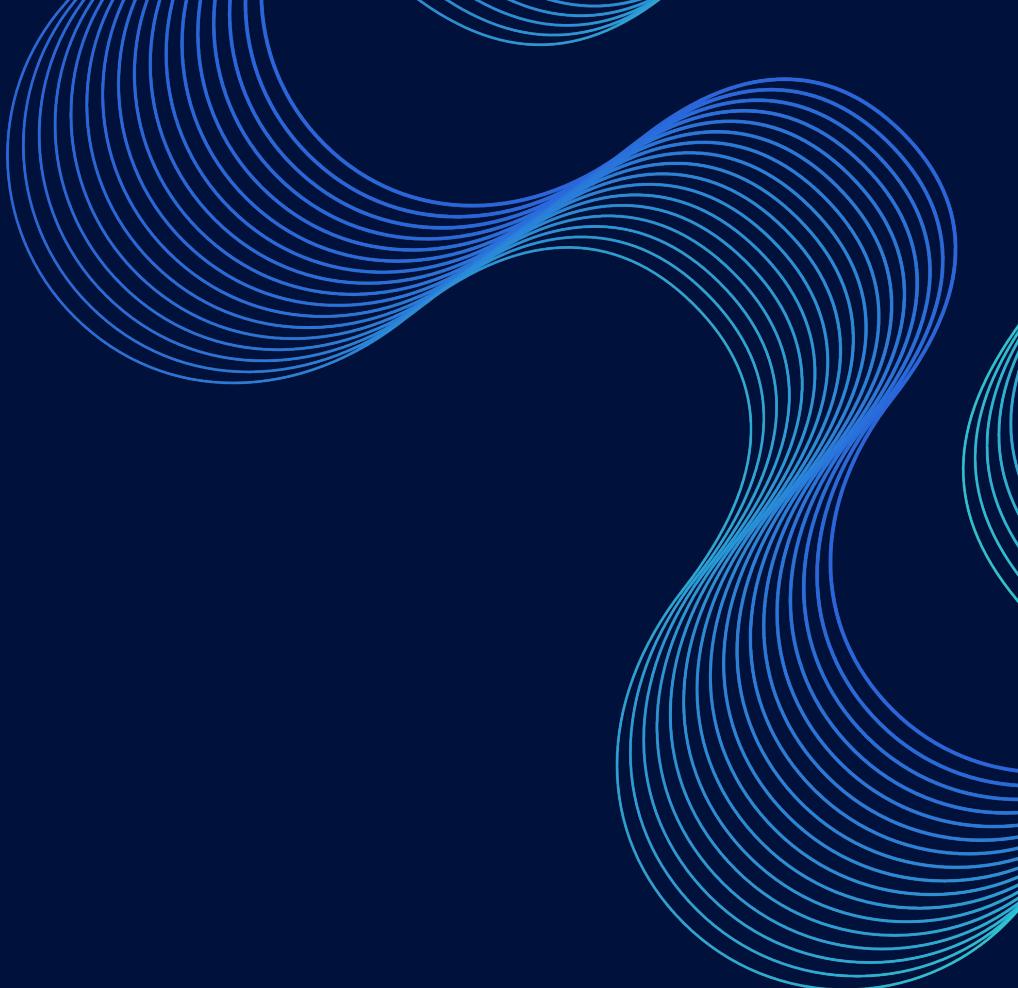




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Are you ready  
to go **beyond**?

Insights Beyond Analytics





Innovation is in our DNA

# We are a consulting firm specialized in **AI, Data & Analytics.**

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Business agility is the ability of an organization to adapt quickly to market changes, both internally and externally. This cannot exist without becoming a truly data-driven company.

SDG Group achieves this by co-creating optimal solutions with its customers, leveraging Data & Analytics services through a unique combination of business domain expertise and state-of-the-art technologies delivered by industry-leading talent.

We are pioneers in AI, Data & Analytics consulting and we are committed to unlocking organizations' hidden potential by offering in-depth analytics expertise.

# SDG Group at a glance



## Global Presence

Customer proximity is our purpose. Our global presence and a leading vision in the practices of Business Analytics and Data-Driven Solutions allow us to serve our customers worldwide at best. **Since November 2020 SDG joined Alten Group** (+57,700 professionals and +4.143 B € Revenues. Listed on Euronext Paris).



## +185M Volume of Activity

A growth mind-set to Keep Moving Forward. While maintaining our **own specialized niche player value proposition** we have achieved a considerable volume of activities provided worldwide in consultancy, design support and the creation of business analytic models and solutions.



## +2500 Employees

**Driven by talent and innovation.** We are constantly growing by attracting and retaining the best talents from the market. Our customers can rely on a skilled team passioned for innovation and committed to our shared fundamental values such as **meritocracy, teamwork, integral honesty and committed to excellence.**



## +700 Customer Base

Our customer at the center. We serve an ever-increasing number of clients around the world. Working side by side with our clients acting as a **Partner. Collaboration based exclusively on the full achievement of the expected results**, evolving from specialist assignment to long-term partnership.

# POPULAR DATA SCIENCE TYPES

Exploring the spectrum of techniques from foundational analysis to advanced artificial intelligence.

## DATA FOUNDATION & PROCESSING



### DATA ENGINEERING

Provides the infrastructure and tools necessary for collecting, storing, and analyzing data. Focuses on data preparation and architecture.



### BIG DATA ANALYTICS

Processing and analysis of vast datasets too large or complex for traditional software. Uncovers hidden patterns and insights.

## CORE ANALYTICS & INSIGHTS



### DESCRIPTIVE ANALYTICS

Summarizes historical data to understand what has happened. Provides a clear picture of past behaviors and trends.



### DIAGNOSTIC ANALYTICS

Delves into the "why" behind observed phenomena. Uses correlation and root cause analysis to identify driving factors.

## FORECASTING & OPTIMIZATION



### PREDICTIVE ANALYTICS

Uses historical data, statistical models, and ML to forecast future trends, behaviors, and outcomes for decision-making.



### PRESCRIPTIVE ANALYTICS

Predicts future outcomes and recommends actions to achieve desired results using optimization and simulation.

## ADVANCED AI & SPECIALIZED APPLICATIONS

**DEEP LEARNING**  
Subset of ML using multi-layered neural networks. Excels at modeling complex patterns in unstructured data.

### NATURAL LANGUAGE PROCESSING (NLP)

Enables computers to understand, interpret, and generate human language. Facilitates communication for applications like chatbots.

### COMPUTER VISION

Enables machines to interpret and understand the visual world. Analyzes images and videos to recognize objects, faces, and scenes.

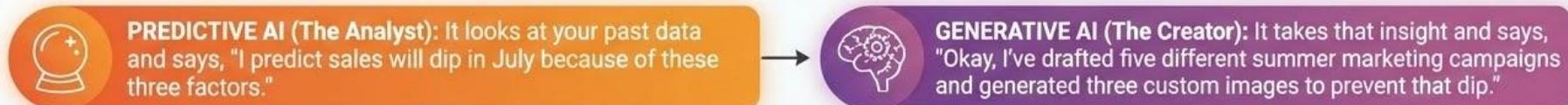
# PREDICTIVE vs. GENERATIVE AI

Understanding the core differences and how they work together.

While **Predictive AI** tells you what is likely to happen, **Generative AI** creates something new based on what it has learned.

 <b>PREDICTIVE AI (Orange Section)</b>	 <b>GENERATIVE AI (Purple Section)</b>
<b>Primary Goal:</b> To forecast or categorize future outcomes.	<b>Primary Goal:</b> To create new, original content.
<b>Input Data:</b> Mostly structured data (numbers, dates, sales history).	<b>Input Data:</b> Massive sets of unstructured data (text, images, code).
<b>Output:</b> A score, a category, or a numerical forecast (e.g., '75% chance of rain').	<b>Output:</b> A brand new object (e.g., a poem, an image, or a functional code snippet).
<b>Example:</b> Predicting which customers will cancel a subscription.	<b>Example:</b> Writing a personalized email to keep those customers.

## HOW THEY WORK TOGETHER (THE "TAG TEAM")



## THE "EVOLUTIONARY" VIEW



# The Perfect AI Storm: Convergence of Compute, Data, and Architecture

The "explosion" of AI wasn't a single invention, but a "perfect storm" of three specific ingredients finally coming together.

## 1. The "Transformer" Breakthrough (The Architecture)

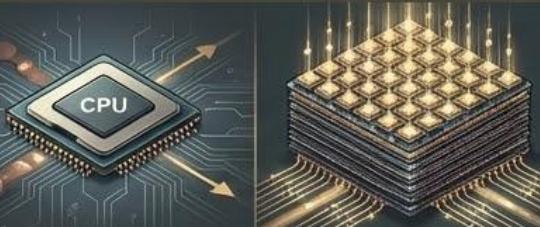
Before → 2017: → Processed one word, "forgot" context →

Before 2017: Processed one word, "forgot" context



- Before 2017: AI processed linearly, "forgetting" context in long sentences.
- 'Attention Is All You Need' paper introduced the Transformer model.
- 'Attention' Mechanism: Looks at entire paragraphs at once, understanding long-range dependencies.
- Enabled Generative AI (like ChatGPT) by understanding context.

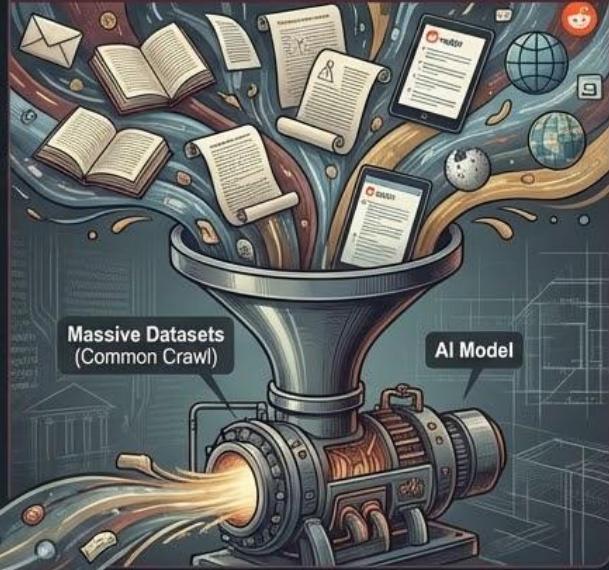
## 2. The GPU Revolution (The Compute)



- AI requires billions of math calculations per second.
- CPUs: Smart, but slow at parallel tasks.
- NVIDIA's GPUs: Originally for gaming, perfect for AI's parallel processing needs.
- Scaling: Chips like H100 enabled unprecedented training scale, physically impossible before.

AI EXPLOSION

## 3. The Digitization of Everything (The Data)



- AI is an engine that runs on data ("fuel").
- By 2020, almost every book, scientific paper, and internet content was digitized.
- **Common Crawl:** Massive datasets allowed feeding AI "the entire internet."
- Provided AI with "common sense" and abilities to code, write, and translate.

# An introduction to foundation models

**Versatility & Scale:** Pre-trained on vast, multimodal datasets (text, image, audio, video) with billions of parameters.

**Transfer Learning:** Designed to apply acquired knowledge to new tasks with minimal additional training (fine-tuning).

**From Understanding to Creation:** Moves beyond standard NLU (understanding) to **Generative AI** (creating new content).

**The "Unified" Solution:** Replaces the need for separate models for individual tasks like sentiment analysis or NER.

Large Language Models are a specialized type of **Artificial Neural Network (ANN)**—mathematical models inspired by the human brain's structure and optimized to solve complex problems through pattern recognition.

## Core Architecture: The Artificial Neuron

- **The Building Block:** The basic unit is the **node** (neuron).
- **Structure:** Organized into layers (Input, Hidden, Output).
- **Parameters:** Connections between neurons have **weights** that represent the strength of the relationship; these are optimized during training.

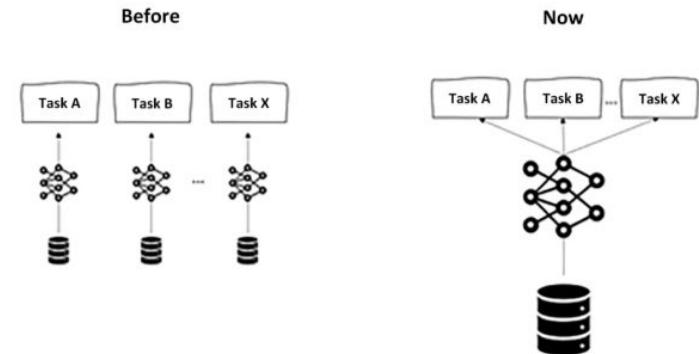


Figure 1.1: From task-specific models to general models

# Under the hood of an LLM

## Processing Text: From Words to Numbers

Since ANNs only process numerical data, unstructured text must undergo two critical transformations:

- **Tokenization:** Breaking text into smaller units (words, subwords, or characters) to create a structured format.
- **Embedding:** Converting tokens into **dense numerical vectors** in a continuous space. These vectors capture semantic meaning and context.

## The Power of Vector Space

Embeddings allow models to perform mathematical operations on language. In a properly trained vector space, semantic relationships are represented by **spatial distance**.

**Key Formula:** King - Man + Woman  $\approx$  Queen

- **Semantic Similarity:** Words with similar meanings are positioned closer together.
- **Context Awareness:** Captures complex relationships (e.g., gender, royalty, or verb tense) through multidimensional geometry.

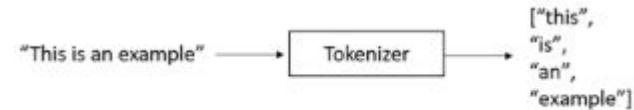


Figure 1.3: Example of tokenization

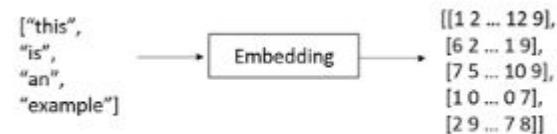


Figure 1.4: Example of embedding

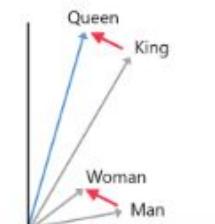


Figure 1.5: Example of words embedding in a 2D space

# Under the hood of an LLM

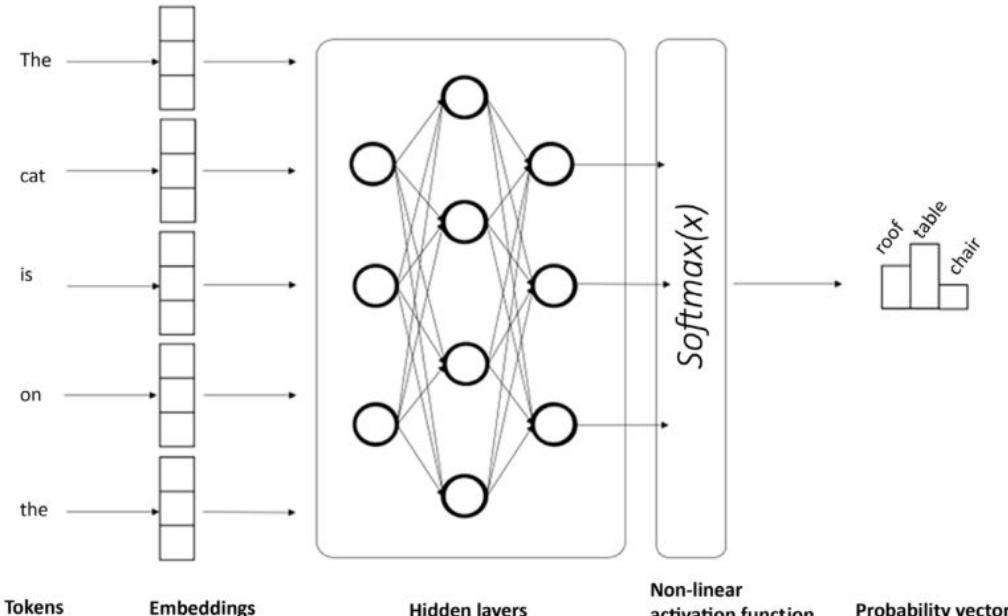


Figure 1.7: Predicting the next most likely word in an LLM

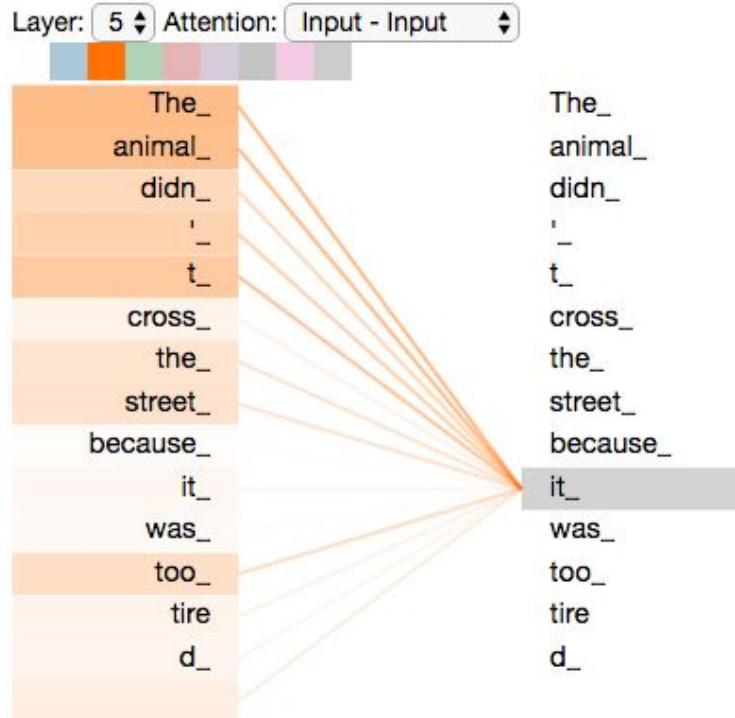
**Next-Token Prediction:** LLMs function as reasoning engines that predict the most likely next word based on a prompt.

**The Role of Bayes' Theorem:** The model updates the probability of a "candidate word" by combining:

- **Prior Probability ( $P(A)$ ):** General frequency of the word in training data.
- **Likelihood ( $P(B|A)$ ):** How well the word fits the specific current context.
- **Posterior Probability ( $P(A|B)$ ):** The final score used to select the most coherent completion.

$$P(\text{"table"}|\text{"The cat is on the..."}) = \frac{P(\text{"table"})P(\text{"The cat is on the table"})}{P(\text{"The cat is on the ... ")}}$$

# Attention is All You Need (Google, 2017)



## The Problem: Contextual Ambiguity

Consider the sentence:

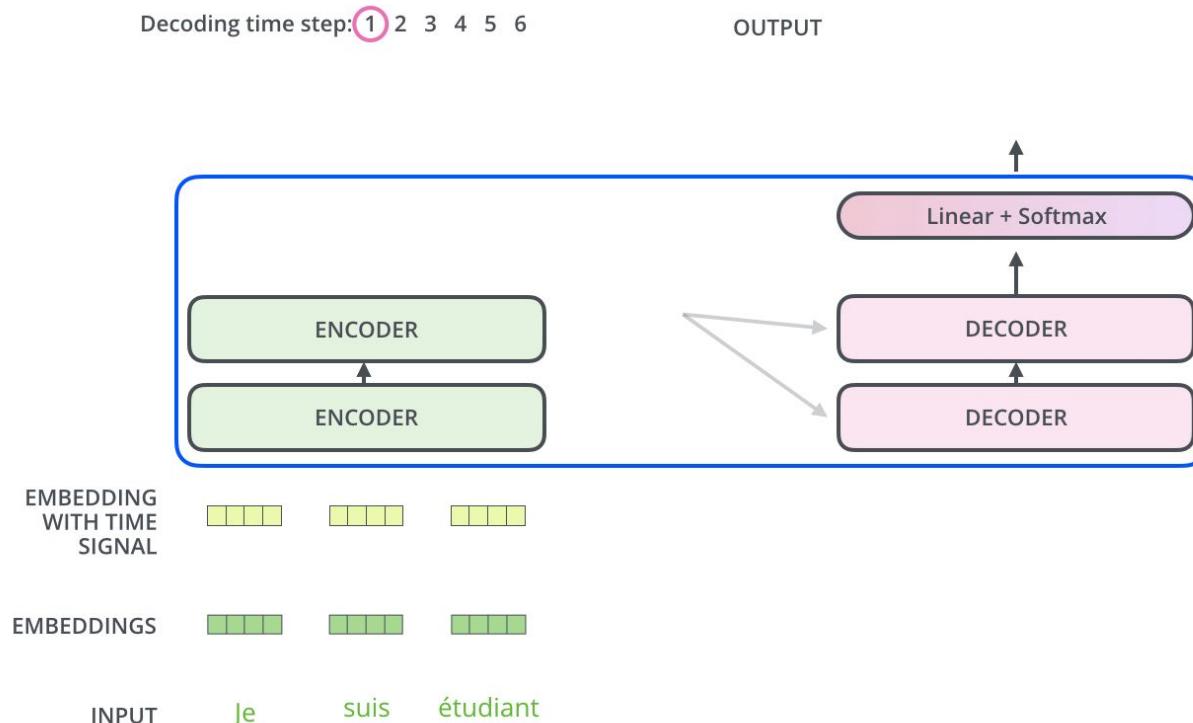
"The *animal* didn't cross the street because *it* was too tired."

- **The Challenge:** For an algorithm, it is unclear if "it" refers to the *animal* or the *street*.
- **The Goal:** To create a "richer" encoding for the word "it" by incorporating information from the most relevant surrounding words.

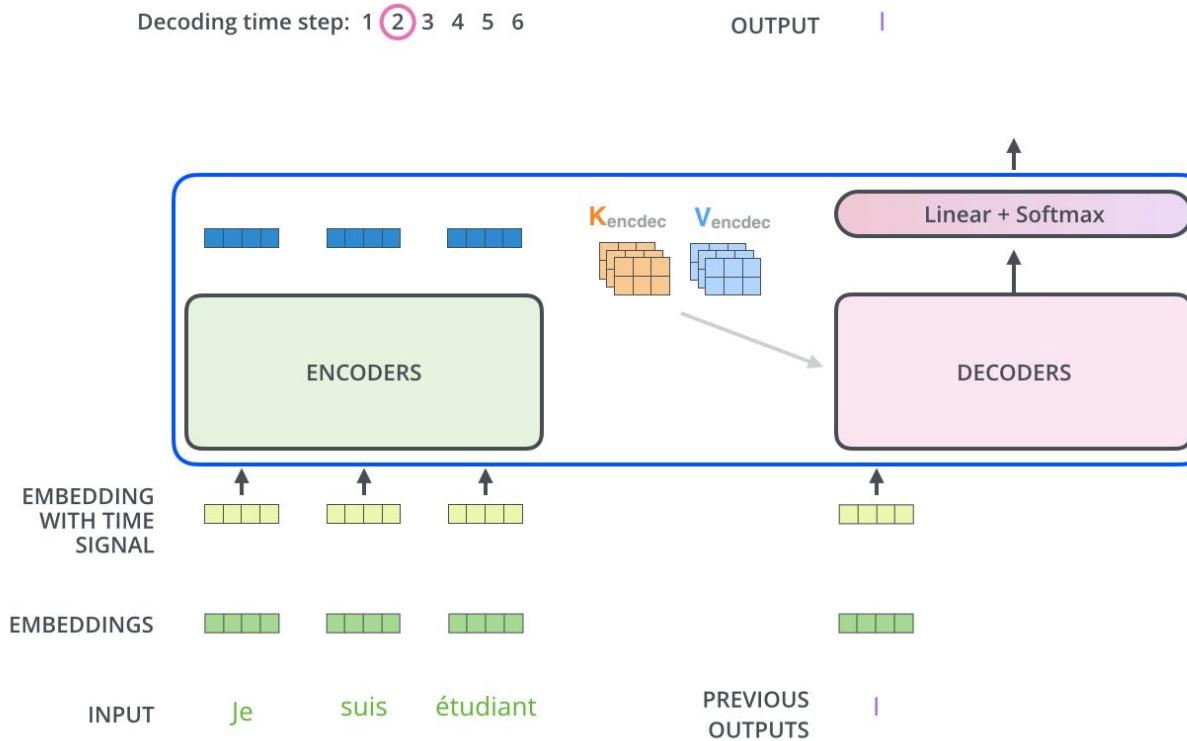
**The Solution: How Self-Attention Works:** As the model processes each word in a sequence, self-attention assigns different "weights" to other words based on their relevance:

- **Dynamic Relationships:** While encoding the word "it," the mechanism places high "attention" on the words "**The animal**."
- **Information "Baking":** Part of the mathematical representation of "animal" is folded into the representation of "it."
- **Global Context:** Unlike older models (RNNs) that process word-by-word, self-attention allows the model to look at the **entire sequence simultaneously** to find clues.

# Encoder - Decoder



# Encoder - Decoder



# AI orchestrators to embed LLMs into applications

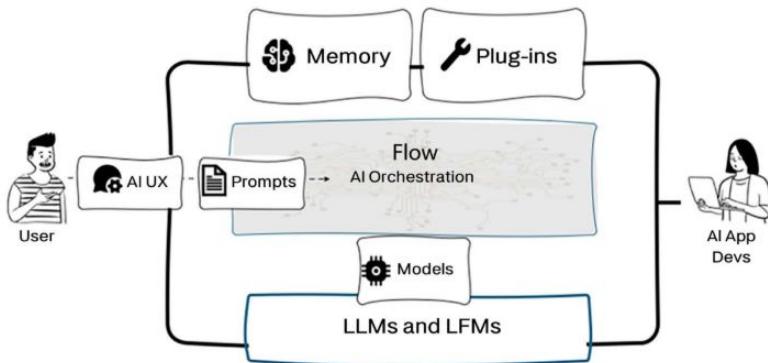


Figure 2.5: High-level architecture of LLM-powered applications

**High-Level Architecture of LLM-Powered Apps:** Modern LLM applications are built on a modular "Backend" that programs the model using natural language.

- **The Model:** Can be **Proprietary** (e.g., GPT-4, Gemini) or **Open-Source** (e.g., Llama, Falcon).
- **The Orchestrator:** Lightweight libraries (e.g., **LangChain**, **ADK**) that connect all components.
- **Plug-ins:** Modules that extend the LLM's functionality (e.g., web search, calculators).

**Memory & VectorDB: Providing Context:** To handle long conversations and specific knowledge, applications use two storage types:

- **Memory:** Stores past interactions so the model can refer back to the conversation history.
- **VectorDB:** A database storing **numerical embeddings**. It enables **semantic search** (finding data by meaning rather than keywords) using tools like FAISS, Pinecone, or Weaviate.

**Prompt Engineering “Programming in English”:** Prompting occurs at two distinct levels:

- **Frontend (User Prompt):** The natural language query entered by the user.
- **Backend (Meta-Prompts/System Messages):** Hidden instructions that "program" the model's behavior (e.g., "Act as a teacher for a 5-year-old").

# LangGraph

## Core Concepts

- **State:** A shared "memory" object that tracks information across the entire workflow.
- **Nodes:** Individual steps (LLMs, tools, or functions) that process and update the State.
- **Edges:** The logic paths connecting nodes, including **Conditional Edges** for decision-making.

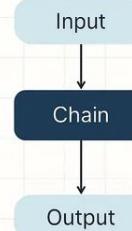
## Why it Matters

- **Cycles:** Unlike linear chains, it allows for **loops** (e.g., "Review → Edit → Repeat").
- **Human-in-the-Loop:** Built-in "breakpoints" to pause for human approval or manual edits.
- **Persistence:** Saves every step automatically, allowing you to "Time Travel" to any previous state for debugging.

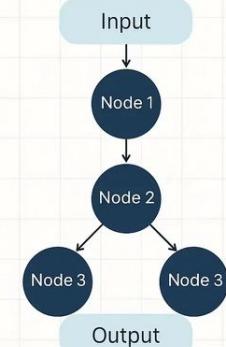
**Bottom Line:** LangGraph provides the **control** of a flowchart with the **reasoning** of an LLM.

## LANGCHAIN VS LANGGRAPH

Execution Flow



Execution Flow



### LLM steps

Use when you need to understand, analyze, generate text, or make reasoning decisions



### Data steps

Use when you need to retrieve information from external sources



### Action steps

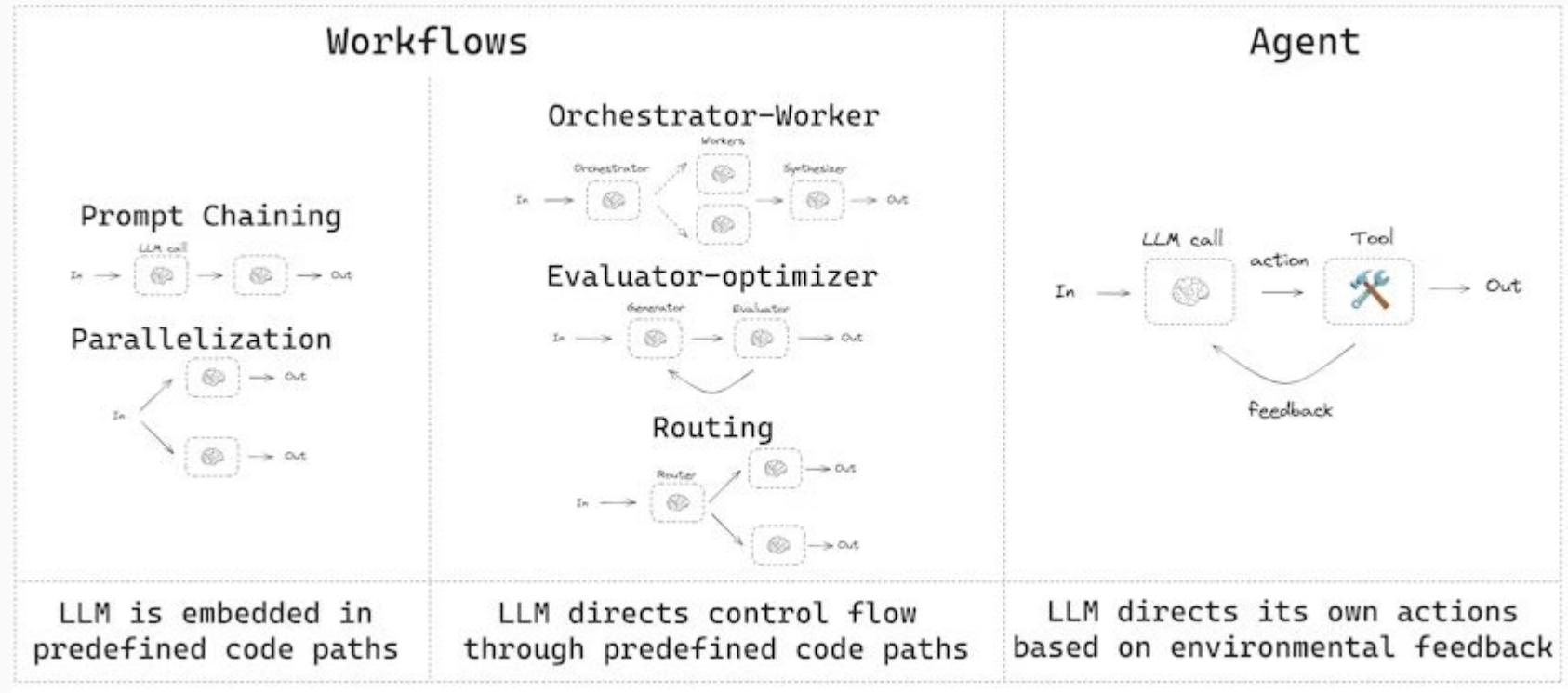
Use when you need to perform external actions



### User input steps

Use when you need human intervention

# LangGraph



# Sources

## Foundational Concepts

- **The "Attention Is All You Need"** | Vaswani et al. (2017)
  - The original research paper introducing the Transformer architecture.
  - [arxiv.org/abs/1706.03762](https://arxiv.org/abs/1706.03762)
- **Illustrated Transformer** | Jay Alammar
  - *A visual deep dive into the architecture powering modern Gen AI.*
  - [jalammar.github.io/illustrated-transformer](https://jalammar.github.io/illustrated-transformer)

## Technical Guides & Documentation

- **Book:** *Building LLM-Powered Applications* by Valentina Alto
  - *A comprehensive guide to designing and deploying AI-driven solutions.*
- **LangGraph Overview** | LangChain Documentation
  - *Frameworks for building stateful, multi-agent applications.*
  - [docs.langchain.com/langgraph](https://docs.langchain.com/langgraph)

## Implementation & Hands-on

- **Project Repository:** [agent4bees](#)
  - *Practical code samples and agentic workflows.*
  - [github.com/MaBr84/agent4bees](https://github.com/MaBr84/agent4bees)