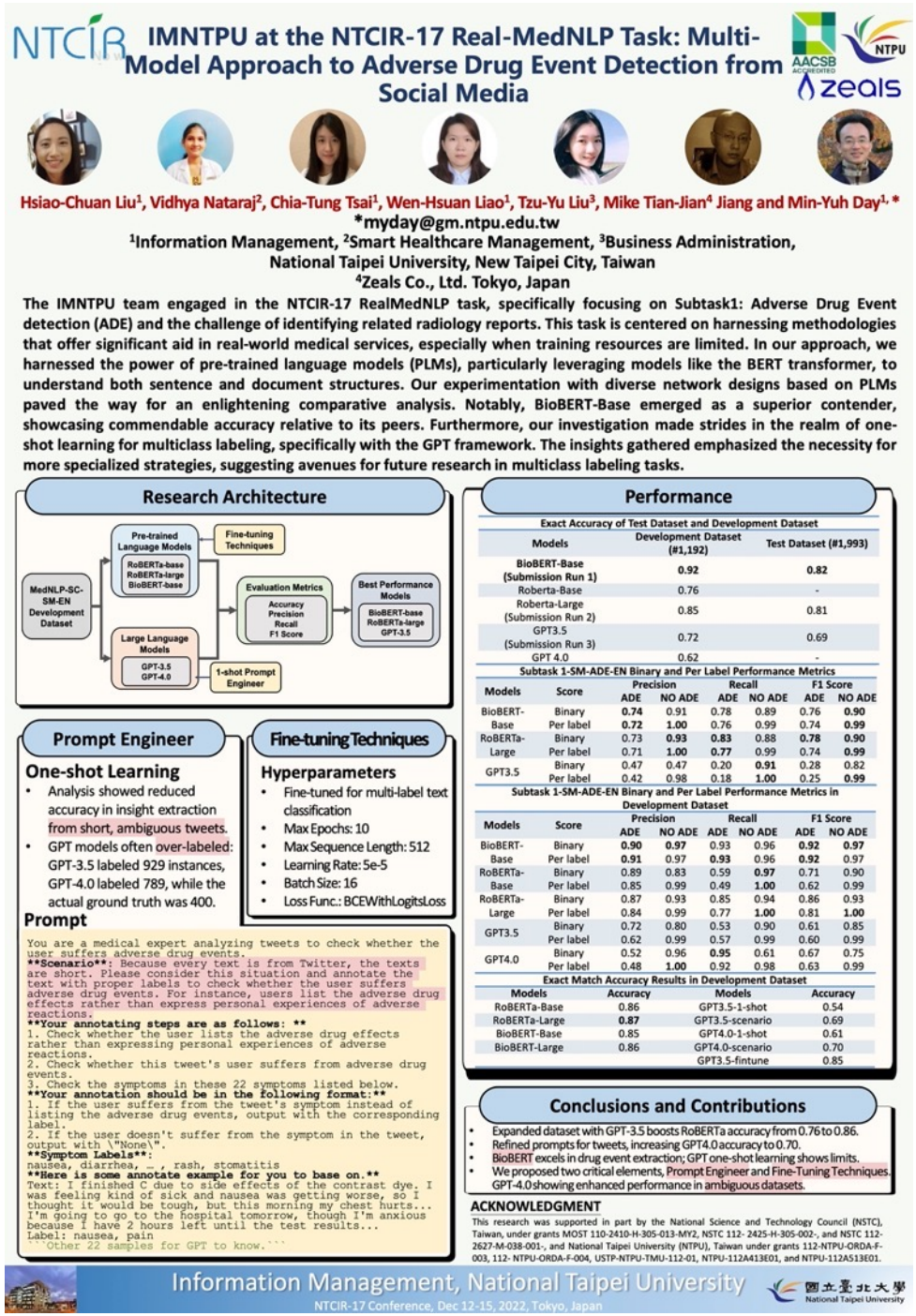
2

2023 NTCIR-17 Best Poster Presentation Award

NTCIR-17 Real MedNLP



IMNTPU at the NTCIR-17 Real-MedNLP Task: Multi-Model Approach to Adverse Drug Event Detection from Social Media

Hsiao-Chuan Liu[1], Vidhya Nataraj[2], Chia-Tung Tsai[1], Wen-Hsuan Liao[1], Tzu-Yu Liu[3], Mike Tian-Jian[4] Jiang and Min-Yuh Day[1,*]
*myday@gm.ntpu.edu.tw
[1]Information Management, [2]Smart Healthcare Management, [3]Business Administration, National Taipei University, New Taipei City, Taiwan
[4]Zeals Co., Ltd. Tokyo, Japan

The IMNTPU team engaged in the NTCIR-17 RealMedNLP task, specifically focusing on Subtask1: Adverse Drug Event detection (ADE) and the challenge of identifying related radiology reports. This task is centered on harnessing methodologies that offer significant aid in real-world medical services, especially when training resources are limited. In our approach, we harnessed the power of pre-trained language models (PLMs), particularly leveraging models like the BERT transformer, to understand both sentence and document structures. Our experimentation with diverse network designs based on PLMs paved the way for an enlightening comparative analysis. Notably, BioBERT-Base emerged as a superior contender, showcasing commendable accuracy relative to its peers. Furthermore, our investigation made strides in the realm of one-shot learning for multiclass labeling, specifically with the GPT framework. The insights gathered emphasized the necessity for more specialized strategies, suggesting avenues for future research in multiclass labeling tasks.

Research Architecture

Prompt Engineer

One-shot Learning

- Analysis showed reduced accuracy in insight extraction from short, ambiguous tweets.
- GPT models often over-labeled: GPT-3.5 labeled 929 instances, GPT-4.0 labeled 789, while the actual ground truth was 400.

Prompt

```
You are a medical expert analyzing tweets to check whether the user suffers adverse drug events.
**Scenario**: Because every text is from Twitter, the texts are short. Please consider this situation and annotate the text with proper labels to check whether the user suffers adverse drug events. For instance, users list the adverse drug effects rather than express personal experiences of adverse reactions.
**Your annotating steps are as follows: **
1. Check whether the user lists the adverse drug effects rather than expressing personal experiences of adverse reactions.
2. Check whether this tweet's user suffers from adverse drug events.
3. Check the symptoms in these 22 symptoms listed below.
**Your annotation should be in the following format:**
1. If the user suffers from the tweet's symptom instead of listing the adverse drug events, output with the corresponding label.
2. If the user doesn't suffer from the symptom in the tweet, output with \"None\".
**Symptom Labels**:
nausea, diarrhea, … , rash, stomatitis
**Here is some annotate example for you to base on.**
Text: I finished C due to side effects of the contrast dye. I was feeling kind of sick and nausea was getting worse, so I thought it would be tough, but this morning my chest hurts... I'm going to go to the hospital tomorrow, though I'm anxious because I have 2 hours left until the test results...
Label: nausea, pain
```Other 22 samples for GPT to know.```
```

Fine-tuning Techniques

Hyperparameters

- Fine-tuned for multi-label text classification
- Max Epochs: 10
- Max Sequence Length: 512
- Learning Rate: 5e-5
- Batch Size: 16
- Loss Func.: BCEWithLogitsLoss

Performance

Exact Accuracy of Test Dataset and Development Dataset

Models	Development Dataset (#1,192)	Test Dataset (#1,993)
BioBERT-Base (Submission Run 1)	**0.92**	**0.82**
Roberta-Base	0.76	-
Roberta-Large (Submission Run 2)	0.85	0.81
GPT3.5 (Submission Run 3)	0.72	0.69
GPT 4.0	0.62	-

Subtask 1-SM-ADE-EN Binary and Per Label Performance Metrics

Models	Score	Precision ADE	Precision NO ADE	Recall ADE	Recall NO ADE	F1 Score ADE	F1 Score NO ADE
BioBERT-Base	Binary	**0.74**	0.91	0.78	0.89	0.76	**0.90**
	Per label	**0.72**	**1.00**	0.76	0.99	0.74	**0.99**
RoBERTa-Large	Binary	0.73	**0.93**	**0.83**	0.88	**0.78**	**0.90**
	Per label	0.71	**1.00**	**0.77**	0.99	0.74	**0.99**
GPT3.5	Binary	0.47	0.47	0.20	**0.91**	0.28	0.82
	Per label	0.42	0.98	0.18	**1.00**	0.25	**0.99**

Subtask 1-SM-ADE-EN Binary and Per Label Performance Metrics in Development Dataset

Models	Score	Precision ADE	Precision NO ADE	Recall ADE	Recall NO ADE	F1 Score ADE	F1 Score NO ADE
BioBERT-Base	Binary	**0.90**	**0.97**	0.93	0.96	**0.92**	**0.97**
	Per label	**0.91**	0.97	**0.93**	0.96	**0.92**	0.97
RoBERTa-Base	Binary	0.89	0.83	0.59	**0.97**	0.71	0.90
	Per label	0.85	0.99	0.49	**1.00**	0.62	0.99
RoBERTa-Large	Binary	0.87	0.93	0.85	0.94	0.86	0.93
	Per label	0.84	0.99	0.77	**1.00**	0.81	**1.00**
GPT3.5	Binary	0.72	0.80	0.53	0.90	0.61	0.85
	Per label	0.62	0.99	0.57	0.99	0.60	0.99
GPT4.0	Binary	0.52	0.96	**0.95**	0.61	0.67	0.75
	Per label	0.48	**1.00**	0.92	0.98	0.63	0.99

Exact Match Accuracy Results in Development Dataset

Models	Accuracy	Models	Accuracy
RoBERTa-Base	0.86	GPT3.5-1-shot	0.54
RoBERTa-Large	**0.87**	GPT3.5-scenario	0.69
BioBERT-Base	0.85	GPT4.0-1-shot	0.61
BioBERT-Large	0.86	GPT4.0-scenario	0.70
		GPT3.5-fintune	0.85

Conclusions and Contributions

- Expanded dataset with GPT-3.5 boosts RoBERTa accuracy from 0.76 to 0.86.
- Refined prompts for tweets, increasing GPT4.0 accuracy to 0.70.
- BioBERT excels in drug event extraction; GPT one-shot learning shows limits.
- We proposed two critical elements, Prompt Engineer and Fine-Tuning Techniques. GPT-4.0 showing enhanced performance in ambiguous datasets.

ACKNOWLEDGMENT

This research was supported in part by the National Science and Technology Council (NSTC), Taiwan, under grants MOST 110-2410-H-305-013-MY2, NSTC 112- 2425-H-305-002-, and NSTC 112-2627-M-038-001-, and National Taipei University (NTPU), Taiwan under grants 112-NTPU-ORDA-F-003, 112- NTPU-ORDA-F-004, USTP-NTPU-TMU-112-01, NTPU-112A413E01, and NTPU-112A513E01.

Information Management, National Taipei University
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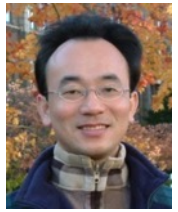
Acknowledgments: Research Projects

1. **Fintech Green Finance for Carbon Market Index, Corporate Finance, and Environmental Policies.** Carbon Emission Sentiment Index with AI Text Analytics
   - NTPU, 113-NTPU_ORDA-F-003, 2023/01/01~2024/12/31
2. **Innovative Agentic AI Technology for Autonomous ESG Report Generation**
   - Industrial Technology Research Institute (ITRI), Fintech and Green Finance Center (FGFC, NTPU), NTPU-114A513E01, 2025/03/01~2025/12/31
3. **Development of a Deep Learning for Dental Implant Detection in Panoramic Radiographs**
   University System of Taipei Joint Research Program (NTPU, TMU), USTP-NTPU-TMU-114-02, 2025/01/01~2025/12/31
4. **Digital Support, Unimpeded Communication: The Development, Support and Promotion of AI-assisted Communication Assistive Devices for Speech Impairment (2/3).** Multimodal Cross-lingual Task-Oriented Dialogue System for Inclusive Communication Support
   - NSTC 113-2425-H-305-002-, 3 Years (2023/05/01-2026/04/30) Year 1: 2024/05/01~2025/04/30
5. **Research on speech processing, synthesis, recognition, and sentence construction of people with language disabilities.** Multimodal Cross-lingual Task-Oriented Dialogue System
   - NTPU, 113-NTPU_ORDA-F-004, 2023/01/01~2025/12/31
6. **Metaverse AI Multimodal Cross-Language Task-Oriented Dialogue System**
   - ATEC Group, Fintech and Green Finance Center (FGFC, NTPU), NTPU-112A413E01, 3 Years (2023/05/01~2026/04/30)
7. **Establishment and Implement of Smart Assistive Technology for Dementia Care and Its Socio-Economic Impacts (3/3).** Intelligent, individualized and precise care with smart AT and system integration
   - NSTC, 113-2627-M-038-001-, 2024/08/01~2025/07/31

https://web.ntpu.edu.tw/~myday/cindex.htm#projects



Acknowledgments: IFIT Lab Members

Intelligent Financial Innovation Technology, IFIT Lab, IM, NTPU

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臺北市立大學資訊科學系
碩士班Seminar

Q & A

Agentic AI for ESG and Digital Sustainability Innovation (代理式 AI 於 ESG 與數位永續創新)

Time: 13:10-15:00, **Wednesday, April 30, 2025**
Place: R314, Gongcheng Building, Department of Computer Science, **University of Taipei**
Host: Prof. Ching-Tai Chen

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國立臺北大學 資訊管理研究所 教授
金融科技暨綠色金融研究中心 主任
永續辦公室 永續發展組 組長

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