

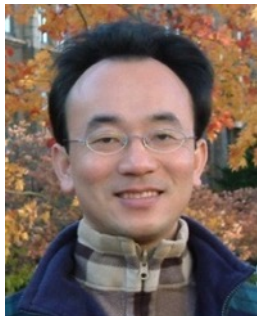
Generative AI and LLMs for Sustainability and ESG Data Analytics (生成式 AI 與 LLM 於永續數據分析)

Time: 19:00-21:00, Monday, November 25, 2024

Place: Room 200301, Daren Building, Computer Science, National Chengchi University (NCCU)

Host: Prof. Jia-Ming Chang

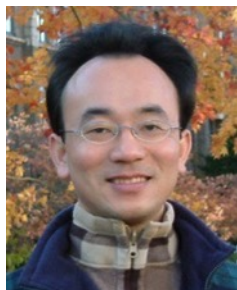
aws
educate | Cloud
Ambassador
2020 Cohort



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(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-)



Outline

- 1. Generative AI:
Powering Digital Sustainability Transformation**
- 2. Generative AI and Large Language Models (LLMs):
Popular Generative AI Applications**
- 3. Generative AI for Sustainability and ESG Data Analytics**

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

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

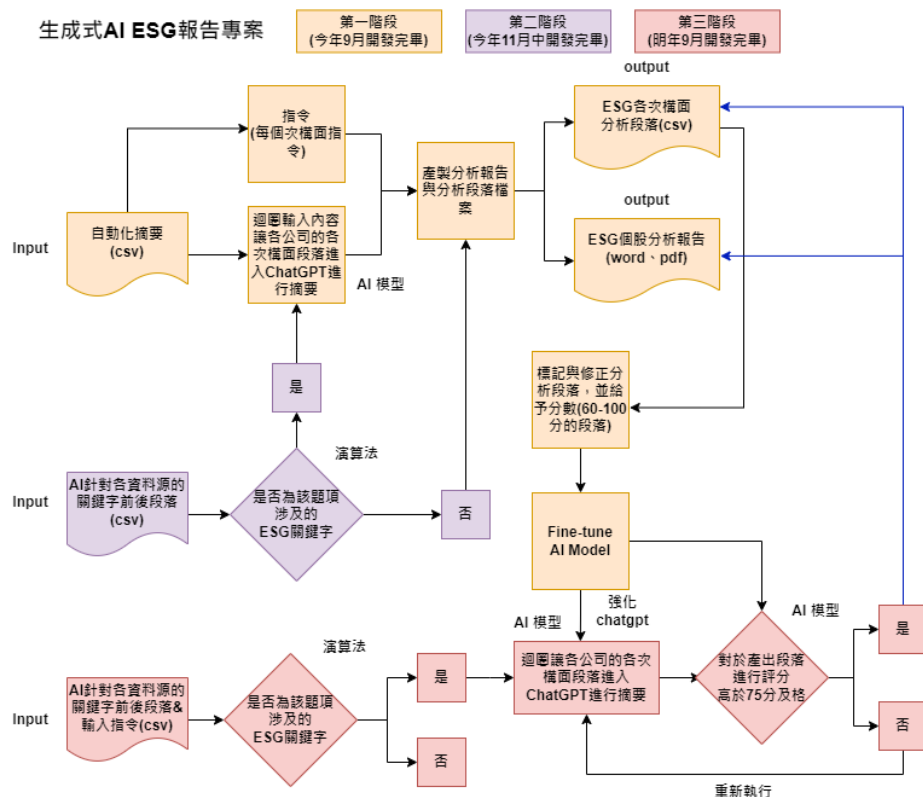


國立臺北大學
National Taipei University



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%

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

Generative AI

Powering

Digital Sustainability

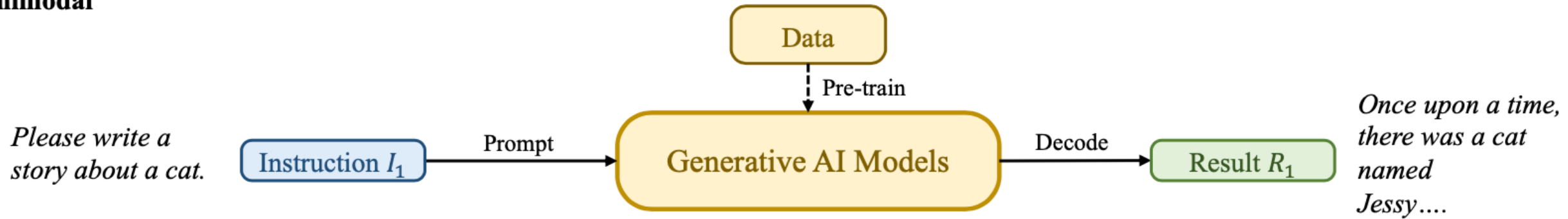
Transformation

Generative AI (Gen AI) AI Generated Content (AIGC)

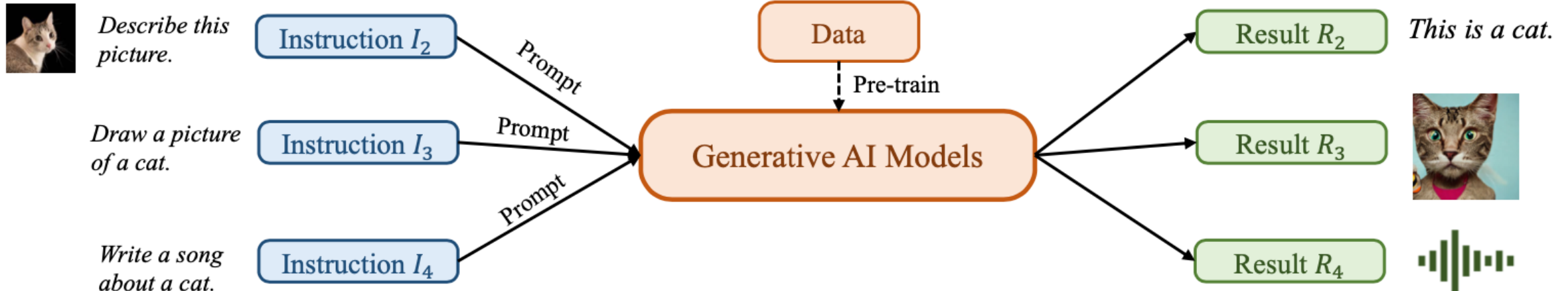
Generative AI (Gen AI)

AI Generated Content (AIGC)

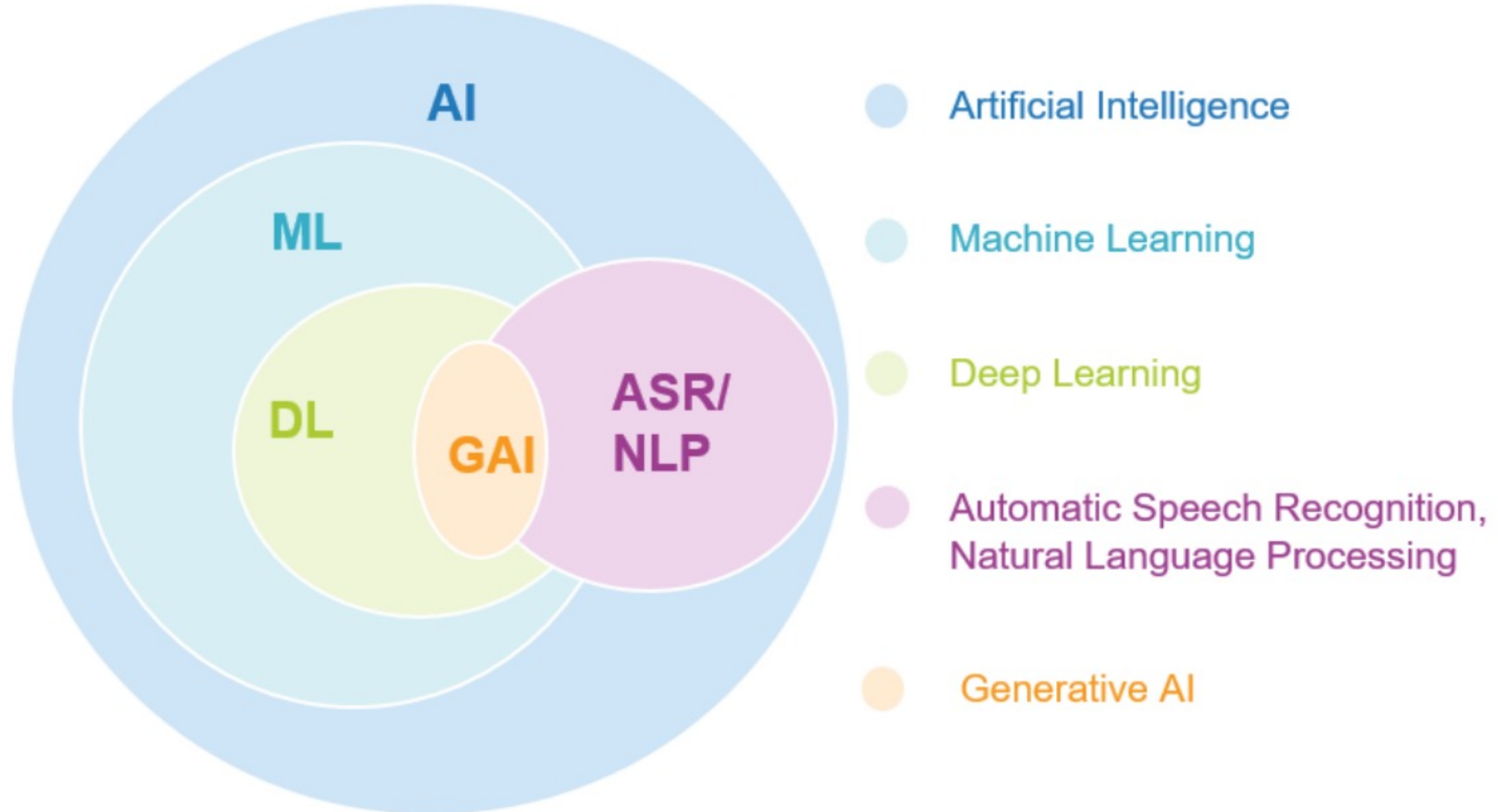
Unimodal



Multimodal



AI, ML, DL, Generative AI



Definition of Artificial Intelligence (A.I.)

Artificial Intelligence

**“... the science and
engineering
of
making
intelligent machines”
(John McCarthy, 1955)**

Artificial Intelligence

**“... technology that
thinks and acts
like humans”**

Artificial Intelligence

**“... intelligence
exhibited by machines
or software”**

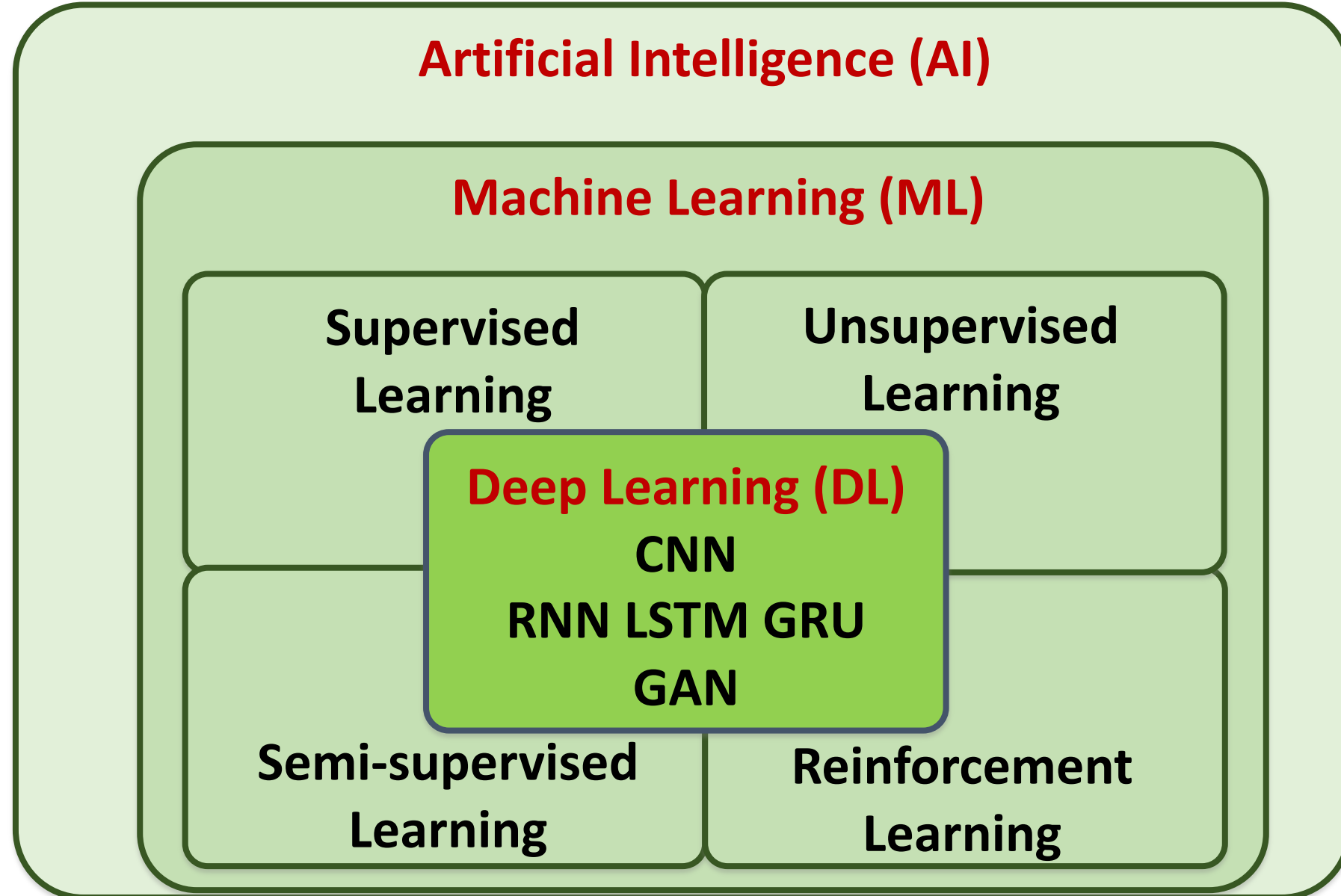
4 Approaches of AI

<p>2.</p> <p>Thinking Humanly: The Cognitive Modeling Approach</p>	<p>3.</p> <p>Thinking Rationally: The “Laws of Thought” Approach</p>
<p>1.</p> <p>Acting Humanly: The Turing Test Approach (1950)</p>	<p>4.</p> <p>Acting Rationally: The Rational Agent Approach</p>

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

AI, ML, DL



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

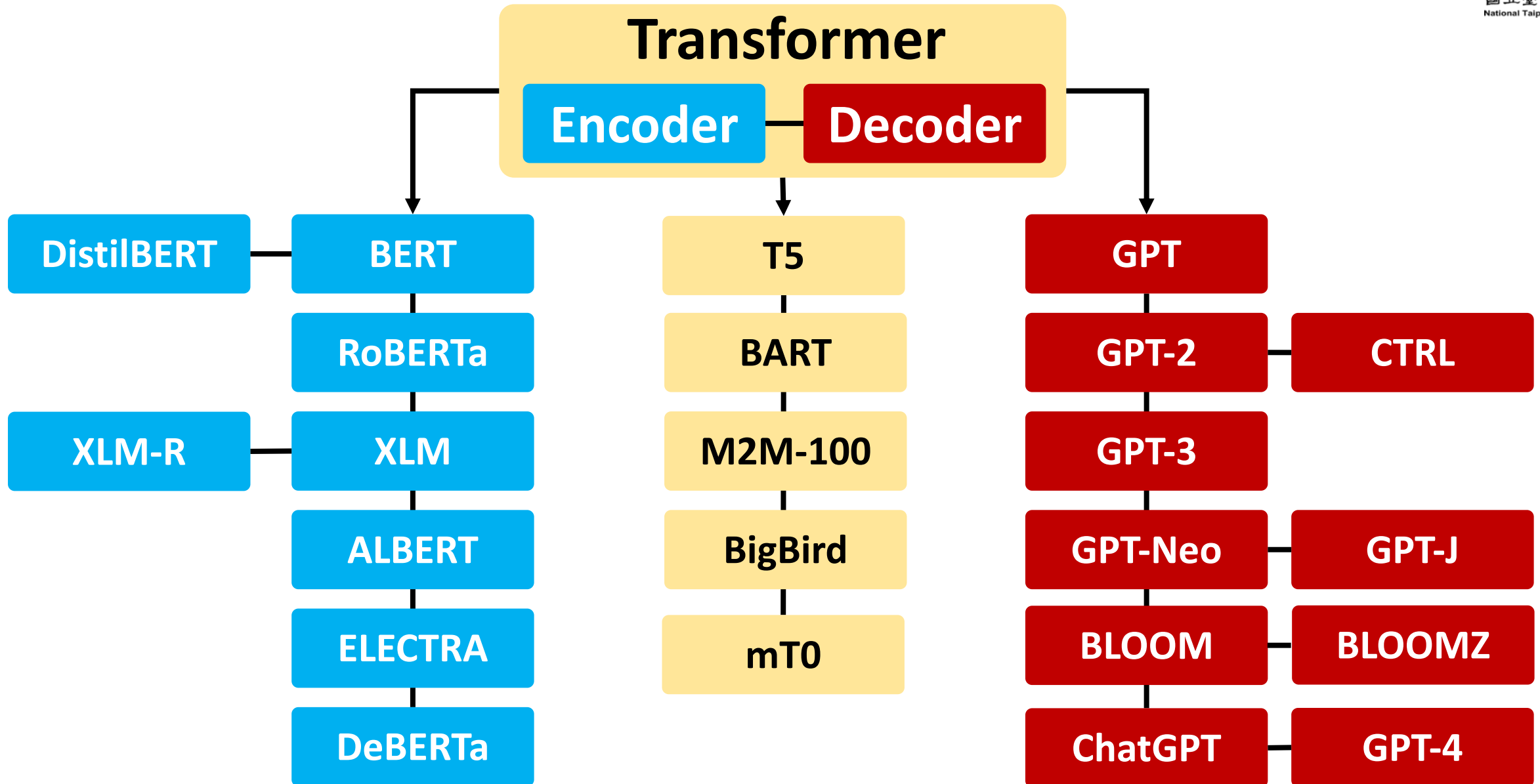
Generative AI

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

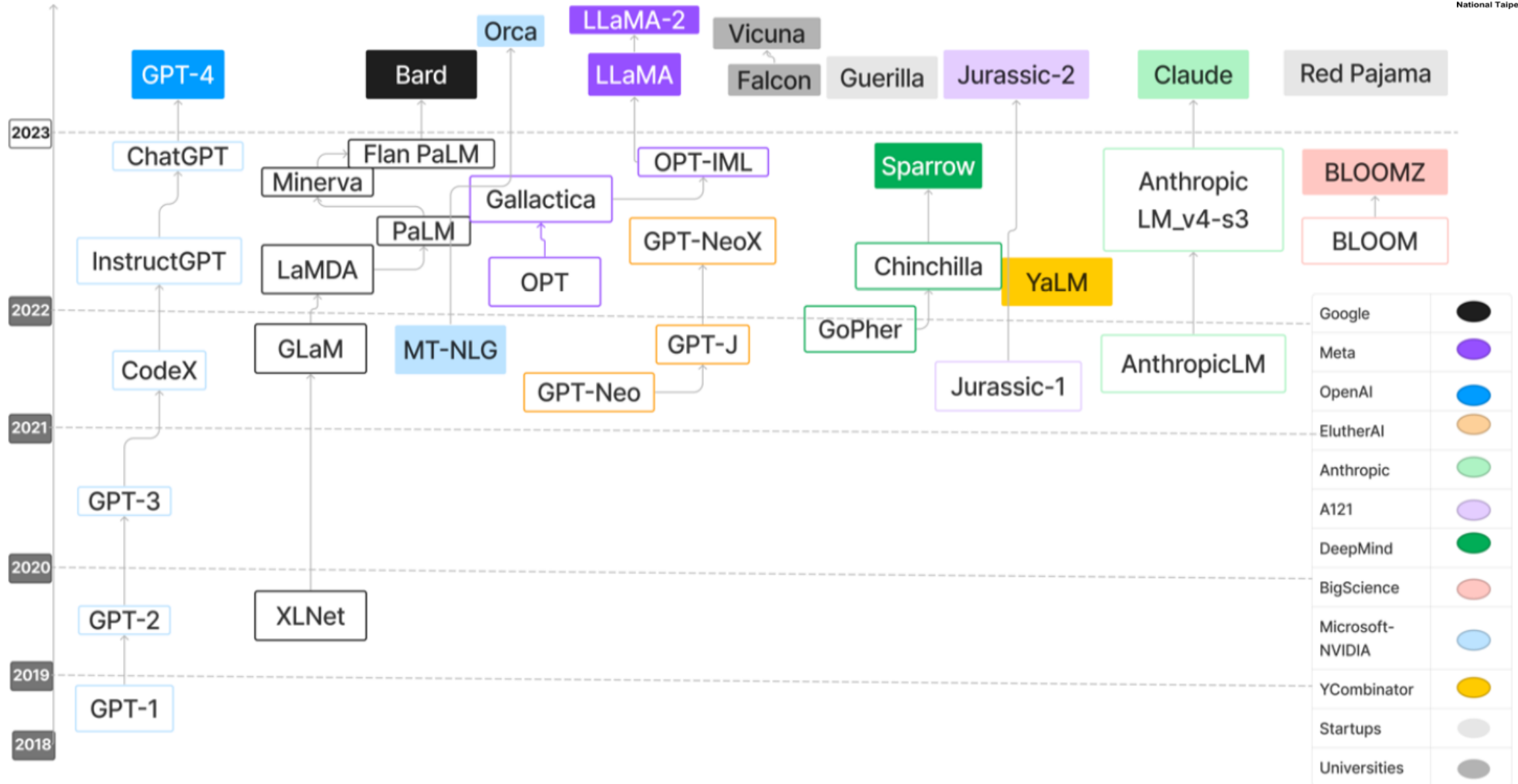
Generative AI and Large Language Models (LLMs): Popular Generative AI Applications

Large Language Models (LLMs) Foundation Models

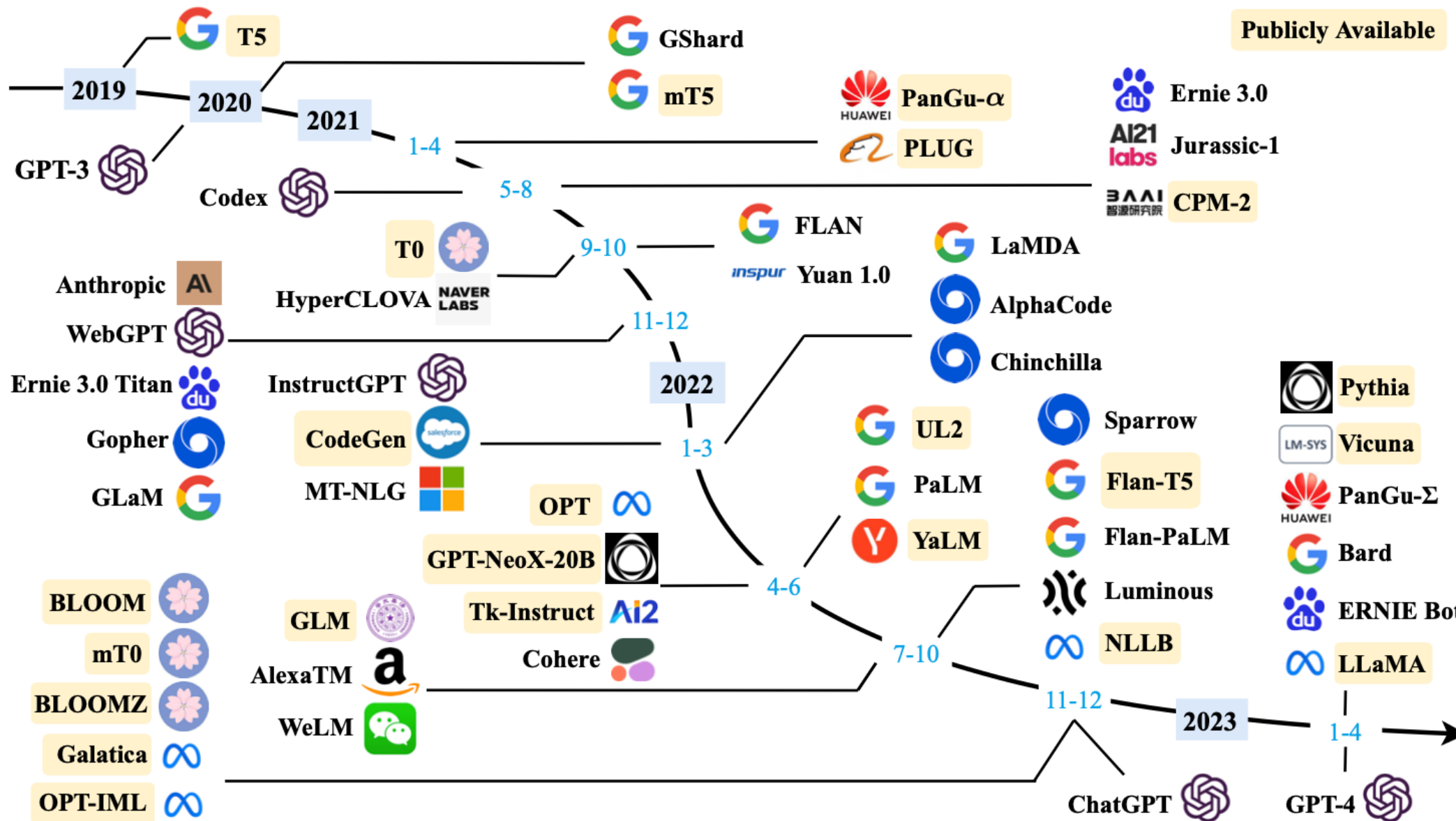
Transformer Models



Large Language Models (LLMs)

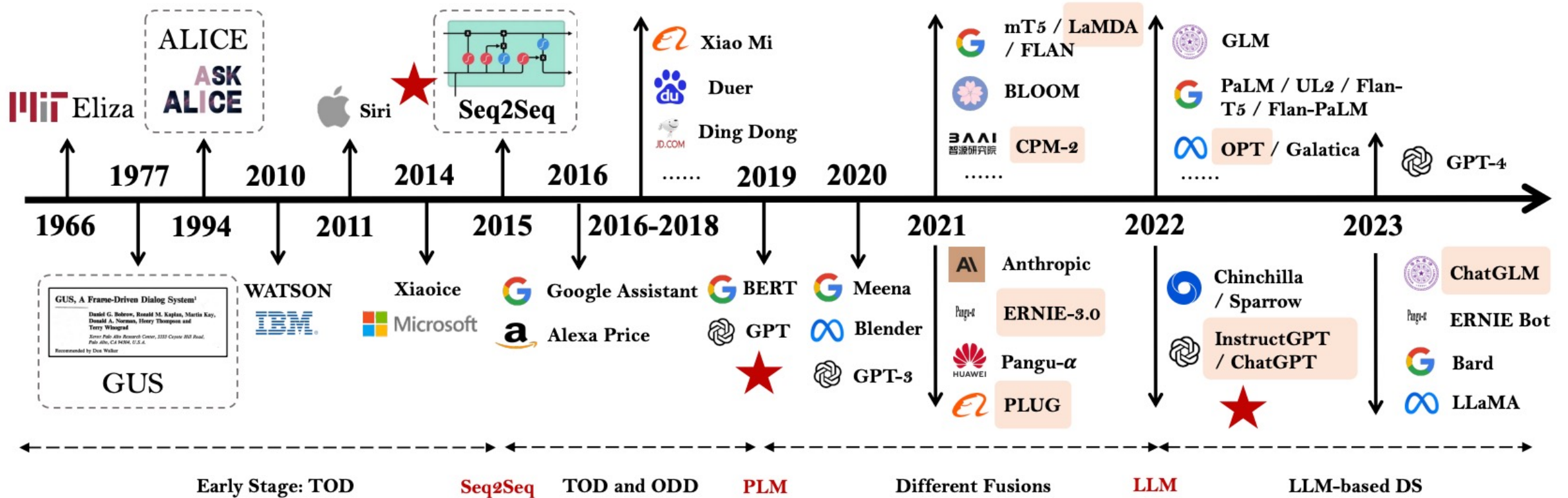


Large Language Models (LLMs) (larger than 10B)



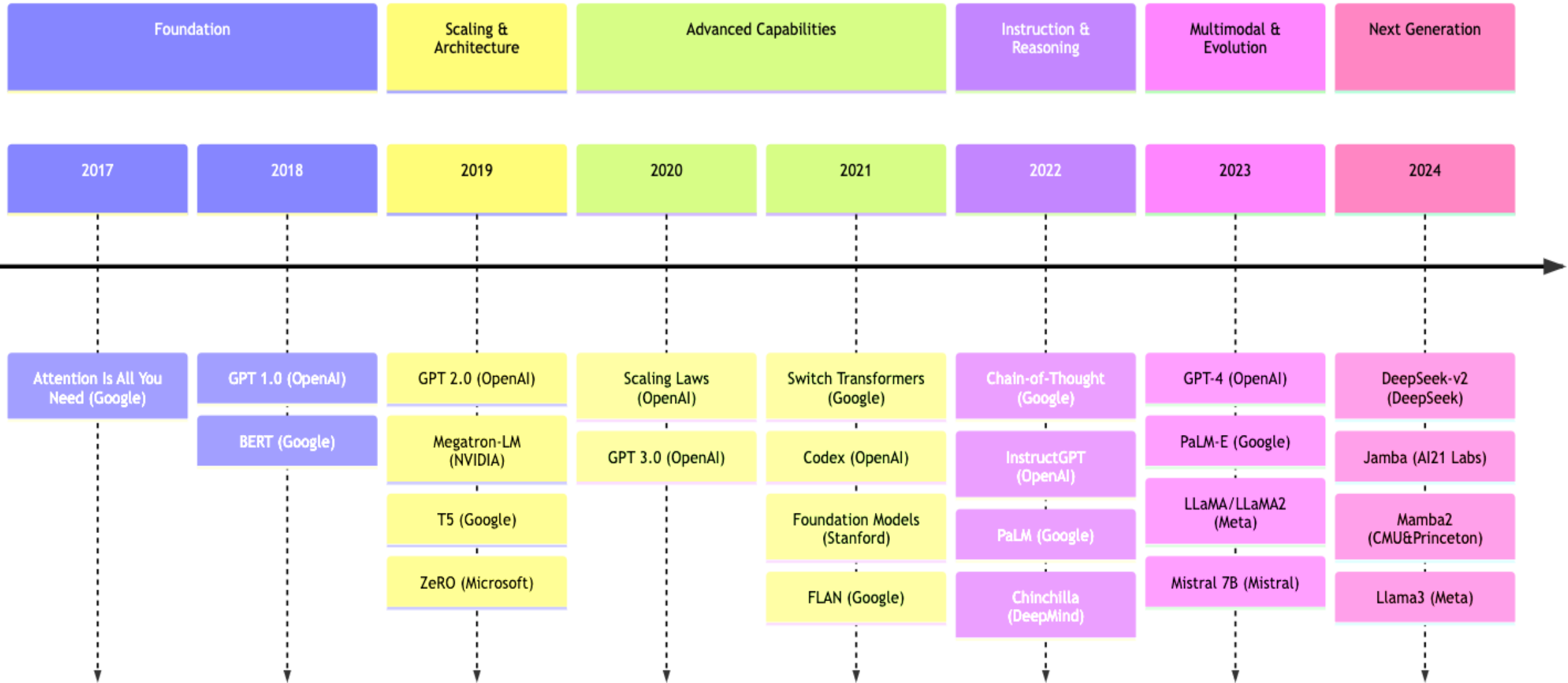
The Development of LM-based Dialogue Systems

- 1) Early Stage (1966 - 2015)
- 2) The Independent Development of TOD and ODD (2015 - 2019)
- 3) Fusions of Dialogue Systems (2019 - 2022)
- 4) LLM-based DS (2022 - Now)


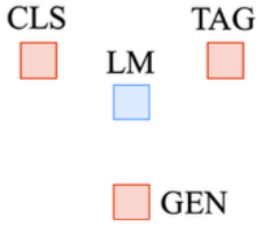
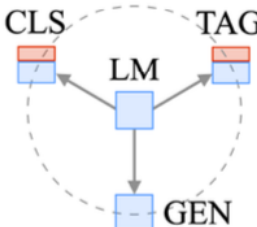
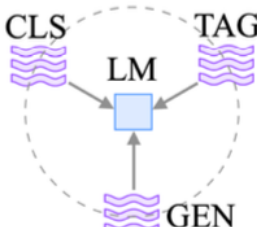


Task-oriented DS (TOD), Open-domain DS (ODD)

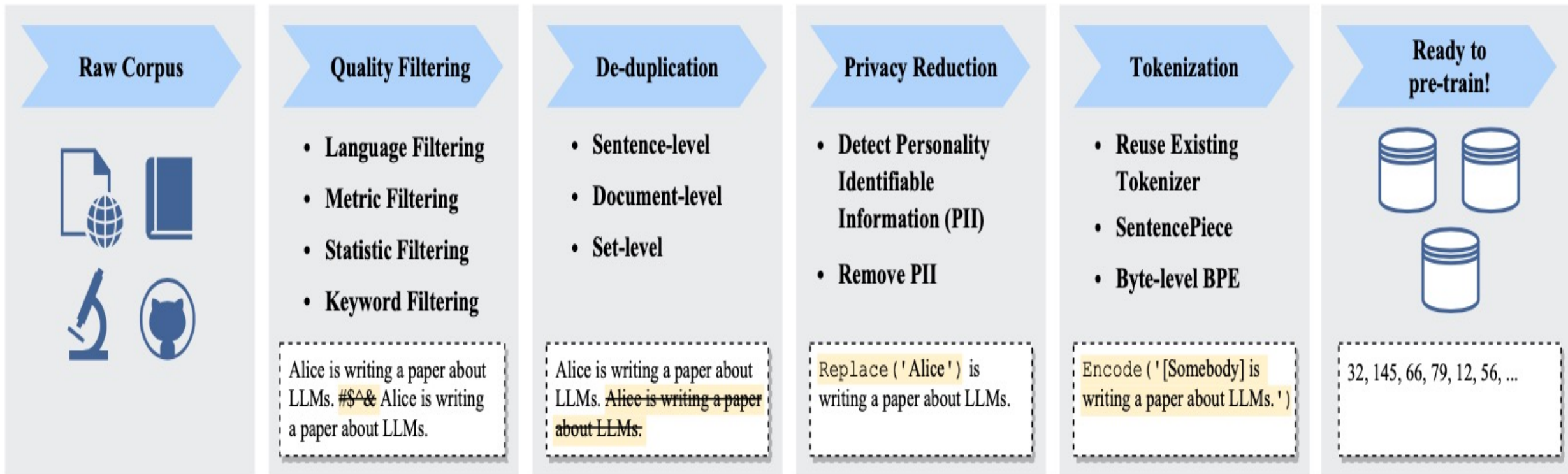
Major GenAI LLMs Research Milestones (2017-2024)



Four Paradigms in NLP (LM)

Paradigm	Engineering	Task Relation
a. Fully Supervised Learning (Non-Neural Network)	Feature (e.g. word identity, part-of-speech, sentence length)	
b. Fully Supervised Learning (Neural Network)	Architecture (e.g. convolutional, recurrent, self-attentional)	
Transfer Learning: Pre-training, Fine-Tuning (FT)		
c. Pre-train, Fine-tune	Objective (e.g. masked language modeling, next sentence prediction)	
GAI: Pre-train, Prompt, and Predict (Prompting)		
d. Pre-train, Prompt, Predict	Prompt (e.g. cloze, prefix)	

Typical Data Preprocessing Pipeline for Pre-training Large Language Models (LLMs)



Generative AI

Text, Image, Video, Audio

Applications

Popular Generative AI

- **OpenAI ChatGPT (GPT-4o, GPT-4)**
- **Claude.ai (Claude 3.5)**
- **Google Gemini**
- **Meta Llama 3.2**
- **Mixtral Pixtral (mistral.ai)**
- **Chat.LMSys.org (lmarena.ai)**
- **Perplexity.ai**
- **Stable Diffusion**
- **Video: D-ID, Synthesia**
- **Audio: Speechify**

LMSYS Chatbot Arena Leaderboard

GPT-4o

Claude 3.5

Rank* (UB)	Rank (StyleCtrl)	Model	Arena Score	95% CI	Votes	Organization	License
1	2	Gemini-Exp-1121	1365	+8/-6	5625	Google	Proprietary
1	1	ChatGPT-4o-latest (2024-11-20)	1361	+4/-5	10658	OpenAI	Proprietary
3	5	Gemini-Exp-1114	1344	+4/-5	12778	Google	Proprietary
4	2	o1-preview	1334	+4/-4	27835	OpenAI	Proprietary
5	7	o1-mini	1308	+3/-4	31992	OpenAI	Proprietary
5	5	Gemini-1.5-Pro-002	1301	+5/-3	27336	Google	Proprietary
7	10	Grok-2-08-13	1289	+4/-3	52102	xAI	Proprietary
7	12	Yi-Lightning	1287	+4/-3	29336	01 AI	Proprietary
7	5	GPT-4o-2024-05-13	1285	+2/-2	111745	OpenAI	Proprietary
8	3	Claude 3.5 Sonnet (20241022)	1282	+4/-3	29454	Anthropic	Proprietary
10	17	Athene-v2-Chat-72B	1274	+8/-6	4354	NexusFlow	NexusFlow
11	18	GLM-4-Plus	1274	+5/-4	28133	Zhipu AI	Proprietary
11	19	GPT-4o-mini-2024-07-18	1273	+3/-3	51690	OpenAI	Proprietary
11	20	Gemini-1.5-Flash-002	1271	+4/-4	21071	Google	Proprietary
11	27	Llama-3.1-Nemotron-70B-Instruct	1269	+5/-6	7270	Nvidia	Llama 3.1
11	7	Claude 3.5 Sonnet (20240620)	1268	+2/-3	86632	Anthropic	Proprietary

Claude 3.5 Sonnet state-of-the-art vision

	Claude 3.5 Sonnet (new)	Claude 3.5 Haiku	Claude 3.5 Sonnet	GPT-4o*	GPT-4o mini*	Gemini 1.5 Pro	Gemini 1.5 Flash
Graduate level reasoning <i>GPQA (Diamond)</i>	65.0% 0-shot CoT	41.6% 0-shot CoT	59.4% 0-shot CoT	53.6% 0-shot CoT	40.2% 0-shot CoT	59.1% 0-shot CoT	51.0% 0-shot CoT
Undergraduate level knowledge <i>MMLU Pro</i>	78.0% 0-shot CoT	65.0% 0-shot CoT	75.1% 0-shot CoT	—	—	75.8% 0-shot CoT	67.3% 0-shot CoT
Code <i>HumanEval</i>	93.7% 0-shot	88.1% 0-shot	92.0% 0-shot	90.2% 0-shot	87.2% 0-shot	—	—
Math problem-solving <i>MATH</i>	78.3% 0-shot CoT	69.2% 0-shot CoT	71.1% 0-shot CoT	76.6% 0-shot CoT	70.2% 0-shot CoT	86.5% 4-shot CoT	77.9% 4-shot CoT
High school math competition <i>AIME 2024</i>	16.0% 0-shot CoT	5.3% 0-shot CoT	9.6% 0-shot CoT	9.3% 0-shot CoT	—	—	—
Visual Q/A <i>MMMU</i>	70.4% 0-shot CoT	—	68.3% 0-shot CoT	69.1% 0-shot CoT	59.4% 0-shot CoT	65.9% 0-shot CoT	62.3% 0-shot CoT
Agentic coding <i>SWE-bench Verified</i>	49.0%	40.6%	33.4%	—	—	—	—
Agentic tool use <i>TAU-bench</i>	Retail 69.2%	Retail 51.0%	Retail 62.6%	—	—	—	—
	Airline 46.0%	Airline 22.8%	Airline 36.0%	—	—	—	—

* Our evaluation tables exclude OpenAI's o1 model family as they depend on extensive pre-response computation time, unlike typical models. This fundamental difference makes performance comparisons difficult.

Llama 3.2 90B vision LLMs

Modality	Category Benchmark	Llama 3.2 11B	Llama 3.2 90B	Claude 3 – Haiku	GPT-4o-mini
Image	College-level Problems and Mathematical Reasoning MMMU (val, 0-shot CoT, micro avg accuracy)	50.7	60.3	50.2	59.4
	MMMU-Pro, Standard (10 opts, test)	33.0	45.2	27.3	42.3
	MMMU-Pro, Vision (test)	23.7	33.8	20.1	36.5
	MathVista (testmini)	51.5	57.3	46.4	56.7
	Charts and Diagram Understanding ChartQA (test, 0-shot CoT relaxed accuracy)*	83.4	85.5	81.7	—
	AI2 Diagram (test)*	91.1	92.3	86.7	—
	DocVQA (test, ANLS)*	88.4	90.1	88.8	—
	General Visual Question Answering VQAv2 (test)	75.2	78.1	—	—
Text	General MMLU (0-shot, CoT)	73.0	86.0	75.2 (5-shot)	82.0
	Math MATH (0-shot, CoT)	51.9	68.0	38.9	70.2
	Reasoning GPQA (0-shot, CoT)	32.8	46.7	33.3	40.2
	Multilingual MGSM (0-shot, CoT)	68.9	86.9	75.1	87.0

Mistral Pixtral Large (124B)

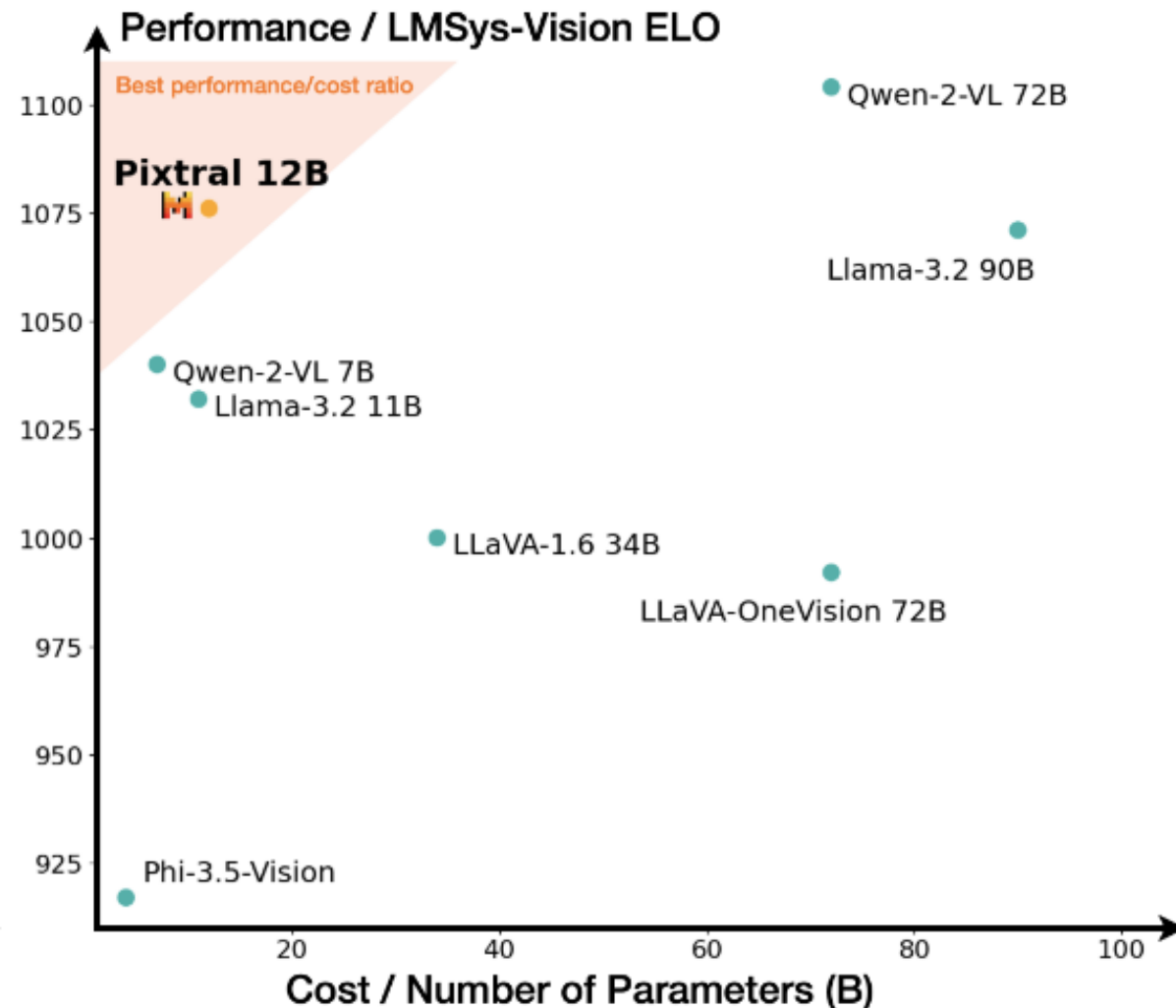
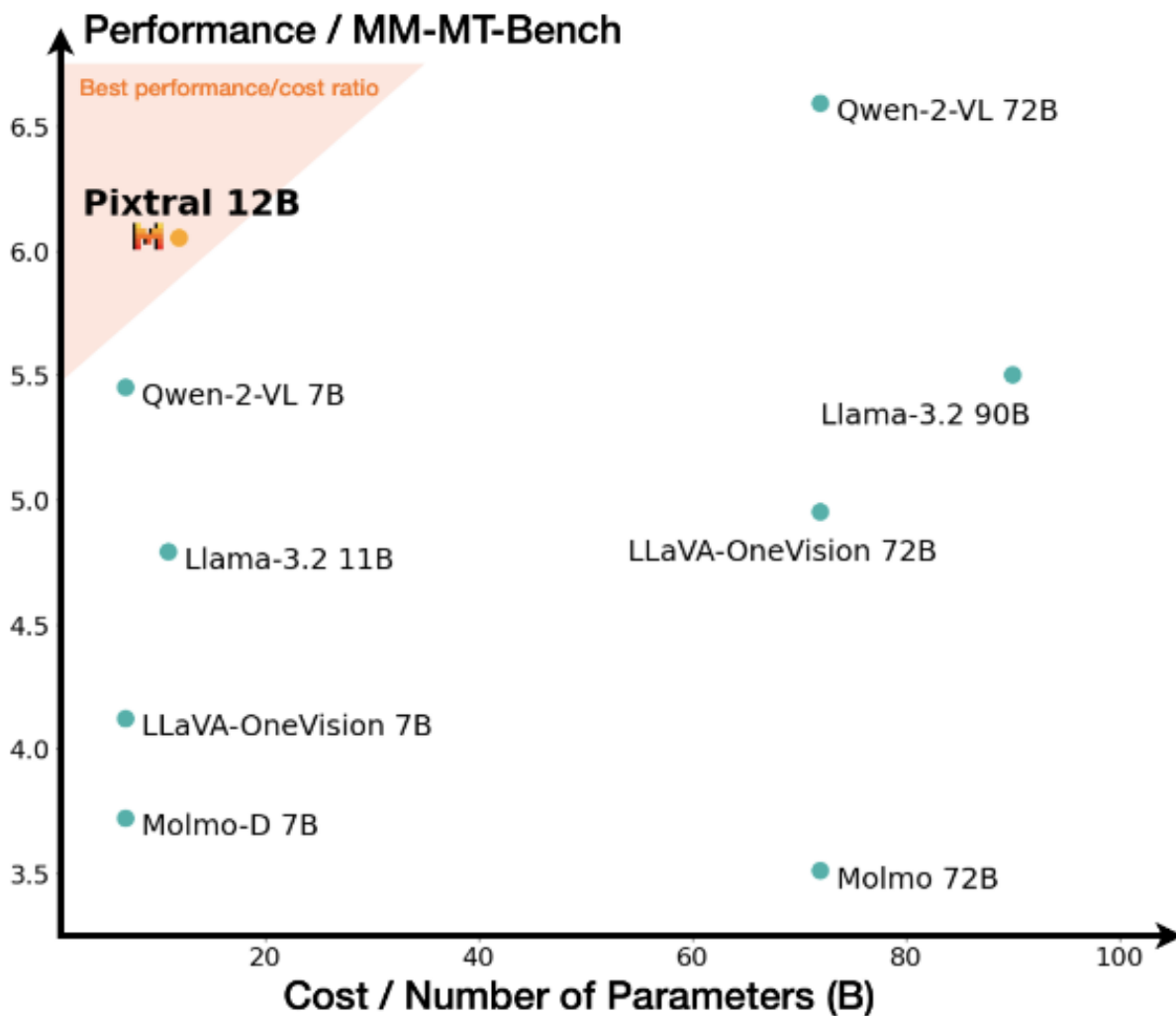
Frontier-class multimodal performance

Model		Mathvista (CoT)	MMMU (CoT)	ChartQA (CoT)	DocVQA (ANLS)	VQAv2 (VQA Match)	AI2D (BBox)	MM MT-Bench
Open Weights	Pixtral Large (124B)	69.4	64.0	88.1	93.3	80.9	93.8	7.4
	Llama-3.2 90B (measured)	49.1	53.7	70.8	85.7	67.0	-	5.5
	Llama-3.2 90B (reported)	57.3	60.3	85.8	90.1	80.2	92.3	-
Closed	Gemini-1.5 Pro (measured)	67.8	66.3	83.8	92.3	70.6	94.6	6.8
	Gemini-1.5 Pro (reported)	68.1	65.9	-	-	-	-	-
	GPT-4o (measured)	65.4	68.6	85.2	88.5	76.4	93.2	6.7
	GPT-4o (reported)	63.8	69.1	85.7	92.8	-	-	-
	Claude-3.5 Sonnet (measured)	67.1	68.4	89.1	88.6	69.5	76.9	7.3
	Claude-3.5 Sonnet (reported)	70.7	70.4	90.8	94.2	-	95.3	-
Unreleased	Llama-3.1 505B (reported)	-	64.5	85.8	92.6	80.2	94.1	-
	Grok-2 (reported)	69.0	66.1	-	93.6	-	-	-

Specific model versions evaluated: Claude-3.5 Sonnet (new) [Oct 24], Gemini-1.5 Pro (002) [Sep 24], GPT-4o (2024-08-06) [Aug 24]

Source: <https://mistral.ai/news/pixtral-large/>

Mistral Pixtral 12B



GPT-4o 與 Claude 3.5 Sonnet

大型語言模型	GPT-4o	Claude 3.5 Sonnet
開發公司	OpenAI	Anthropic
模型架構	Transformer	Transformer
設計目標	提供較輕量級的語言模型，用於效率和成本敏感的場景	提供安全、符合人類價值觀的回應，強調倫理和安全
性能表現	提供與 GPT-4 相近的語言處理能力，但可能稍微減少在生成創意性方面的能力	重視回應的可靠性和安全性，創意性稍弱但更合規
應用場景	適合需要快速響應和資源效率的應用場景，如即時對話系統	教育、醫療、法務等對內容安全性要求較高的領域
回應可靠性	高，但可能在複雜任務中表現稍弱於完整的 GPT-4	非常高，經過強化訓練以避免有害或不準確的回應
創意性	中等至高，適合一般創意性要求的應用場景	中等，重視內容的安全性和符合道德規範
可解釋性	中等，生成過程相對可控	更容易控制生成過程，回應更加可預測和可靠
市場定位	適合對資源使用和效率有高要求的用戶	適合需要高安全性和道德合規的應用場景

OpenAI ChatGPT 4o

ChatGPT 4o ▾

IM

ChatGPT 4o ▾

Model

GPT-4o

Great for most tasks

GPT-4o with canvas BETA

Collaborate on writing and code

o1-preview

Uses advanced reasoning

o1-mini

Faster at reasoning

More models >

Temporary chat

What can I help with?

請撰寫 生成式AI 和 通用人工智慧 的簡報

請撰寫 生成式AI 和 通用人工智慧 的簡報



Create image



Summarize text



Brainstorm



Get advice

More

ChatGPT can make mistakes. Check important info.

?

<https://chatgpt.com/?model=gpt-4o>

ChatGPT 4o

請撰寫 生成式AI 和 通用人工智慧 的簡報

ChatGPT 4o

請撰寫 生成式AI 和 通用人工智慧 的簡報



以下是關於生成式 AI 和通用人工智慧 (AGI) 的簡報草稿，供你參考。簡報內容包括定義、應用、挑戰及未來展望。你可以根據需要進行修改和擴充。

簡報標題：生成式 AI 與通用人工智慧的現況與未來

第一頁：簡報概覽

- 簡介
- 生成式 AI 的定義與應用
- 通用人工智慧 (AGI) 的定義與應用
- 生成式 AI 和 AGI 的挑戰
- 未來展望



Message ChatGPT



ChatGPT can make mistakes. Check important info.

<https://chatgpt.com/?model=gpt-4o>

ChatGPT 4o

請以表格方式分析比較
生成式AI 和
通用人工智慧

請以表格方式分析比較 生成式AI 和 通用人工智慧



以下是生成式 AI 和通用人工智慧 (AGI) 的比較分析表格：

比較項目	生成式 AI (Generative AI)	通用人工智慧 (AGI, Artificial General Intelligence)
定義	能夠生成類似於人類創造的數據或內容的人工智慧技術。	具備人類水準的智能，能夠理解、學習並應用知識來解決廣泛問題的 AI 系統。
主要技術	深度學習、生成對抗網絡 (GANs)、自然語言處理 (NLP)。	高級認知架構、深度學習、強化學習、推理與決策算法。
應用範圍	內容創作 (文本、音樂、藝術)、虛擬角色、醫療影像生成、設計。	跨領域問題解決、科學研究、自動化研究、人機協作。
技術成熟度	已經在多個領域實現了實際應用，技術相對成熟。	仍在研究和探索階段，尚未實現全面應用。
倫理問題	內容真實性 (如Deepfake)、版權與所有權爭議。	道德控制與監管挑戰、社會影響 (如失業、法律問題)。
挑戰	計算資源需求大、內容監管難度高。	技術實現難度高、道德與倫理風險大、可能引發社會變革。
未來發展	更高效的模型、擴展應用場景 (教育、娛樂、健康等)。	實現真正的 AGI、建立安全和倫理的框架、促進社會適應和轉型。
目標	生成高質量的內容以輔助或替代人類創作。	模擬或超越人類智慧，能夠處理多種任務，推動科學和技術進步。

這個表格提供了一個清晰的視角來比較生成式 AI 和通用人工智慧的各個方面，幫助理解它們之間的差異和各自的潛力。



生成式 AI 和通用人工智慧 (AGI) 的比較分析表

比較項目	生成式 AI (Generative AI)	通用人工智慧 (AGI, Artificial General Intelligence)
定義	能夠生成類似於人類創造的數據或內容的人工智慧技術。	具備人類水準的智能，能夠理解、學習並應用知識來解決廣泛問題的 AI 系統。
主要技術	深度學習、生成對抗網絡 (GANs)、自然語言處理 (NLP)。	高級認知架構、深度學習、強化學習、推理與決策算法。
應用範圍	內容創作（文本、音樂、藝術）、虛擬角色、醫療影像生成、設計。	跨領域問題解決、科學研究、自動化研究、人機協作。
技術成熟度	已經在多個領域實現了實際應用，技術相對成熟。	仍在研究和探索階段，尚未實現全面應用。
倫理問題	內容真實性（如Deepfake）、版權與所有權爭議。	道德控制與監管挑戰、社會影響（如失業、法律問題）。
挑戰	計算資源需求大、內容監管難度高。	技術實現難度高、道德與倫理風險大、可能引發社會變革。
未來發展	更高效的模型、擴展應用場景（教育、娛樂、健康等）。	實現真正的 AGI、建立安全和倫理的框架、促進社會適應和轉型。
目標	生成高質量的內容以輔助或替代人類創作。	模擬或超越人類智慧，能夠處理多種任務，推動科學和技術進步。

Claude 3.5 Sonnet

✱ Good morning, MYDAY

請撰寫 生成式AI 和 通用人工智慧 的簡報


請撰寫 生成式AI 和 通用人工智慧 的簡報



Claude 3.5 Sonnet ▾

Use **shift + return** for new line




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 Use a project ▾

<https://claude.ai/>


Claude 3.5 Sonnet

請撰寫
生成式AI
和
通用人工
智慧的
簡報





Claude  Generative AI and Artificial General Intelligence Presentation Outline ▾  


 請撰寫 生成式AI 和 通用人工智慧 的簡報 




好的,我可以為您準備一份關於生成式AI和通用人工智慧的簡報。我會使用Markdown格式創建一個簡報大綱,然後我們可以一起完善它。


 生成式AI和通用人工智慧簡報大綱
Click to open document


這是一個生成式AI和通用人工智慧簡報的基本大綱。我們可以根據您的具體需求進行調整和深化。您希望在這個大綱的基礎上做什麼修改或添加嗎?或者您需要我詳細解釋某個部分嗎?

 Copy  Retry  

 Claude can make mistakes. Please double-check responses.

 Reply to Claude...  

 Claude 3.5 Sonnet ▾

← 生成式AI和通用人工智慧簡報大綱 

生成式AI和通用人工智慧簡報

1. 引言




- AI技術的快速發展
- 本簡報的主要內容:生成式AI和通用人工智慧(AGI)

2. 生成式AI

2.1 定義

- 什麼是生成式AI?
- 與傳統AI的區別

2.2 主要技術

Last edited just now   

<https://claude.ai/>

Claude 3.5 Sonnet

請以表格
方式分析
比較
生成式AI
和
通用人工
智慧

M 請以表格方式分析比較 生成式AI 和 通用人工智慧

當然,我可以為您製作一個比較生成式AI和通用人工智慧(AGI)的表格。這樣的表格可以清晰地展示兩者之間的主要差異和特點。



生成式AI與通用人工智慧(AGI)比較表
Click to open document

這個表格提供了生成式AI和通用人工智慧(AGI)在多個方面的比較。它涵蓋了定義、當前狀態、能力範圍、應用等多個方面。這樣的比較可以幫助我們更好地理解這兩種AI技術的異同。

您對這個比較表格有什麼看法嗎？是否有任何方面您想要進一步探討或修改？我可以根據您的需求提供更多細節或調整表格的內容。

Copy Retry Share



Claude can make mistakes. Please double-check responses.

Reply to Claude...



Claude 3.5 Sonnet

← 生成式AI與通用人工智慧(AGI)比較表



特性	生成式AI	通用人工智慧
定義	能夠創造新內容（如文本、圖像、音頻）的AI系統	具有人類水平
當前狀態	已經實現並廣泛應用	仍處於理論和
智能範圍	專注於特定領域或任務	跨領域的通用
學習能力	基於訓練數據學習,通常需要大量數據	理論上能夠自
創造力	在特定領域展現創造力（如藝術創作、文字生成）	預期在多個領
推理能力	有限,主要基於統計模型和模式識別	預期具有類人
自主性	有限,通常需要人類指導和輸入	理論上具有高
情感和意識	不具備真正的情感和自我意識	可能具備類似
應用範例	ChatGPT, DALL-E, Midjourney	目前尚無真正
主要優勢	提高特定任務的效率,增強創意表達	潛在地解決複
主要挑戰	數據偏見,版權問題,內容真實性	技術實現難度
對社會的影響	已經開始改變多個行業的工作方式	可能帶來深遠
發展階段	快速發展和應用階段	基礎研究階段
時間框架	現在	未來（時間不

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生成式AI與通用人工智慧(AGI)比較表

特性	生成式AI	通用人工智慧(AGI)
定義	能夠創造新內容（如文本、圖像、音頻）的AI系統	具有人類水平智能,能在多個領域表現出智能行為的AI系統
當前狀態	已經實現並廣泛應用	仍處於理論和研究階段
智能範圍	專注於特定領域或任務	跨領域的通用智能
學習能力	基於訓練數據學習,通常需要大量數據	理論上能夠自主學習和遷移學習
創造力	在特定領域展現創造力（如藝術創作、文字生成）	預期在多個領域都具有創造力
推理能力	有限,主要基於統計模型和模式識別	預期具有類人的推理和問題解決能力
自主性	有限,通常需要人類指導和輸入	理論上具有高度自主性
情感和意識	不具備真正的情感和自我意識	可能具備類似人類的情感和自我意識（仍有爭議）
應用範例	ChatGPT, DALL-E, Midjourney	目前尚無真正的AGI系統
主要優勢	提高特定任務的效率,增強創意表達	潛在地解決複雜的跨領域問題
主要挑戰	數據偏見,版權問題,內容真實性	技術實現難度大,安全性和倫理問題
對社會的影響	已經開始改變多個行業的工作方式	可能帶來深遠的社會經濟變革（尚未實現）
發展階段	快速發展和應用階段	基礎研究階段
時間框架	現在	未來（時間不確定）

OpenAI ChatGPT (GPT-4) DALL·E 3

Vector graphic of a flowchart depicting the integration of generative AI in the education process, from content creation to virtual experiments, personalized learning, and innovative learning.



Chat with Open Large Language Models: Chatbot Arena

Expand to see the descriptions of 72 models

llama-3.2-vision-90b-instruct

Model A

llama 3.2

Large Language Models for Data Science

Step 1: Introduction to Large Language Models

Large Language Models (LLMs) are a type of artificial intelligence (AI) designed to process and understand human language. They are trained on vast amounts of text data, enabling them to learn patterns, relationships, and context within language. LLMs have become increasingly popular in recent years due to their ability to generate human-like text, answer questions, and even create content.

Step 2: Applications of Large Language Models in Data Science

LLMs have numerous applications in data science, including:

- **Text Analysis:** LLMs can be used to analyze large datasets of text, such as customer reviews or social media posts, to extract insights and sentiment.
- **Natural Language Processing (NLP):** LLMs can be used for NLP tasks like text classification, named entity recognition, and language translation.

claude-3-5-sonnet-20241022

Model B

claude 3.5 sonnet

Large Language Models for Data Science

Let me provide a comprehensive overview of how Large Language Models (LLMs) can be used in Data Science:

Key Applications of LLMs in Data Science:

1. Data Analysis & Exploration
 - Natural language queries to databases
 - Data summarization and insights generation
 - Exploratory data analysis assistance
 - Pattern recognition and trend identification
2. Code Generation & Assistance
 - Writing data processing scripts
 - Generating SQL queries
 - Creating data visualization code
 - Debugging and code optimization
3. Data Preprocessing
 - Feature engineering suggestions

👉 A is better 👉 B is better 🤝 Tie 👎 Both are bad

👉 Enter your prompt and press ENTER

Send

<https://lmarena.ai/>



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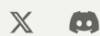
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Upgrade to Claude-2 or GPT-4, boost Copilot uses, and upload more files.

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Large Language Models for Data Science

Sources

What Is a Large Language Model and What Can...

snowflake • 1

What are Large Language Models? | NVIDIA

nvidia • 2

Catch Up On Large Language Models | by...

towardsdatascien... • 3



View 3 more

Answer

Large Language Models (LLMs) are advanced AI systems designed to understand human language intricacies and generate intelligent, creative responses to queries ¹. They are deep learning algorithms that can recognize, summarize, translate, predict, and generate content using very large datasets ². LLMs are trained on enormous data sets typically measured in petabytes, sourced from books, articles, websites, and other text-based sources ¹. They are dynamic tools that are continuously updated and refined as new data becomes available ¹.

In the field of data science, LLMs can potentially transform how teams source, manage, and analyze data ¹. They are used in numerous data science applications, and their ability to process and interpret vast amounts of text data has made them an indispensable part of

Ask follow-up...



Copilot



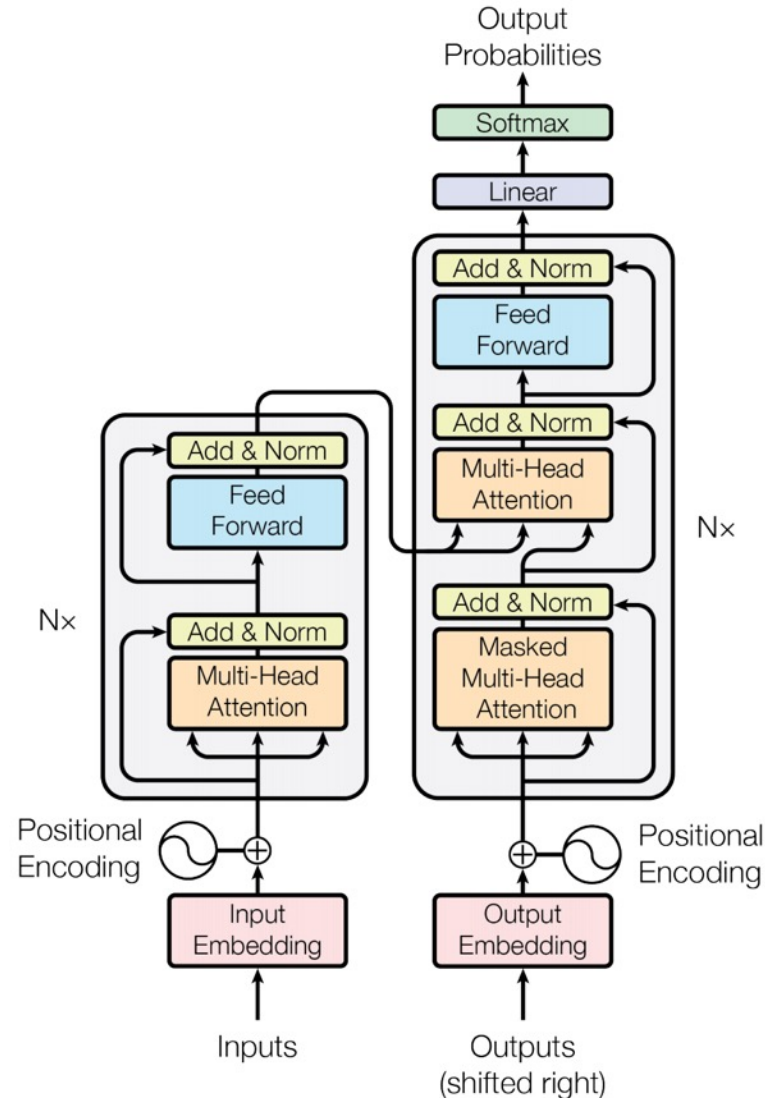
social media posts or customer reviews, to determine whether the overall sentiment is

<https://www.perplexity.ai/>

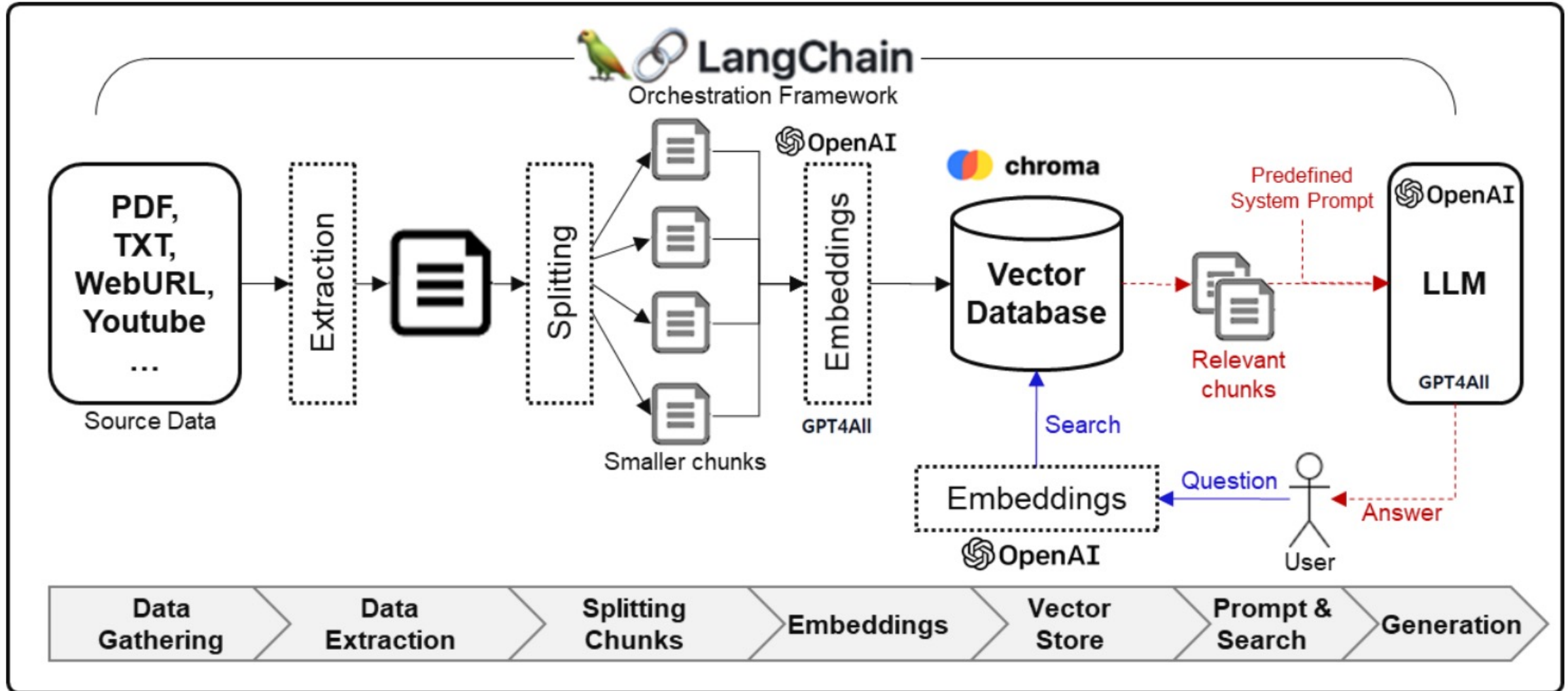


Transformer (Attention is All You Need)

(Vaswani et al., 2017)



Framework for Implementing Generative AI Services using RAG Model

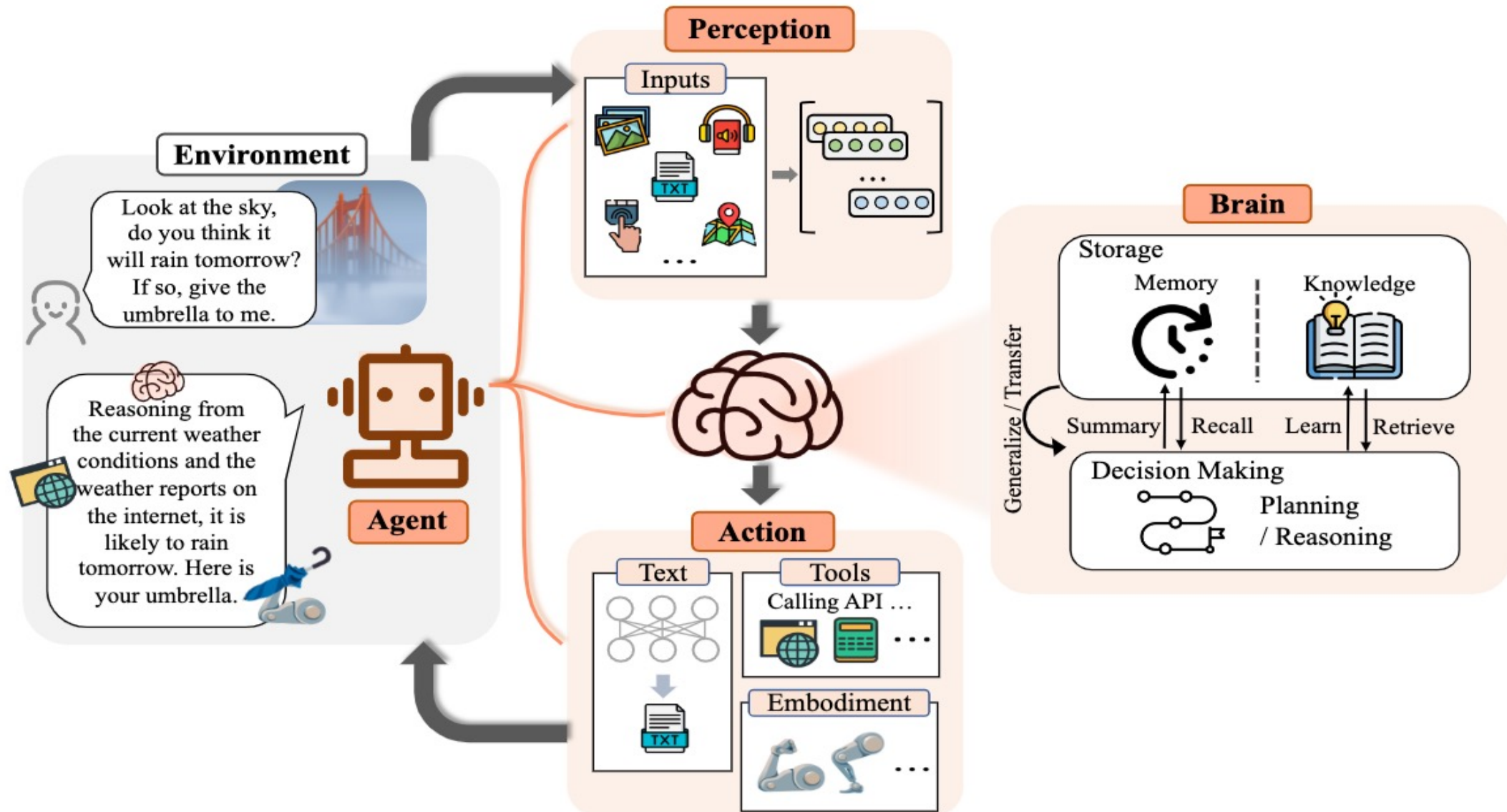


Factuality Enhancement of Large Language Models (LLMs)

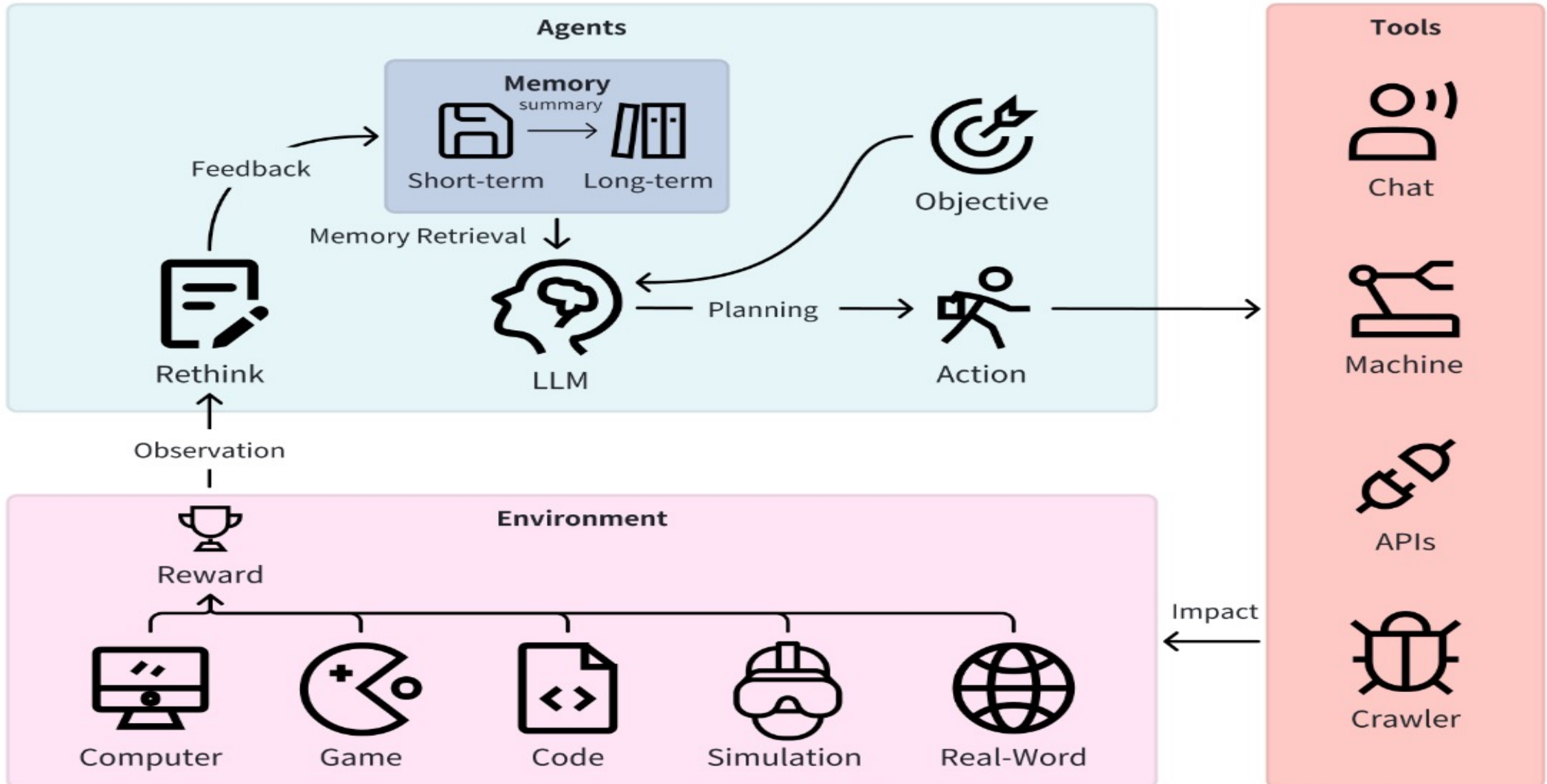
Factuality Enhancement of Large Language Models

Standalone LLMs		Retrieval Augmented Generation			Domain Factuality Enhancement		
Supervised Finetuning		Normal RAG Setting			Domain enhancement techniques		
Continual SFT	Model Editing	Post-editing			Continue-SFT	Continue Pretraining	
Pretraining-based		Interactive Retrieval			Train From Scratch	External Knowledge	
Initial Pretraining	Continual Pretraining	CoT-based Retrieval	Agent-based Retrieval		Domains		
Prompt Engineering		Retrieval Adaption			Healthcare and medicine	Finance and Ecommerce	
Multi-Agent		Prompt-based	SFT-based	RLHF-based	Legal/Law	Geoscience and Environment	
Inference and Decoding		Retrieval on External Memory			Education	Food Industry	Home Renovation
		Retrieval on KGs/Databases					

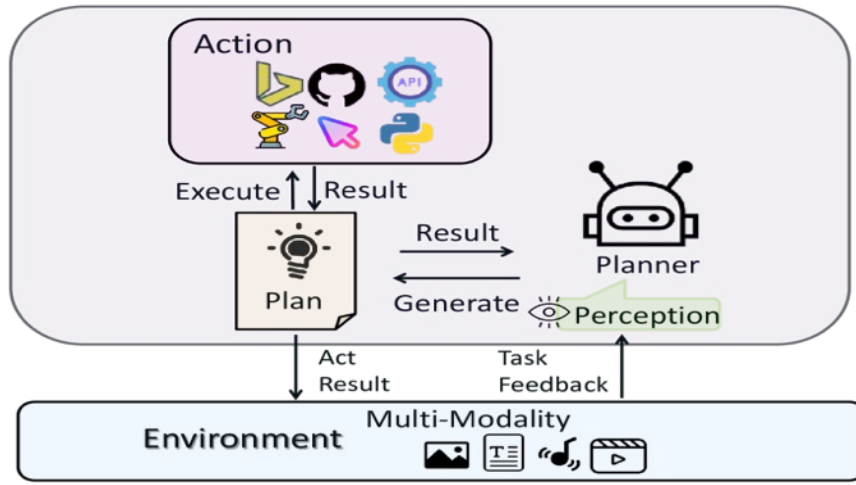
Large Language Model (LLM) based Agents



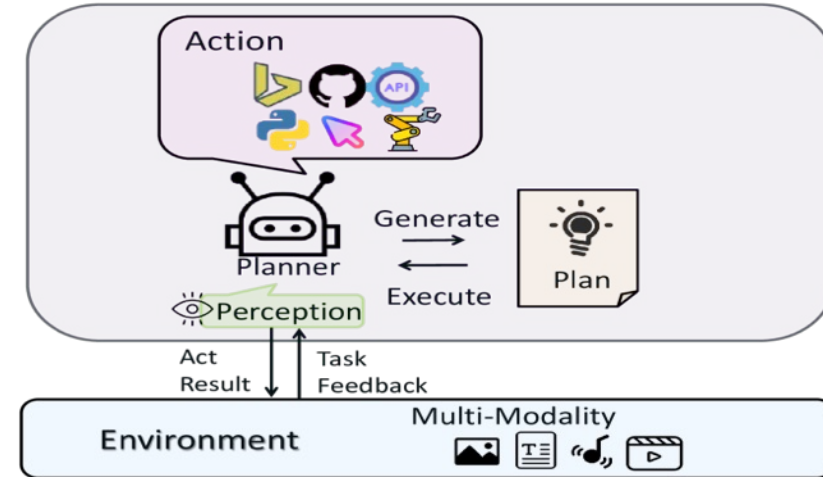
LLM-based Agents



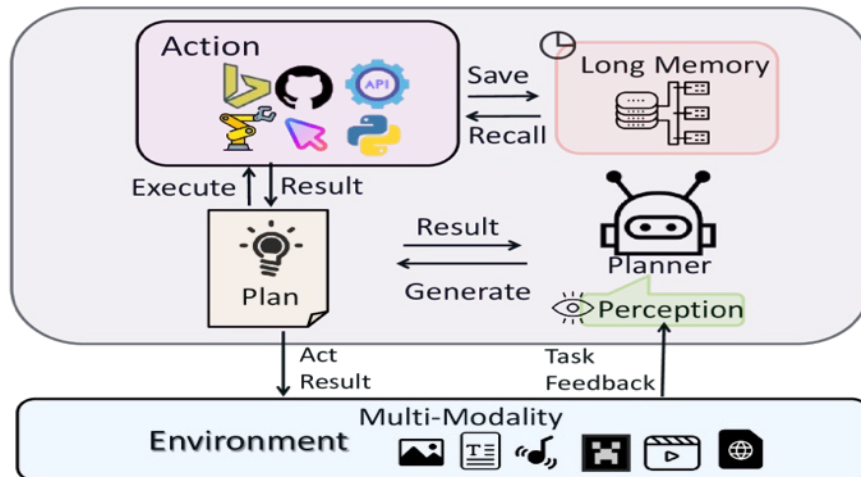
Large Multimodal Agents (LMA)



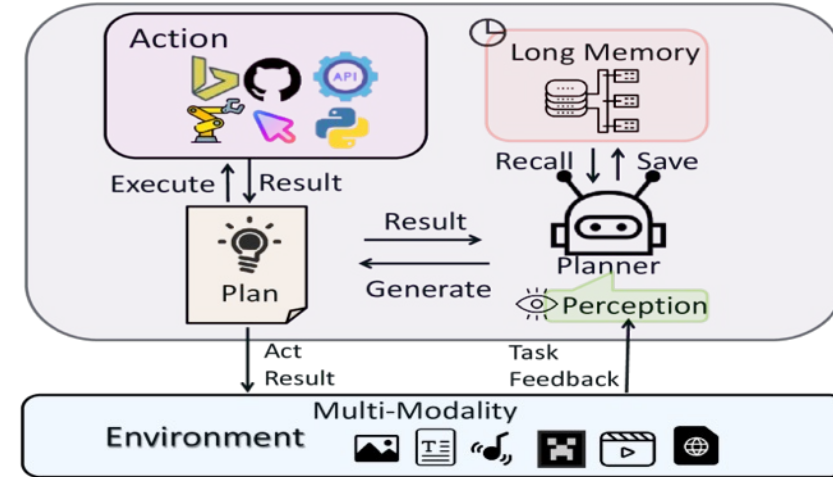
(a)



(b)

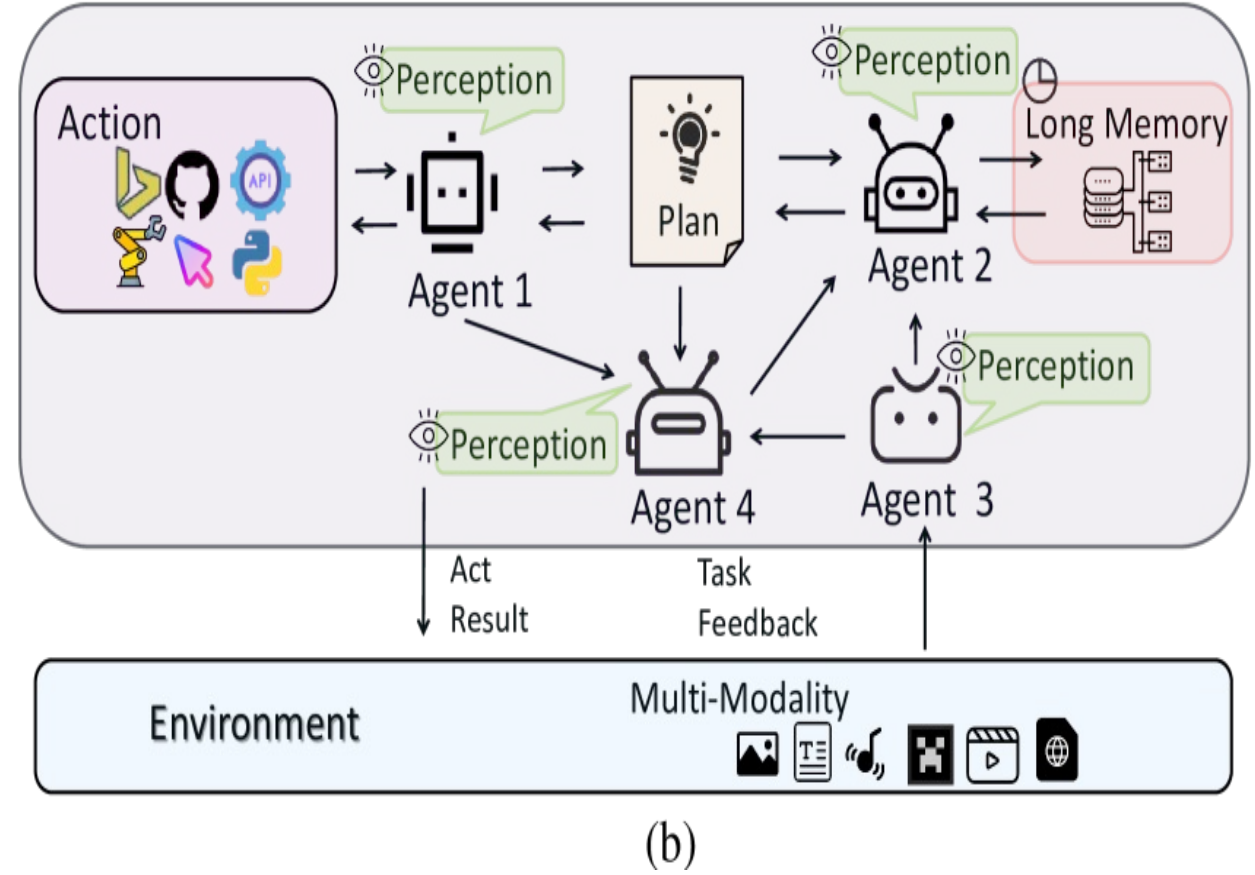
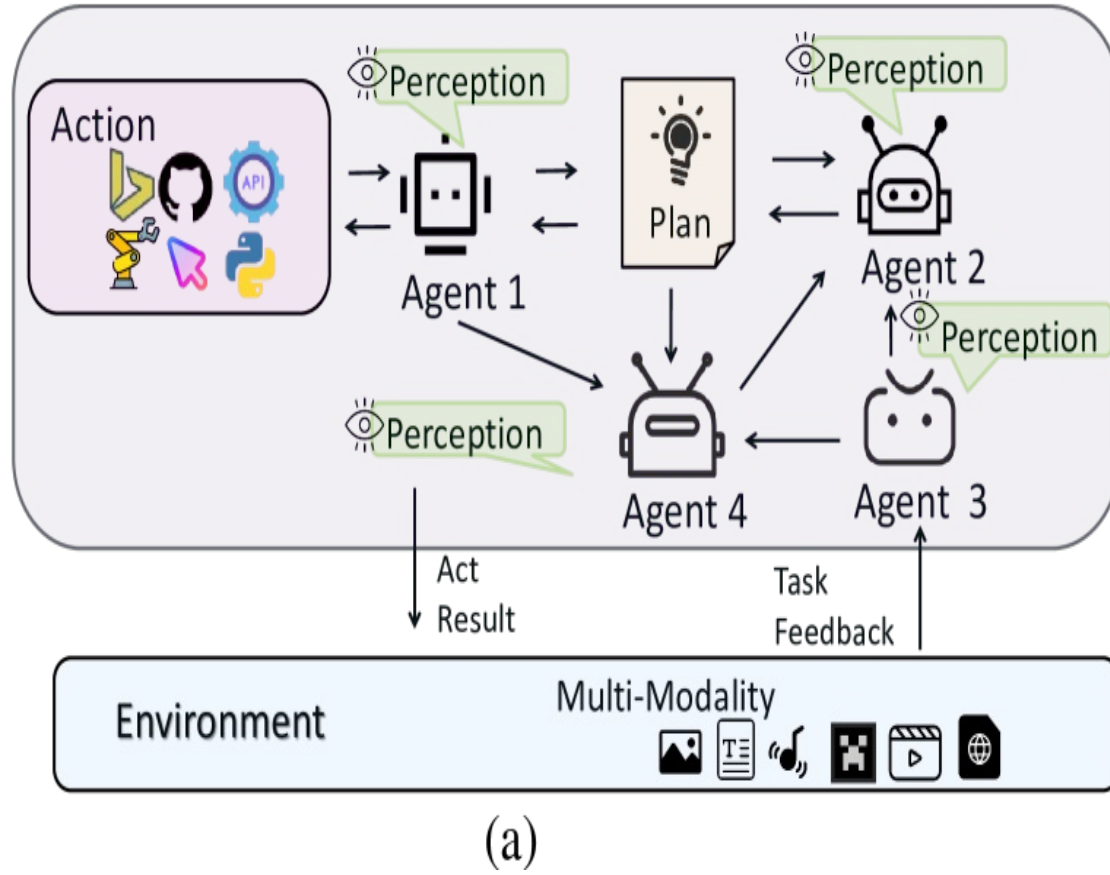


(c)



(d)

Large Multimodal Agents (LMA)



Generative AI for Sustainability and ESG Data Analytics

ESG:

Environmental

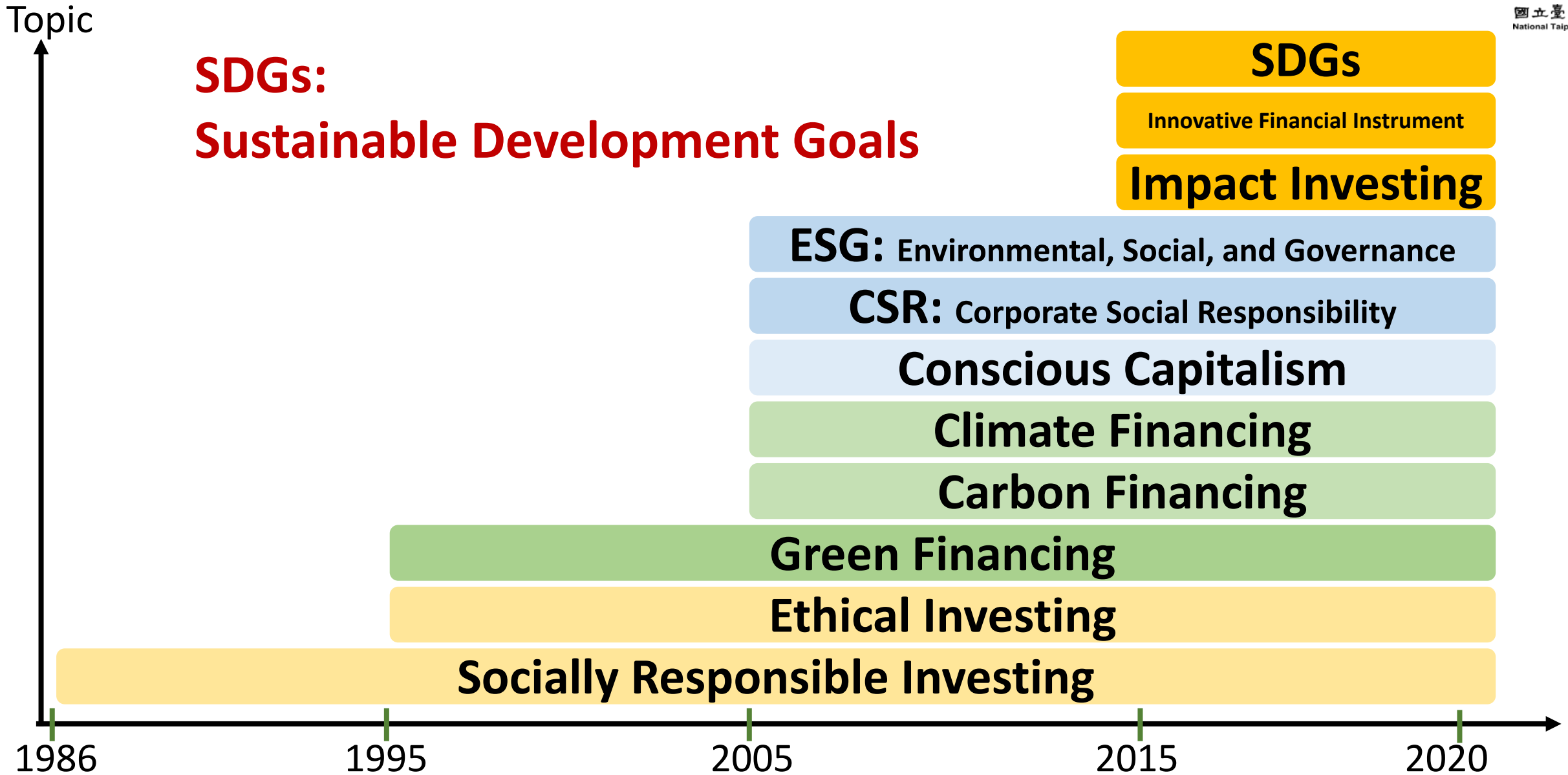
Social

Governance

CSR: Corporate Social Responsibility

Evolution of Sustainable Finance Research

SDGs:
Sustainable Development Goals



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)



Sustainable Development Goals (SDGs) and 5P

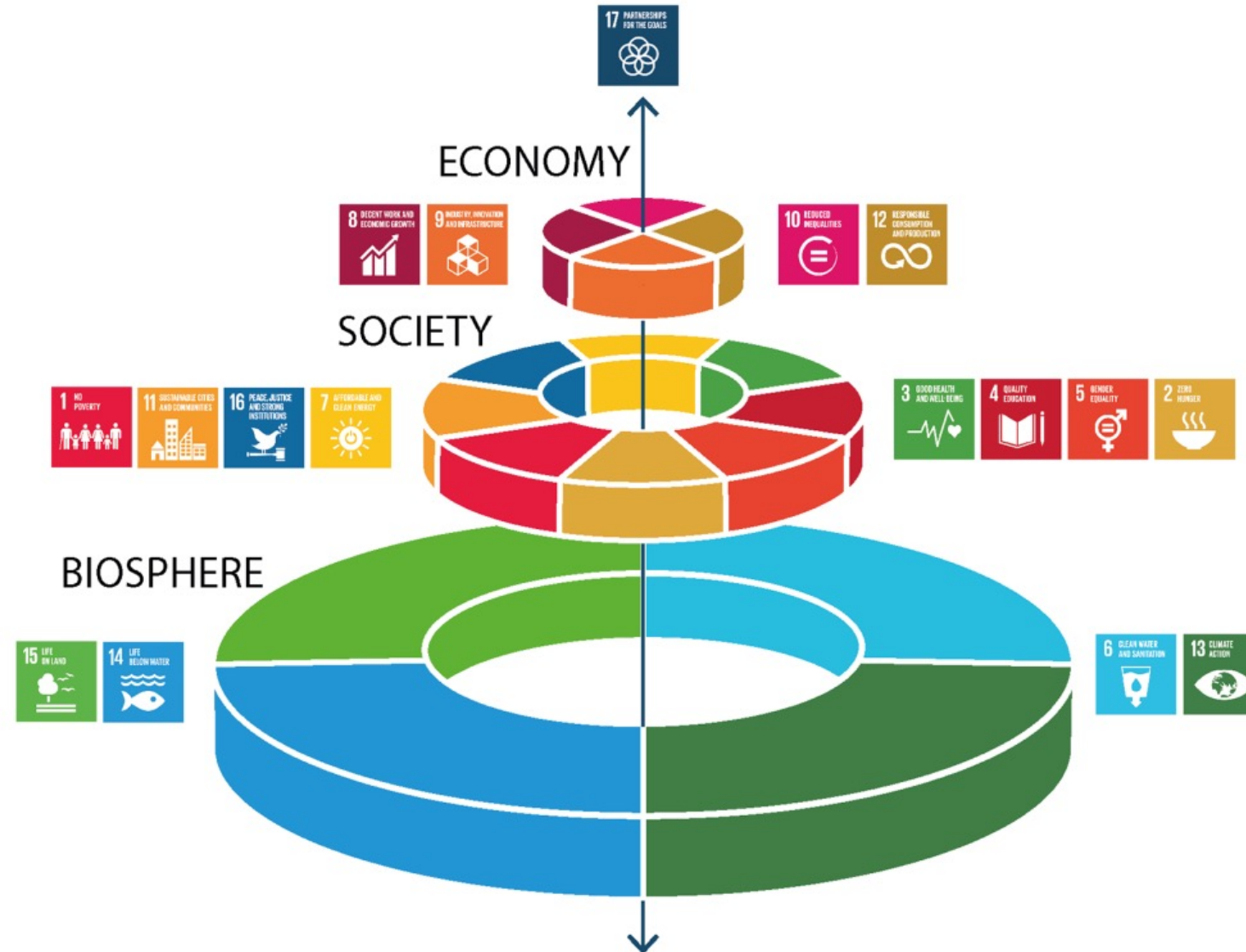
Partnership

Peace

Prosperity

People

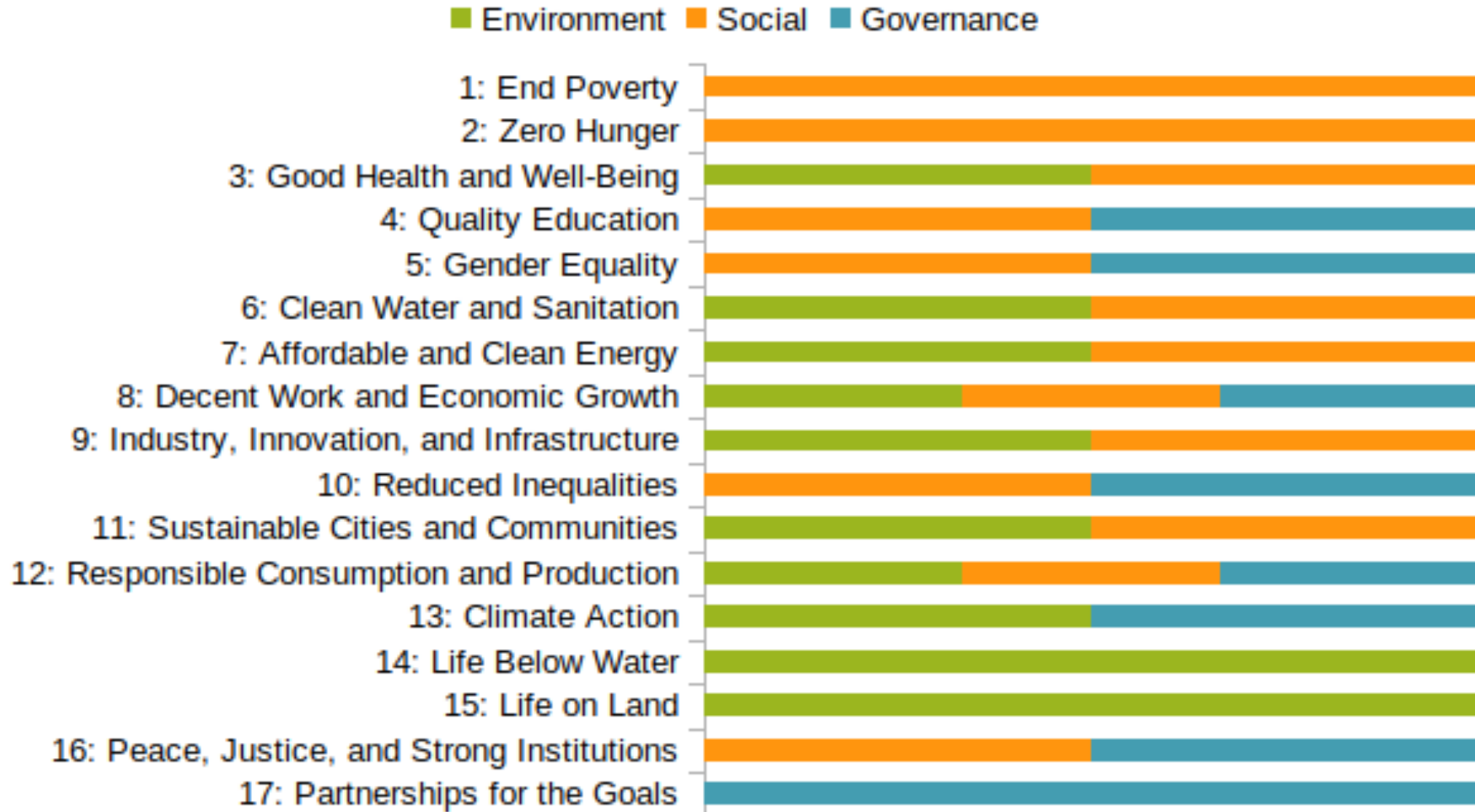
Planet



ESG to 17 SDGs



ESG to 17 SDGs



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

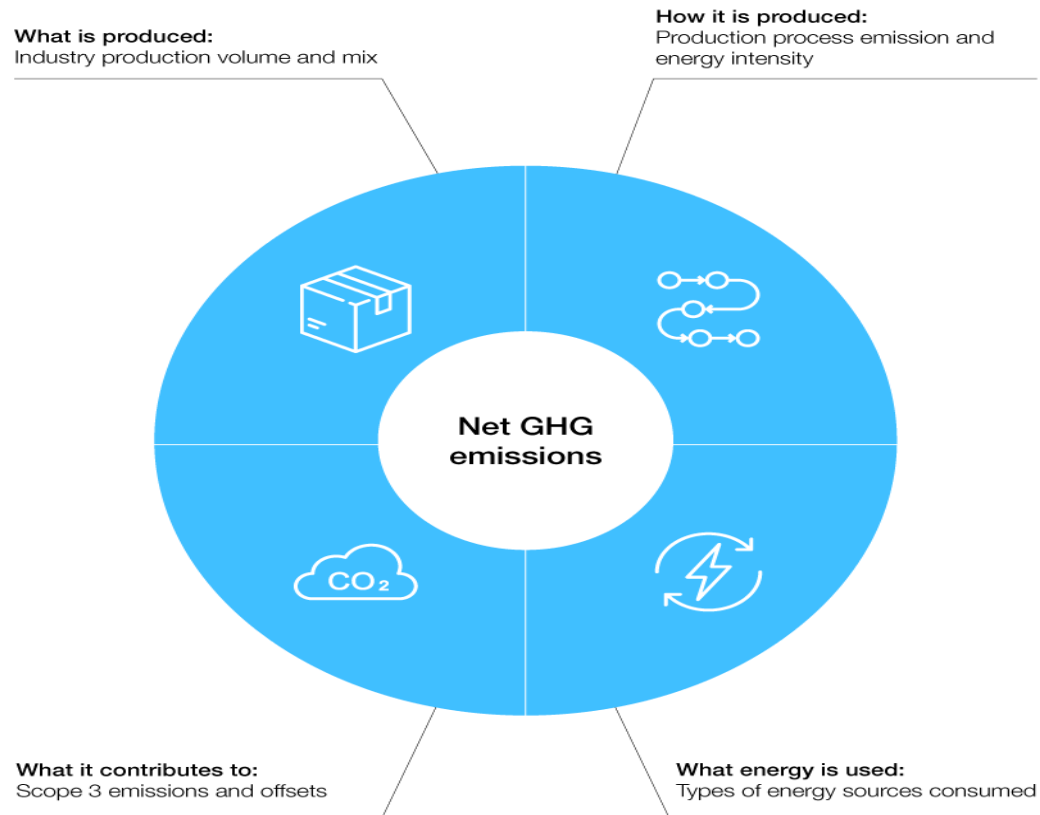
- **Engagement**

- Enhancing the pace and scale of net zero action

Net-Zero Transformation Enablers

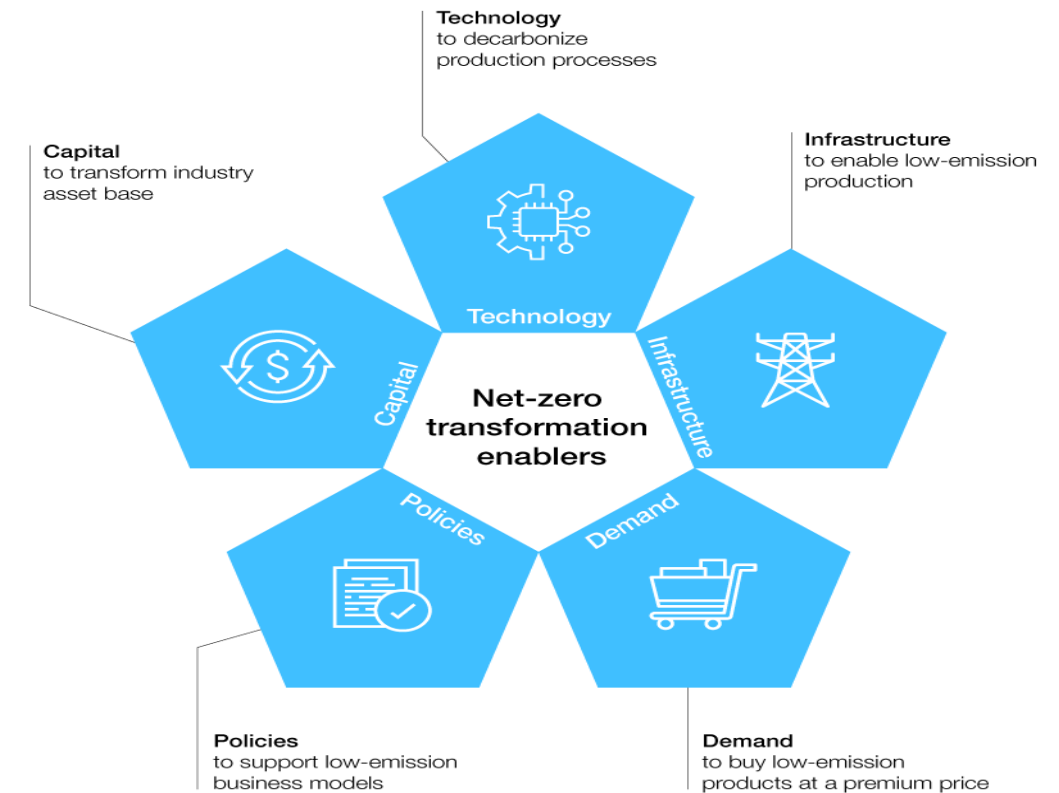
Net-zero industry **performance**

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

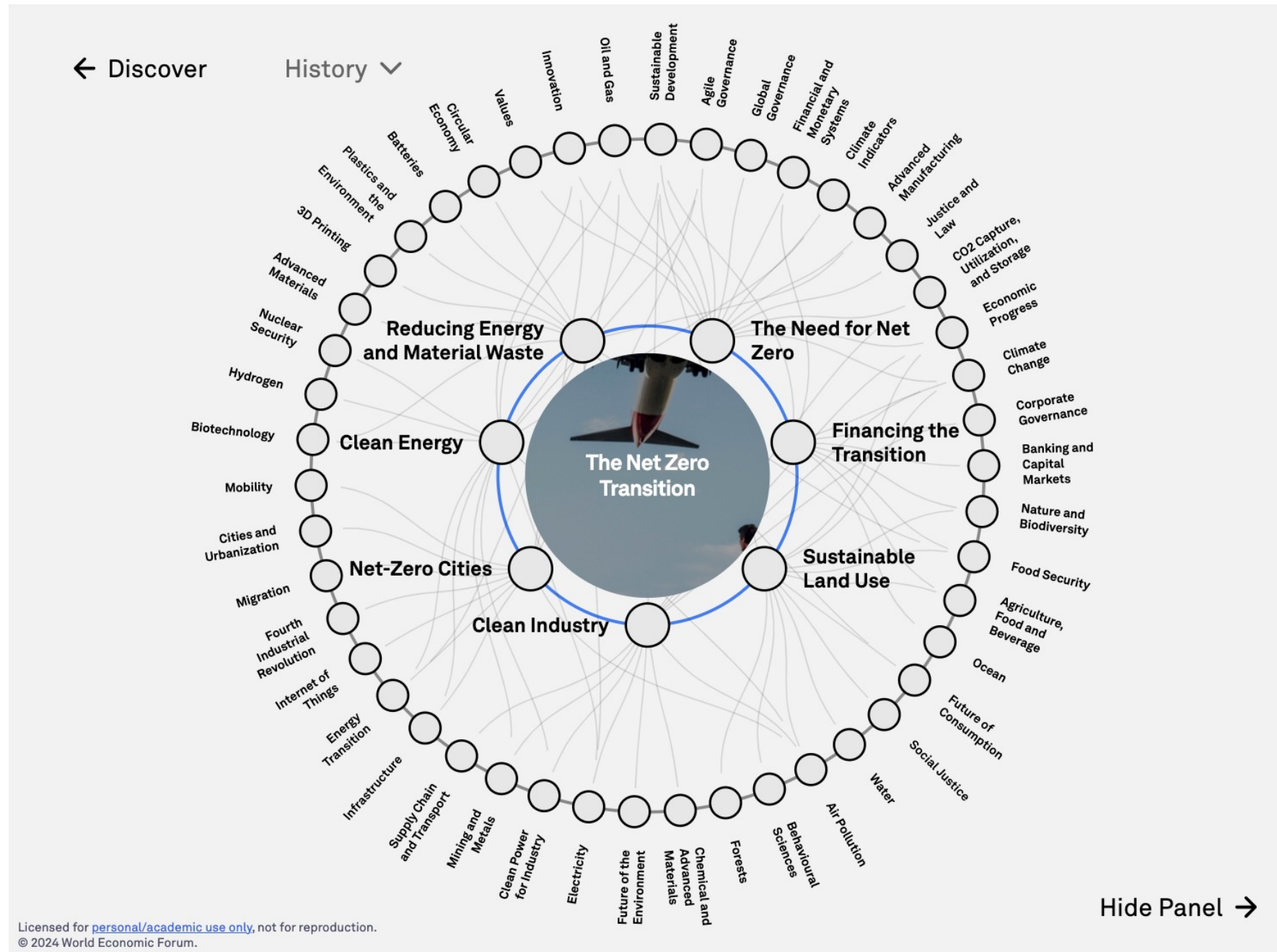


Net-zero industry **readiness**

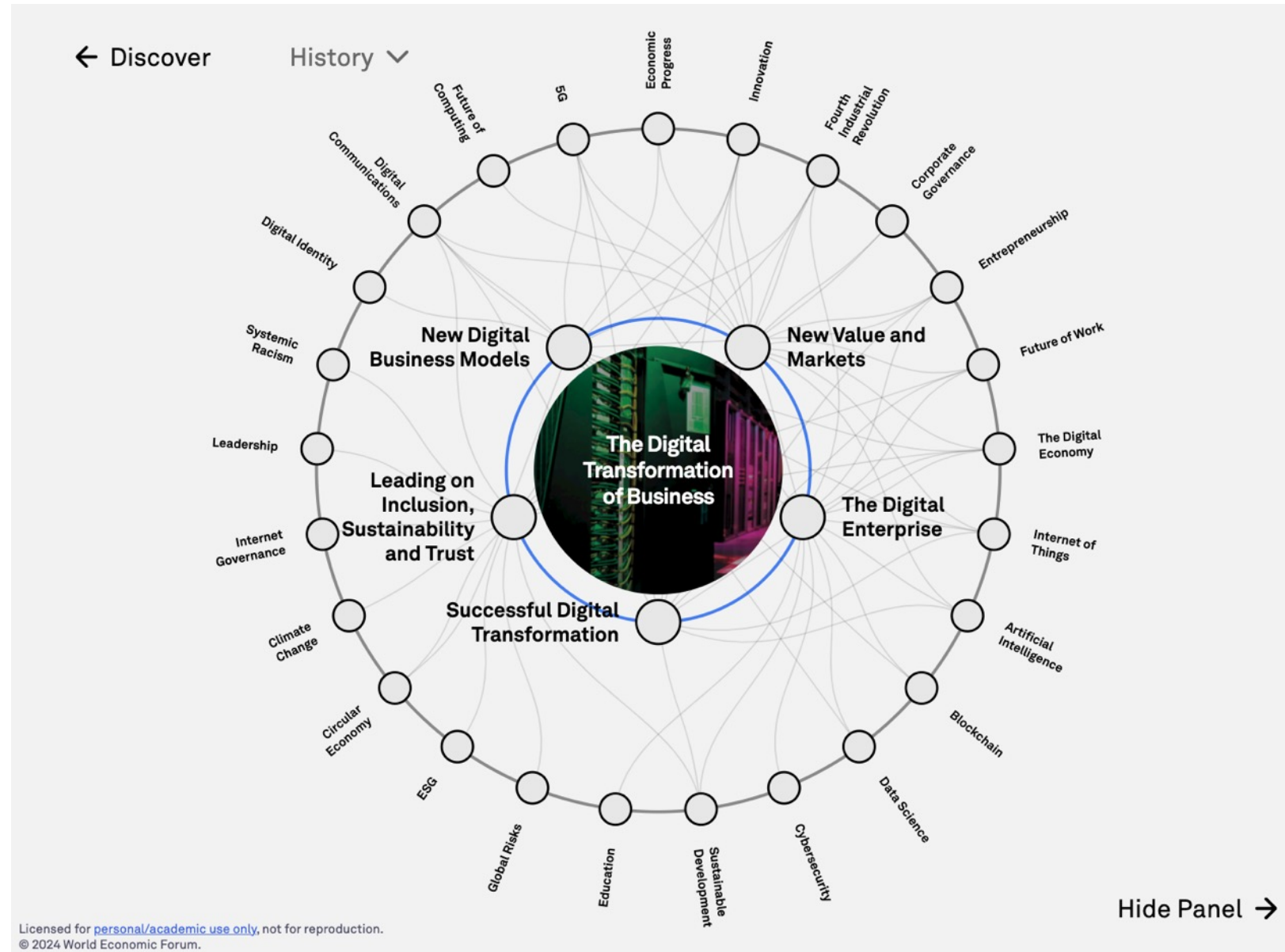
The five enabling dimensions of industry net-zero transformation:



The Net Zero Transition



The Digital Transformation of Business



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

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.

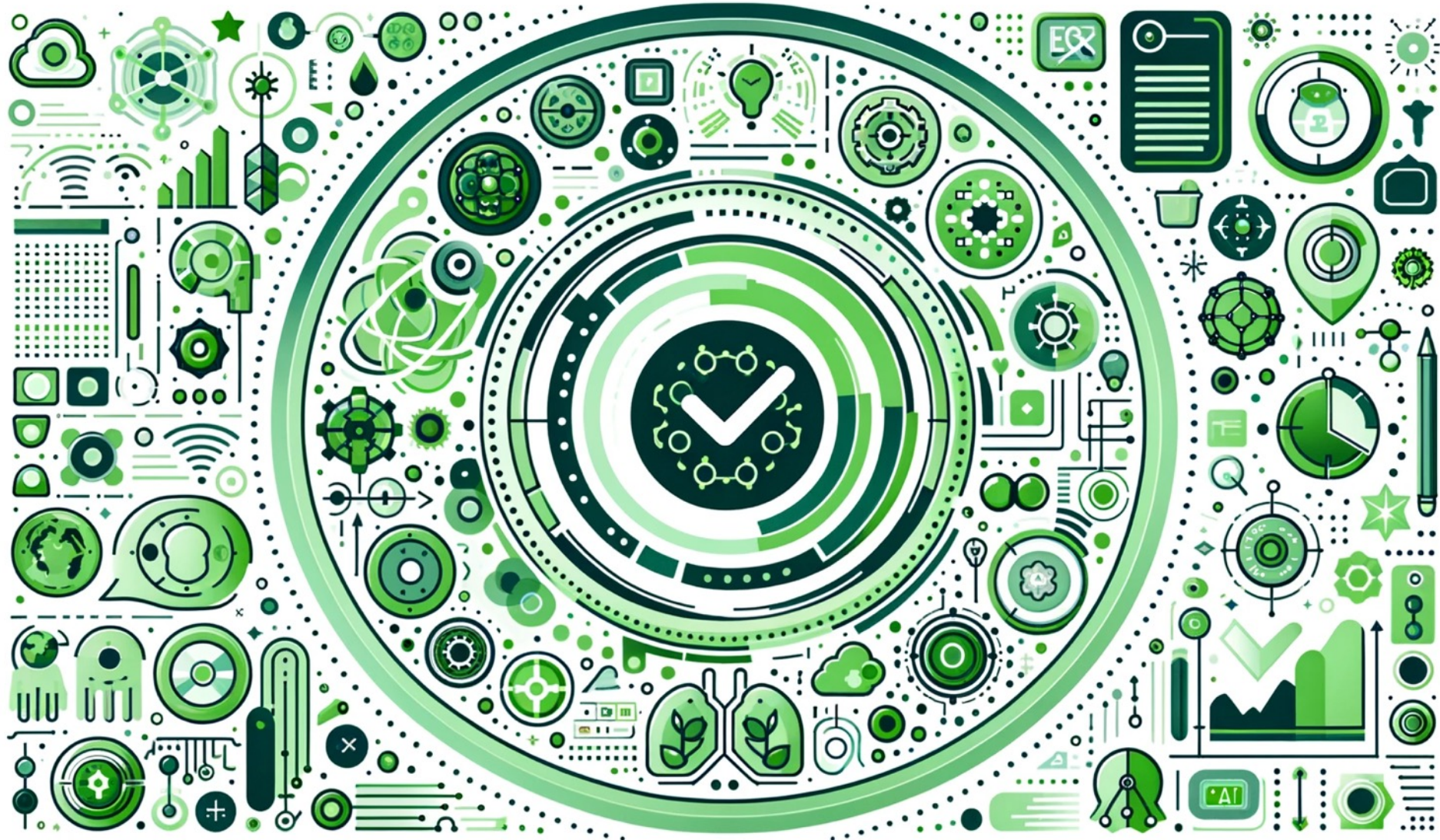
Generative AI and LLMs for Sustainability and ESG Data Analytics



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)



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SASB (Sustainability Accounting Standards Board)

IFRS Foundation

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An aerial photograph showing a winding river through a lush green landscape, bordered by a dense forest of tall evergreen trees.

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NEWS

About the International Sustainability Standards Board

The Trustees of the IFRS Foundation announced the formation of the International Sustainability Standards Board (ISSB) on 3 November 2021 at **COP26 in Glasgow**, following strong market demand for its establishment. The ISSB is developing—in the public interest—standards that will result in a high-quality, comprehensive global baseline of sustainability disclosures focused on the needs of investors and the financial markets.

Sustainability factors are becoming a mainstream part of investment decision-making. There are increasing calls for companies to provide high-quality, globally comparable information on sustainability-related risks and opportunities, as indicated by feedback from many consultations with market

Related information

[Sustainability FAQs](#)

[General Sustainability-related Disclosures project](#)

[Climate-related Disclosures project](#)

[Consolidated organisations](#)

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

TCFD

(Task Force on Climate-related Financial Disclosures)



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



ABOUT US | IFRS ACCOUNTING | IFRS SUSTAINABILITY

Home > ISSB and TCFD

ISSB and TCFD

The Financial Stability Board has announced that the work of the TCFD has been completed, with the ISSB's Standards marking the '**culmination of the work of the TCFD**'.

Companies applying IFRS S1 *General Requirements for Disclosure of Sustainability-related Financial Information* and IFRS S2 *Climate-related Disclosures* will meet the TCFD recommendations as the recommendations are fully incorporated into the ISSB's Standards.

Companies can continue to use the **TCFD recommendations** should they choose to do so, and some companies may still be required to use the TCFD recommendations. Using the recommendations is a good entry point for companies as they move to use the ISSB's Standards.

The IFRS Foundation has **published a comparison** of the requirements in IFRS S2 and the TCFD recommendations.

Related Information

[IFRS Foundation welcomes culmination of TCFD work and transfer of TCFD monitoring responsibilities to ISSB from 2024](#)

[Comparison: IFRS S2 Climate-related Disclosures with the TCFD Recommendations](#)

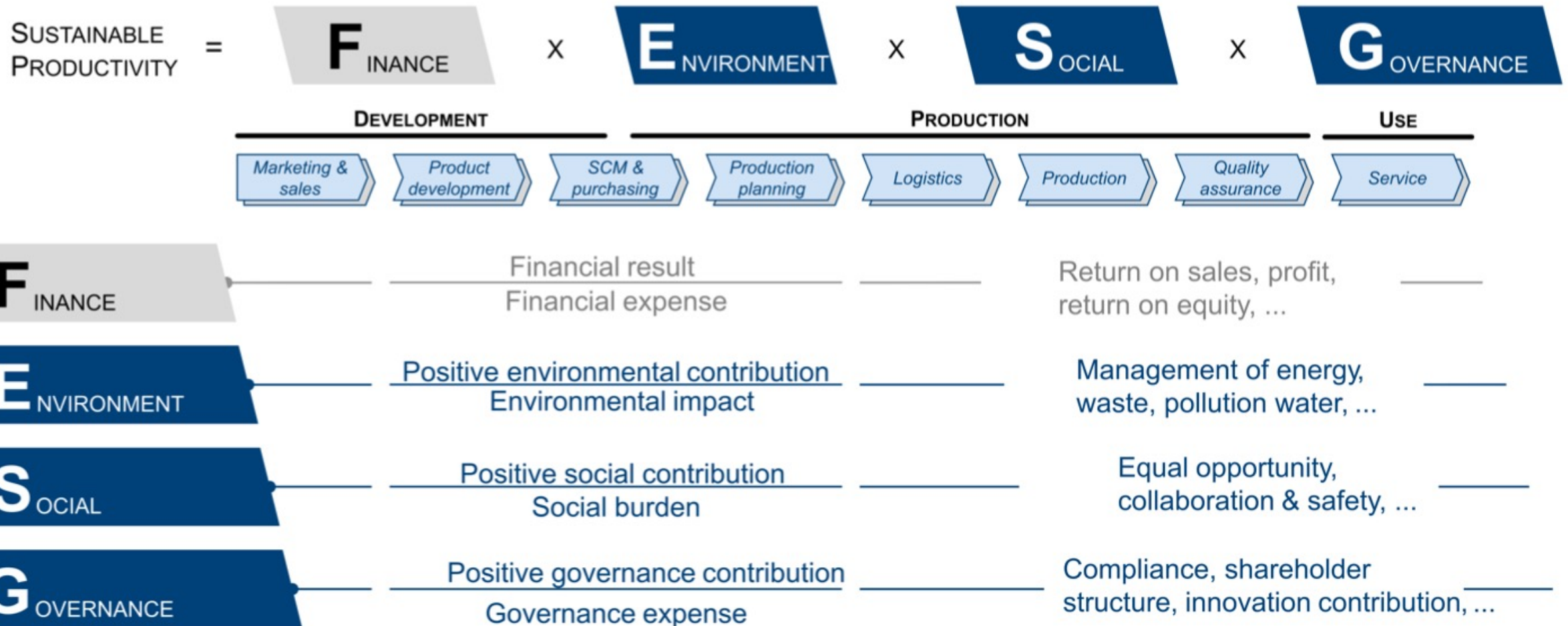
[Resource: Making the transition from TCFD to ISSB](#)

[IFRS Sustainability Standards Navigator](#)

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

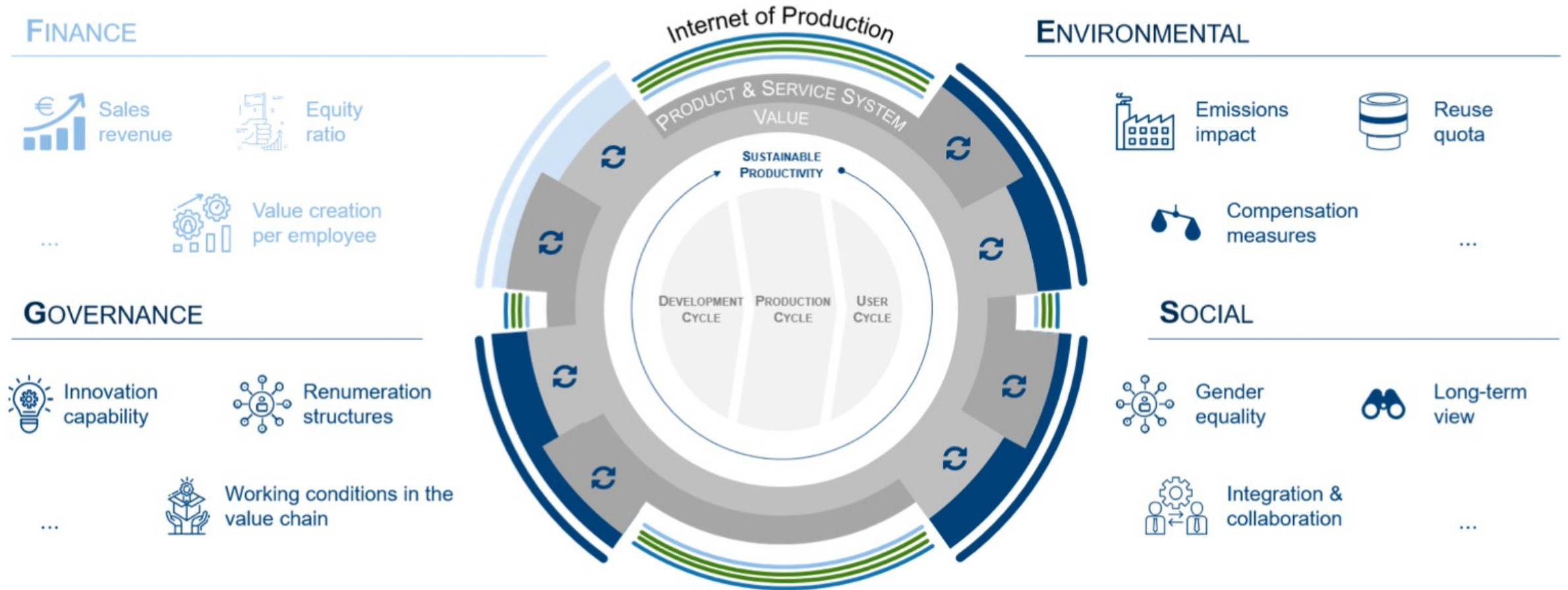
Sustainable Productivity:

Finance ESG



Sustainable Resilient Manufacturing

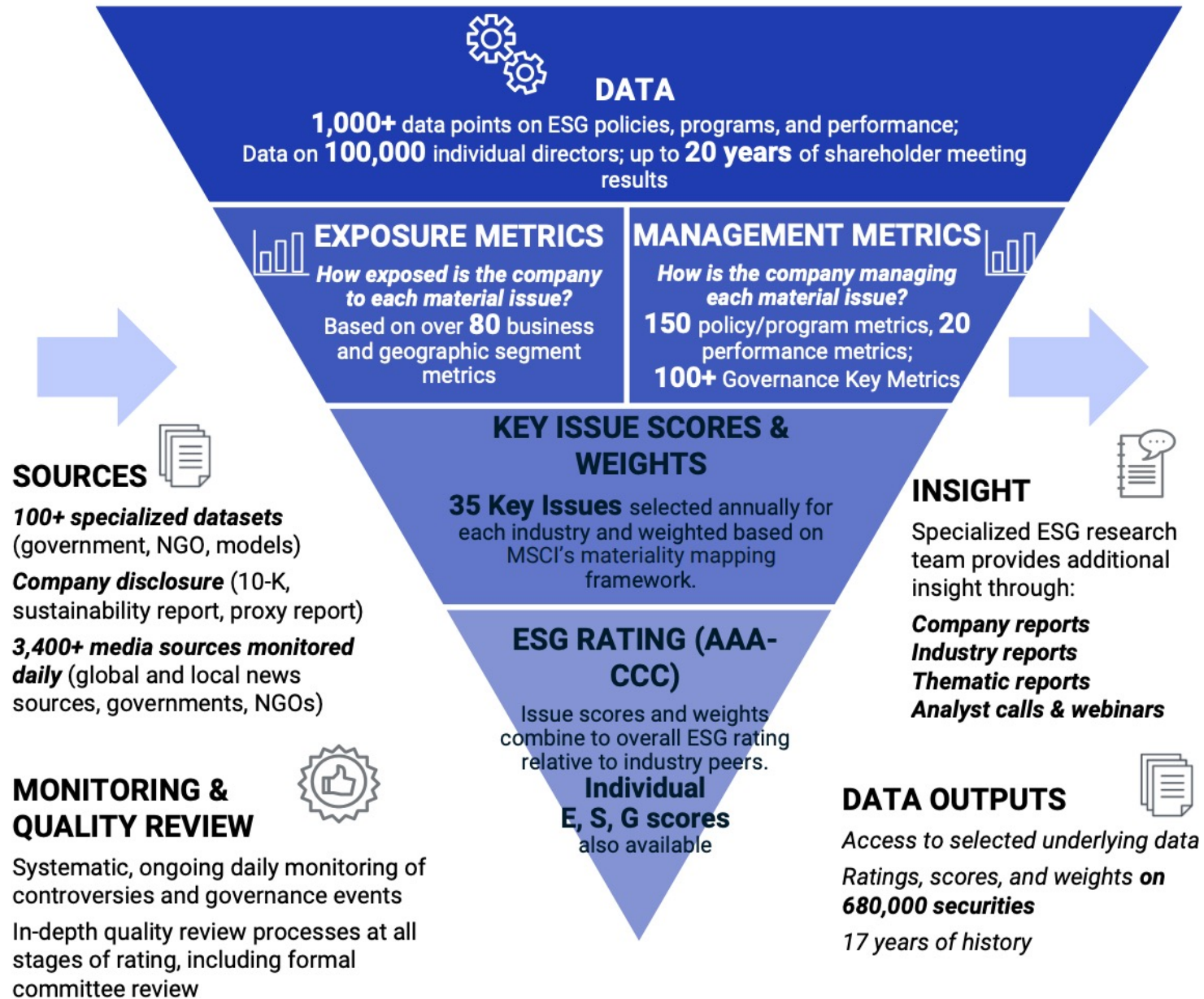
ESG



ESG Indexes

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

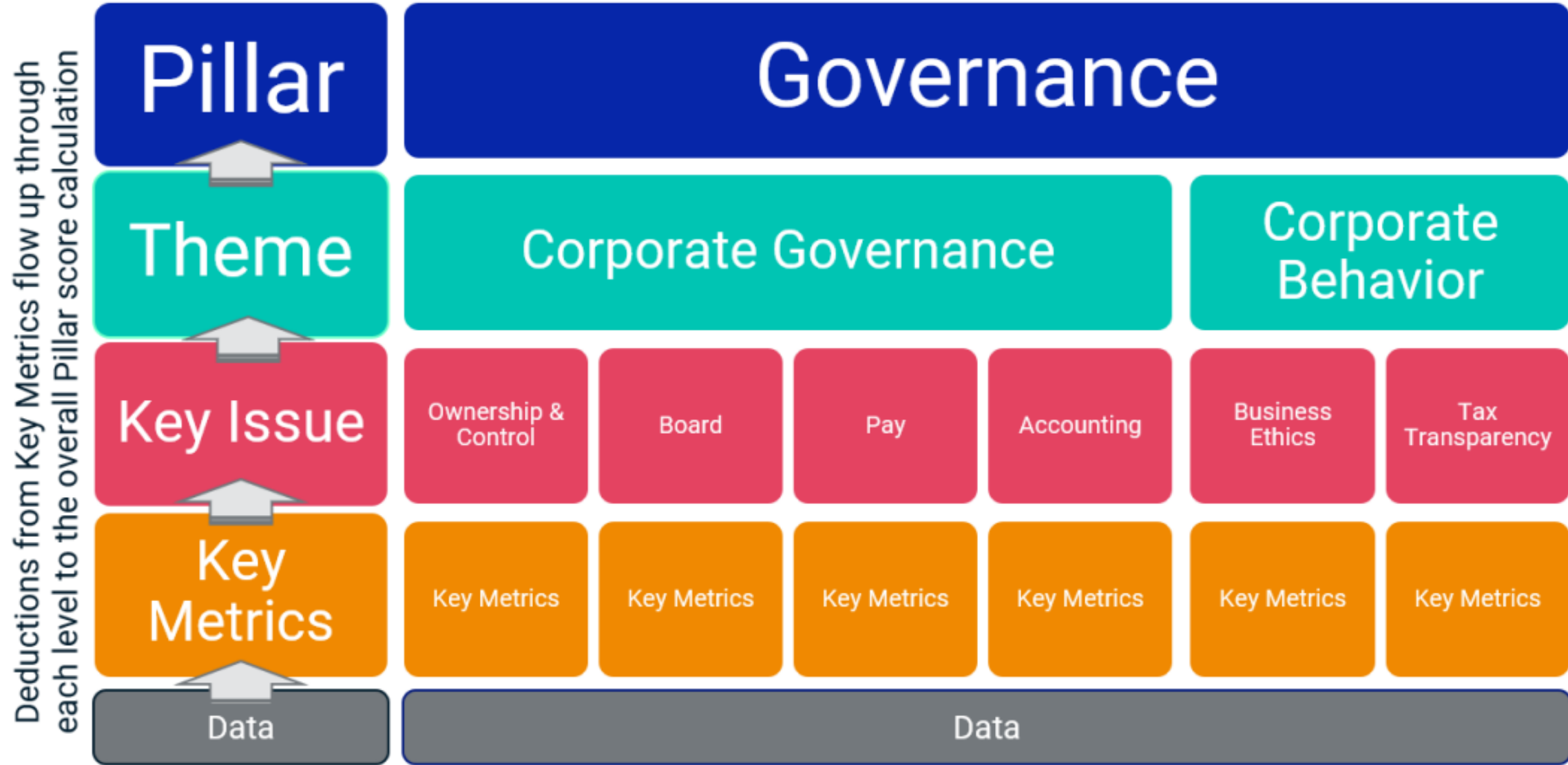
MSCI ESG Rating Framework



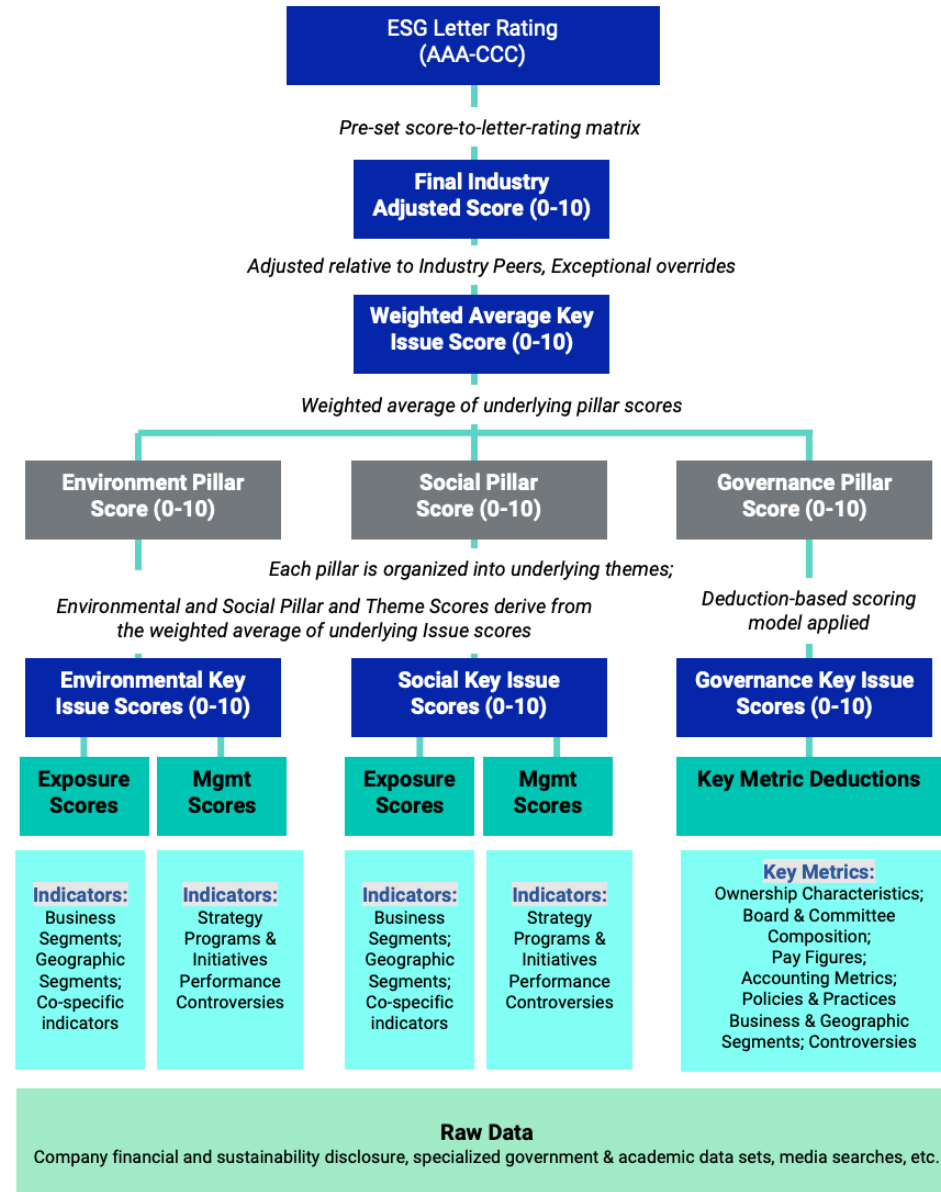
MSCI ESG Key Issue Hierarchy

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

MSCI Governance Model Structure



MSCI Hierarchy of ESG Scores



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**

FTSE Russell ESG Ratings



**Analyst-based
approach**

Sustainalytics

ESG Risk Ratings

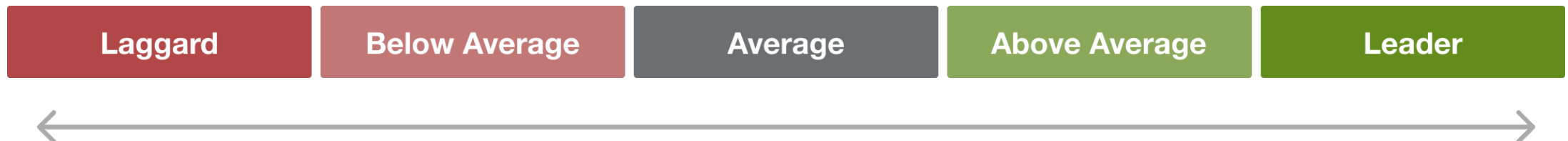
Sustainalytics' ESG Risk Ratings measure a company's exposure to industry-specific material ESG risks and how well a company is managing those risks.

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

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.



Analyst-driven vs. AI-driven ESG

Analyst-driven ESG research

Derives ratings in a structured data model



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

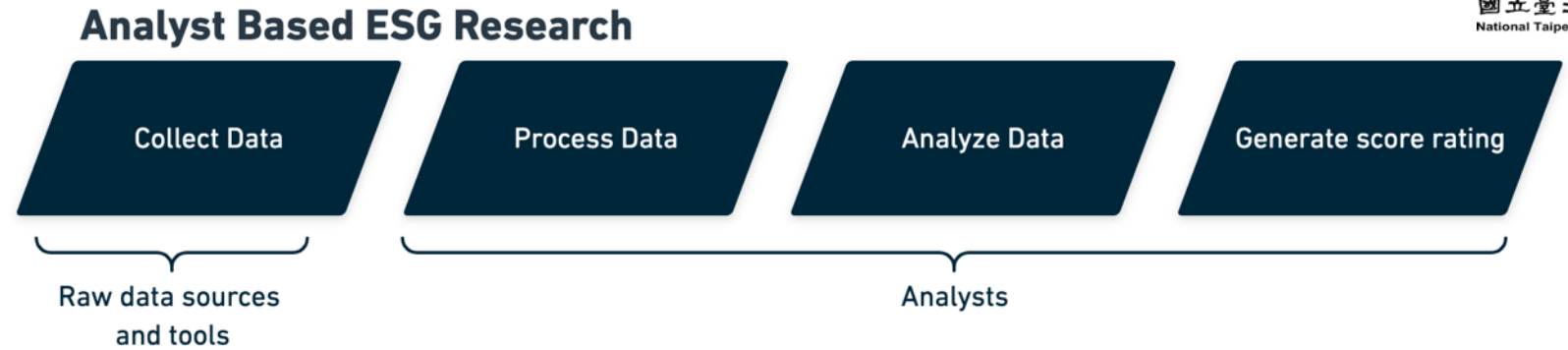
AI-driven ESG research

Derives signals from unstructured data

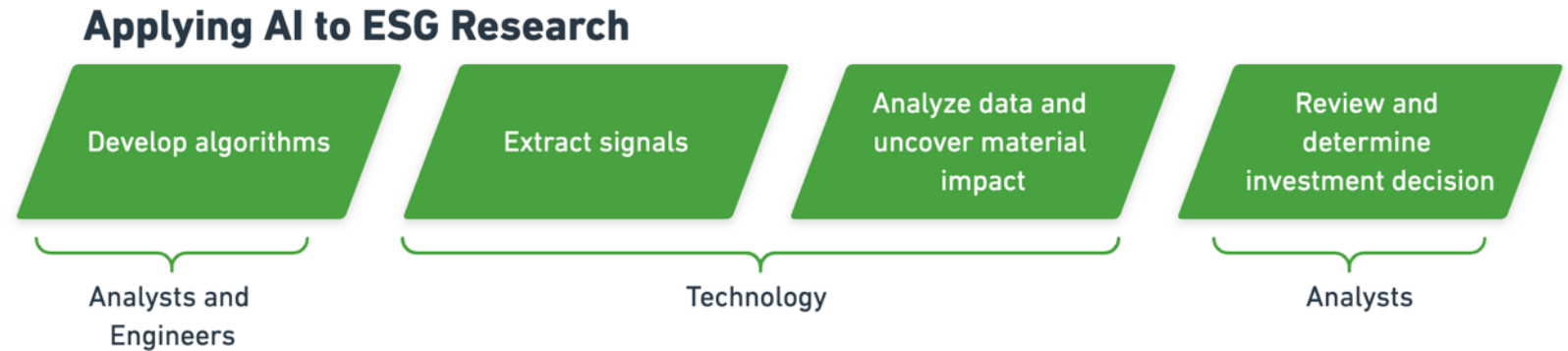


Analyst expertise at the beginning of the process produces consistent results

Analyst based ESG Research

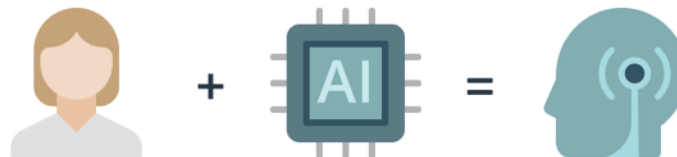


AI based ESG Research



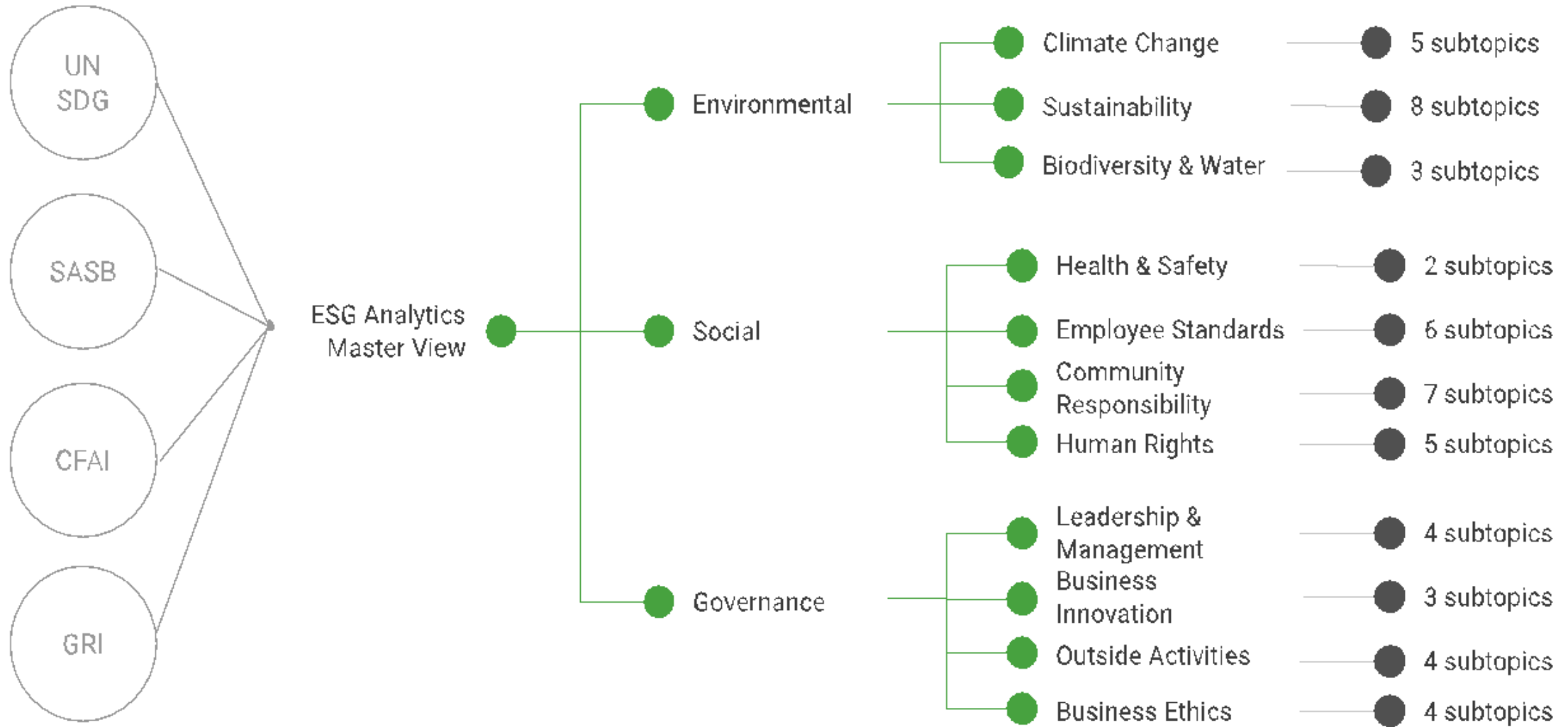
It would take an analyst over 5 years to do what our AI can in 1 week

Combining analysts with AI creates gives you the full picture



ESG ANALYTICS
Invest where it matters.

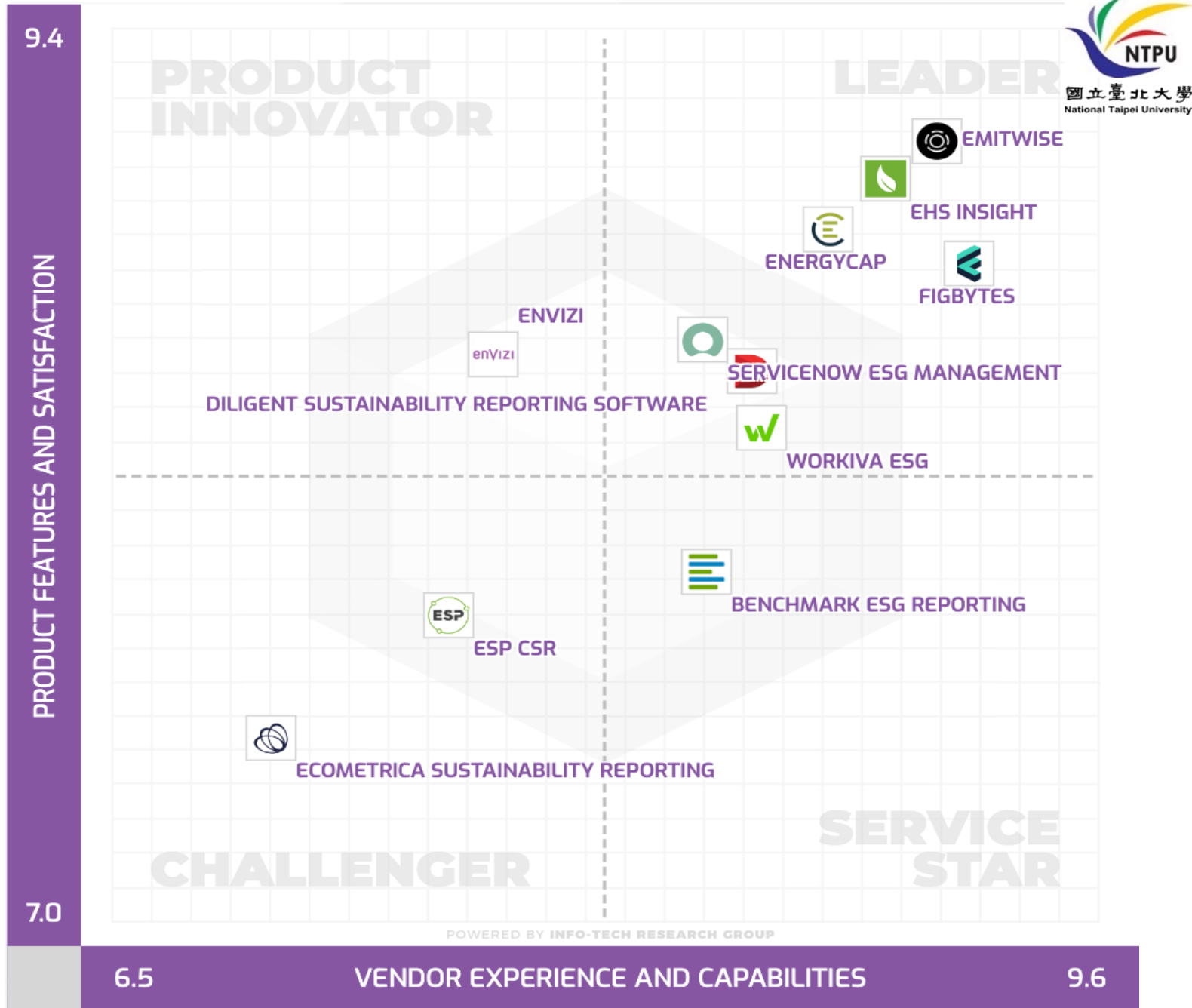
ESG Analytics: NLP Taxonomy



ESG ANALYTICS

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.



Future Directions

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

Conclusion

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

Summary

- 1. Generative AI:
Powering Digital Sustainability Transformation**
- 2. Generative AI and Large Language Models (LLMs):
Popular Generative AI Applications**
- 3. Generative AI for Sustainability and ESG Data Analytics**

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

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

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NTCIR-16 2022 NTCIR-16 Best Poster Presentation Award

NTCIR-16 FinNum-3

NTCIR

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



Yung-Wei Teng¹, Pei-Tz Chiu¹, Ting-Yun Hsiao¹, Mike Tian-Jian Jiang² and Min-Yuh Day^{1,*}

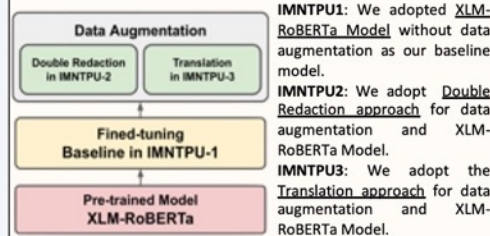
¹ Information Management, National Taipei University, New Taipei City, Taiwan

² Zeals Co., Ltd. Tokyo, Japan

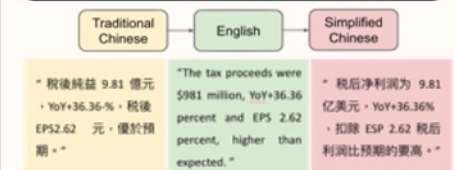
*myday@gm.ntpu.edu.tw

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



Translation Approach



Performance

Run	Chinese Dataset		English Dataset	
	Dev Set F1-Score (%)	Test Set F1-Score (%)	Dev Set F1-Score (%)	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 <mask> 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 <mask> 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-105-013-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.

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NTCIR-17 Best Poster Presentation Award

NTCIR-17 FinArg-1

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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 Tsai¹, Wen-Hsuan Liao¹, Hsiao-Chuan Liu¹, Vidhya Nataraj², Tzu-Yu Liu³, Mike Tian-Jian Jiang⁴ and Min-Yuh Day^{1,*}

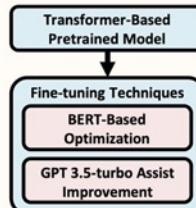
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In recent years, there has been a surge of interest in argument-based sentiment analysis and the identification of argumentative relationships in social media. These tasks encompass **sentiment analysis of premises and claims**, as well as the **classification 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



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.

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%

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-112A513E01.



Information Management, National Taipei University

NTCIR-17 Conference, December 12-15, 2023, Tokyo, Japan



2

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NTCIR-17 Best Poster Presentation Award

NTCIR-17 Real MedNLP



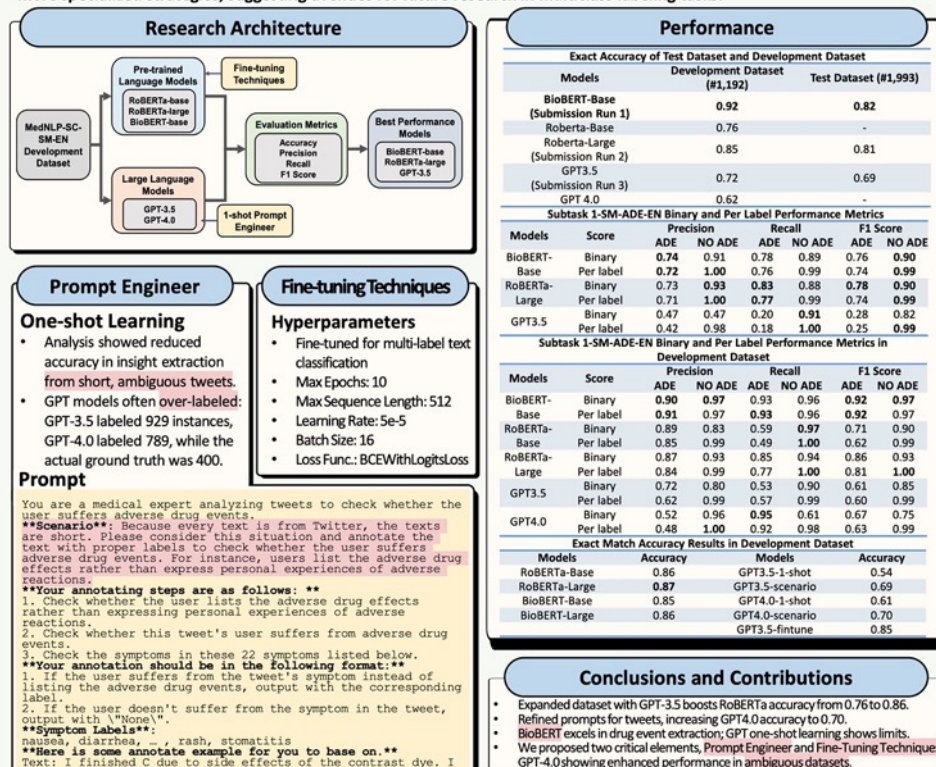
Hsiao-Chuan Liu¹, Vidhya Nataraj², Chia-Tung Tsai¹, Wen-Hsuan Liao³, Tzu-Yu Liu³, Mike Tian-Jian⁴ Jiang and Min-Yuh Day^{1,*}

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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.



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-112A413E01.

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. **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
3. **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
4. **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)
5. **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
6. **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
7. **Prospective longitudinal study on peri-implant bone loss associated with peri-implantitis**
 - USTP (NTPU, TMU), USTP-NTPU-TMU-113-03, 2024/01/01~2024/12/31

Acknowledgments: IFIT Lab Members



Intelligent Financial Innovation Technology, IFIT Lab, IM, NTPU

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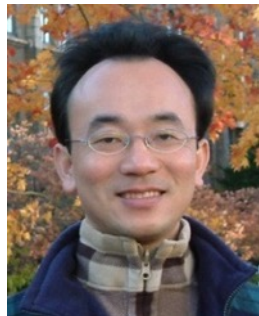
Generative AI and LLMs for Sustainability and ESG Data Analytics (生成式 AI 與 LLM 於永續數據分析)

Time: 19:00-21:00, Monday, November 25, 2024

Place: Room 200301, Daren Building, Computer Science, National Chengchi University (NCCU)

Host: Prof. Jia-Ming Chang

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Ambassador
2020 Cohort



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