Deep Learning (DL) Architectures and Transfer Learning for Tabular, Unstructured, Sequential and Time-Dependent Data

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Deep Learning (DL) Fundamentals and Architectures

Understanding neural networks for tabular, unstructured, and time-dependent data.

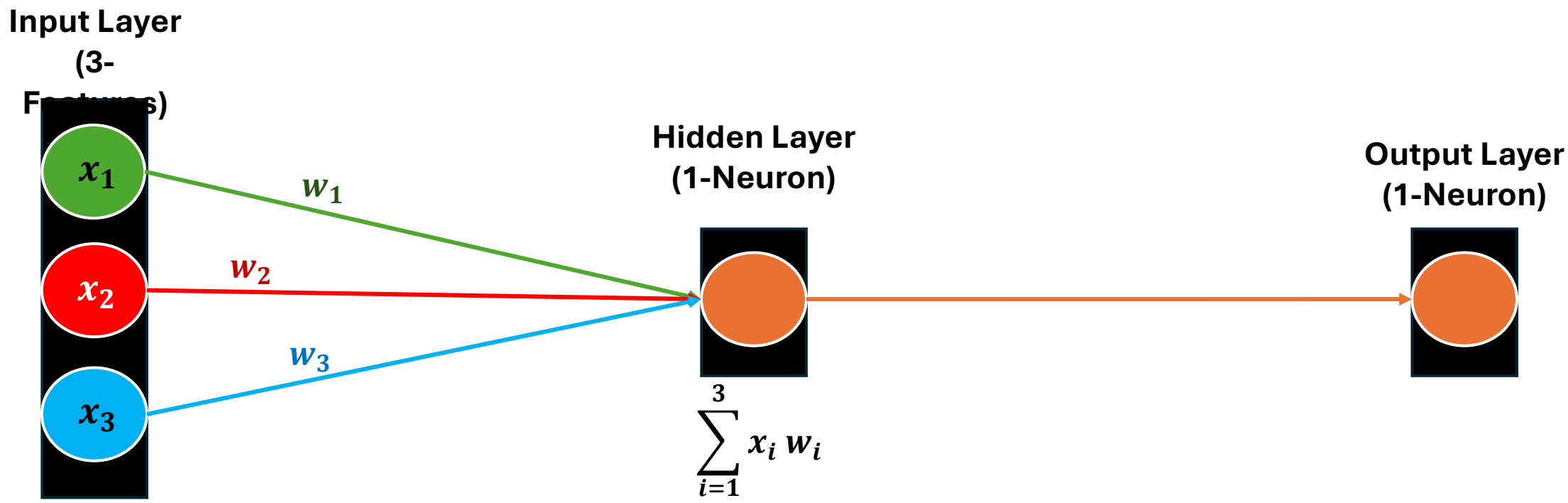
What is Deep Learning (DL)?

- **Deep Learning** leverages layers of neurons that form connections, transform data, and extract insights for regression, classification, ranking, forecasting, risk analysis, data mining, data compression, and generative AI
- Consists of several layers including:
  - **Input:** Receives raw data (tabular, audio, videos, images, and text)
  - **Hidden:** Each layer transforms data into meaningful representations understood by the network (called **feature maps** or **embeddings**)
  - **Output**: Gives final output(s) to user
- **Weights** are connecting neurons between layers, update through **backpropagation**
  - Starts as random number, then optimized during training (epochs) to better values

Neural Networks for Predictive Analytics

- Neural Networks can be designed for *regression* or *classification* by **output layer function**
  - **Regression Network** → Output function: Linear activation function
  - **Classification Network** → Output function: *Sigmoid* (binary classification) or *Softmax* (multiple classification) activation function
- Networks require significant amounts of labeled data to correctly map results and *generalize* to unseen data
- Feature engineering is automatically handled by the network → layers transform data for you
- Networks can estimate non-linear, multi-dimensional decision boundaries and prediction functions

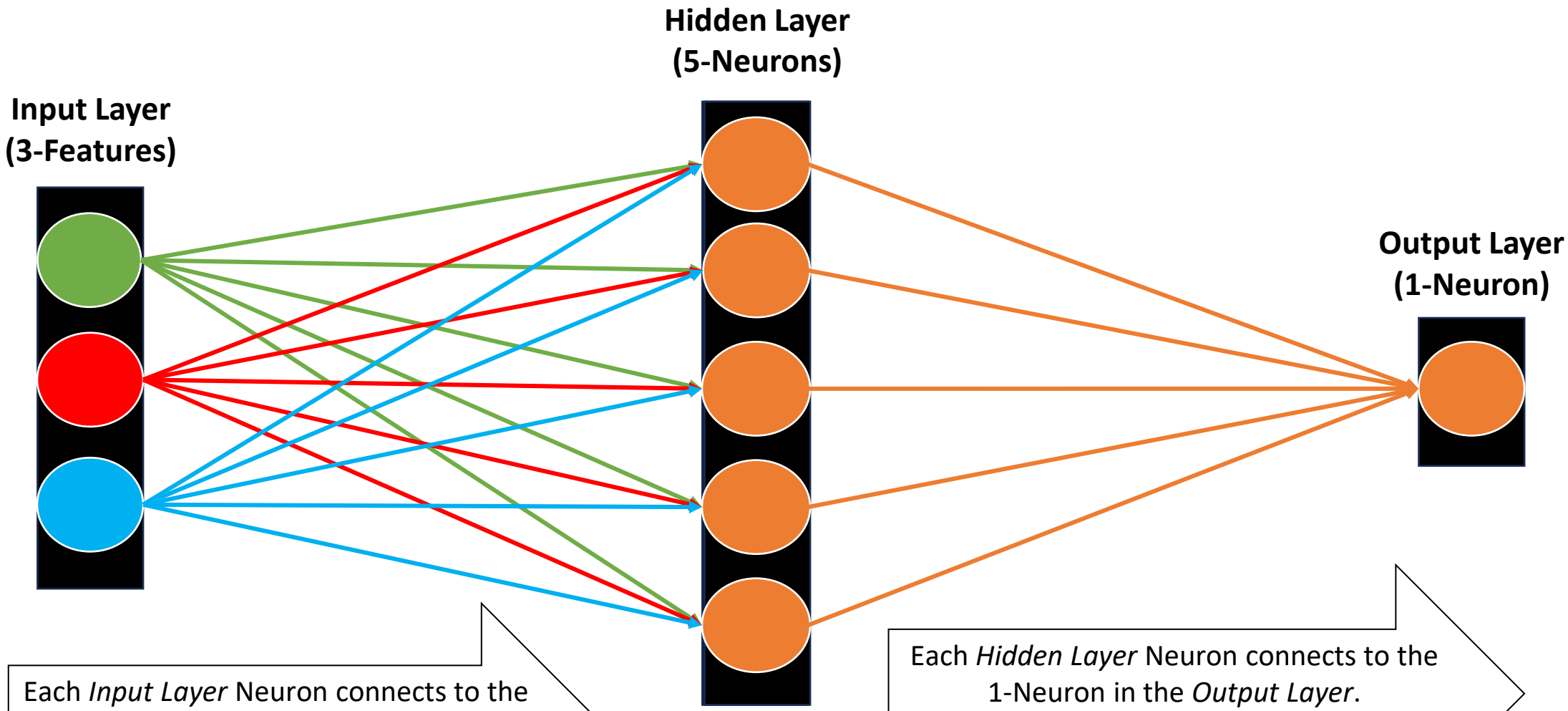
Visualizing a Simple Dense Network



Each *Input Layer* Neuron connects to the 5-Neurons in the *Hidden Layer*.
$3 \times 1 = 3$ total connections.

Each *Hidden Layer* Neuron connects to the 1-Neuron in the *Output Layer*.
$1 \times 1 = 1$ total connection.

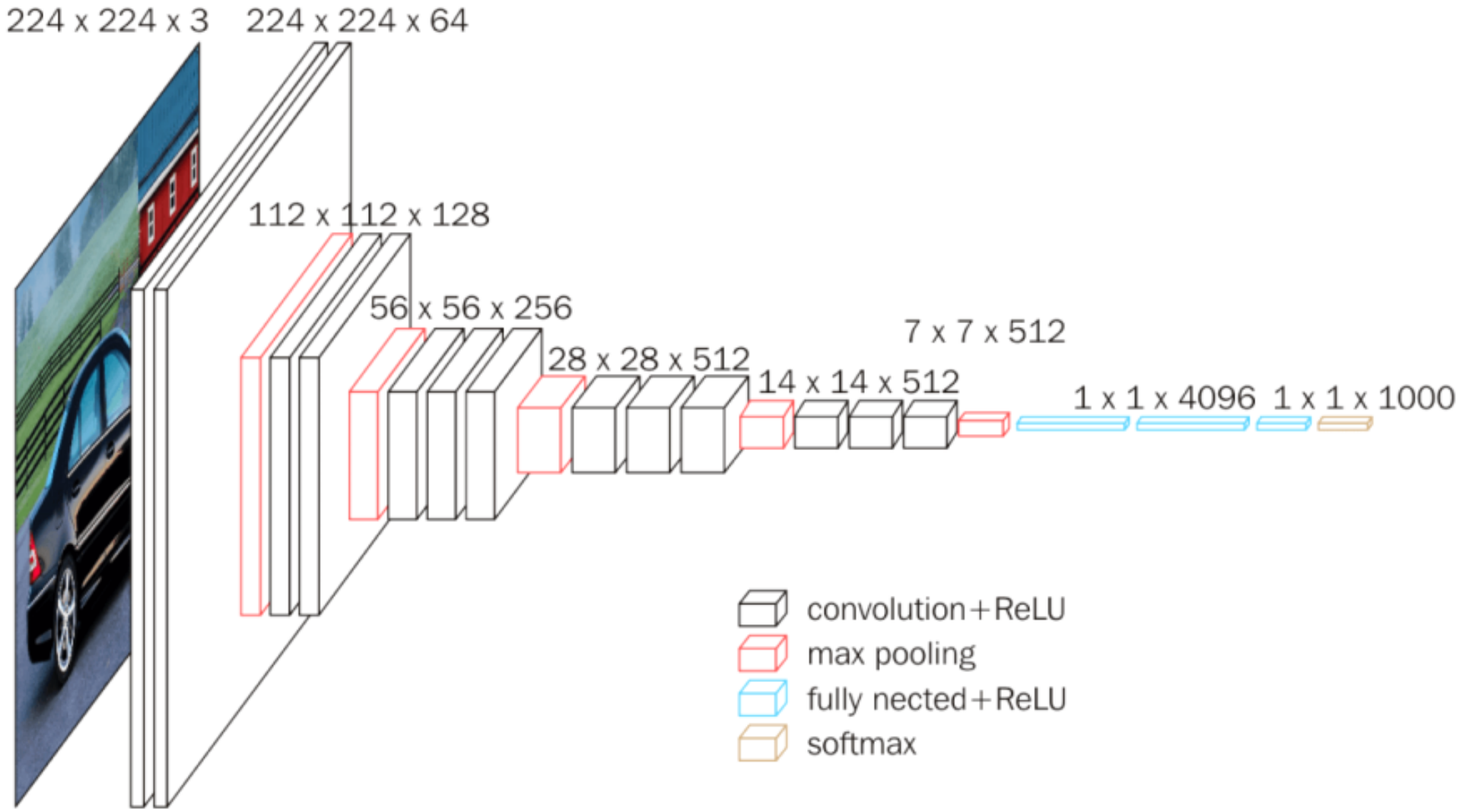
Visualizing a Hidden Layer with Multiple Neurons



Neural Networks for Content Generation

- Convolutional Neural Networks (CNNs) extract features, characteristics, and edges from images
  - Preserves information from nearby pixels in images → **spatial associations**
  - Useful for **object detection**, **image segmentation**, and **classification** tasks
- Neural Networks are also powerful generative models
  - **Variational Autoencoders** (**VAEs**) learn the *distribution* that training data come from and attempt to generate new observations from *learned distribution*
  - **Generative Adversarial Networks** (**GANs**) involve a *feedback-Network* that rates the quality of generated observations from the generative Network
    - Network continues training until it produces output deemed high quality

Visualizing a Convolutional Neural Network

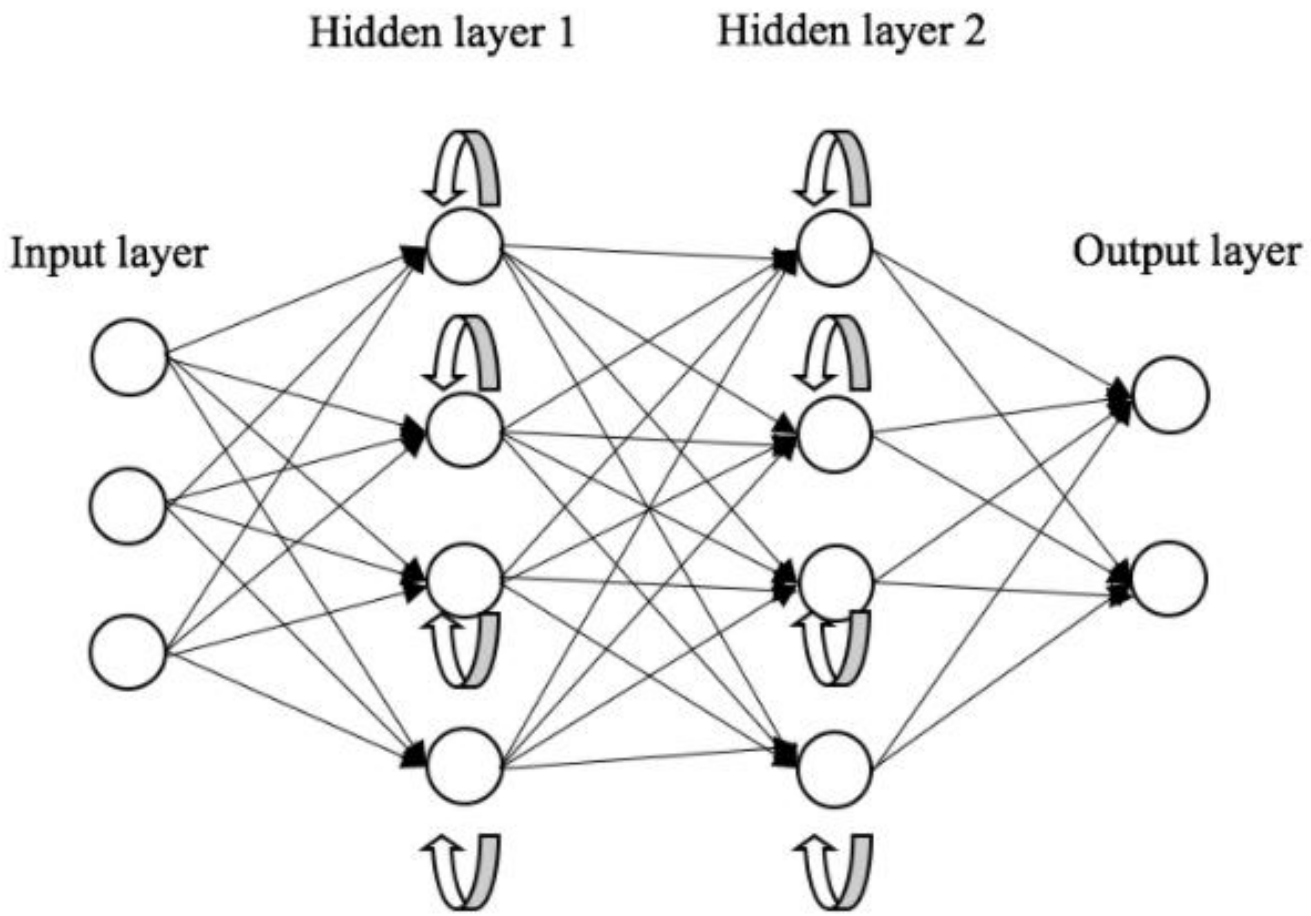


Convolutional Neural Networks (CNNs)

- Examines relationships between features using *moving windows* that shift across dataset
  - Kernels (also called filters) scan vectors (columns) or multi-dimensional arrays (i.e., images, matrices) to identify **signals**, **patterns**, and **edges**
  - **Naturally handles unstructured data types** → automatic feature extraction
  - Base layers identify key characteristics / patterns, middle layers target finer-details, and last layers focus on fine-tuning to specific task / industry / objective
- Designed to recognize patterns, extract meaningful identifiers, and parse data to create **feature maps** from original data
- Does not maintain memory of previous inputs → each input assumed **independent**

How Feature Mapping Works

Visualizing a Recurrent Neural Network



General Form of RNNs

Recurrent Neural Networks (RNNs)

- Inputs are assumed dependent on each other → nearby time steps, or words in a sequence, are assumed associated (**not independent**)
- **RNNs maintain memory** and **move one-by-one across time steps / words in sequence**
  - RNN takes new input and combines next input with memory (hidden state)
  - Gives prediction and loop continues, **sequentially**, until all inputs are exhausted
- **Suffers from vanishing gradient problem** → long-term memory is forgotten and information from early hidden states not used
  - **Long Short-Term Memory (LSTM)** introduce gates (what info to remember / forget)
  - **Gated Recurrent Units (GRU)** are simpler memory managers than LSTMs, faster but less complex

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Exploring the Next Frontier with Generative AI Workflows

Harnessing encoder, decoder, and hybrid transformer models to create content, capture context, and enable reasoning with information retrieval.

Generative AI Architectures

- **Transformers** key to generative AI workflows → parallelize **attention** layers in neural networks and replace sequential networks such as RNNs and LSTMs
- **Encoder-Only architectures** excel at representation learning, embeddings, and retrieval; power search, classification, and semantic similarity
  - Create contextual representations (vector embeddings) from input tokens
  - Examples include **BERT** and **RoBERTa**
- **Decoder-Only architectures** provide autoregressive generation for text, code, simulations, and creative tasks; optimized for long-form output
  - Each output token *only* focuses on previous token(s), does not see ahead of current token → examples include GPT family & LLaMa family

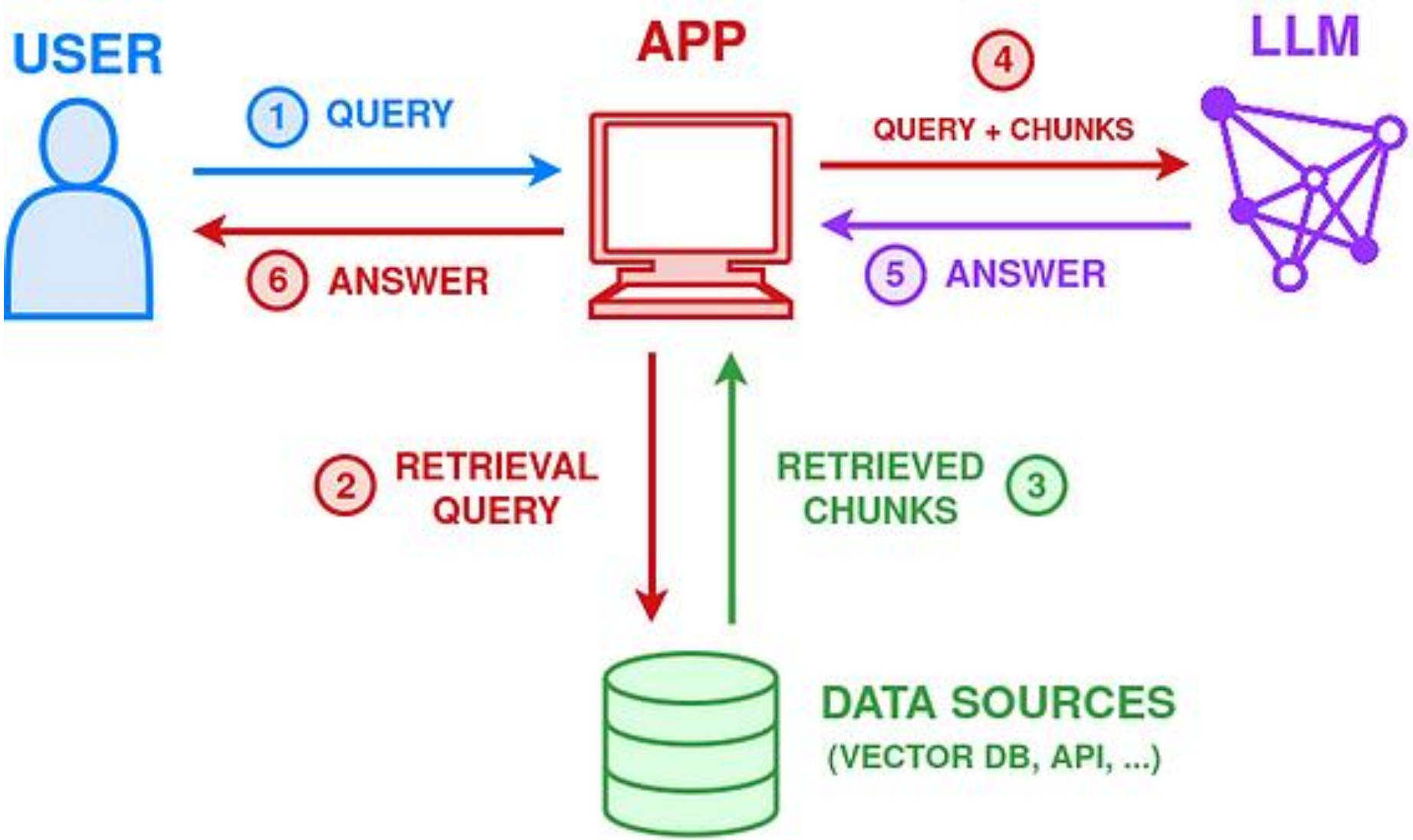
Generative AI Architectures

- **Encoder-Decoder architectures** are ideal for translation, summarization, multimodal reasoning; integrate comprehension + generation
  - Encoder-part transforms input sequence to vector embeddings
  - Decoder-part consumes vector embeddings and generates output sequence
    - Encoder-part builds a rich representation by reading entire input sequence and transforming into latent (vector) space
    - Decoder generates tokens **one-at-a-time** using **casual attention** to maintain sequence order
  - Unlike Decoder-Only architectures, Encoder-Decoder transformers excel at summarization and translation tasks by focusing generation guided by input context

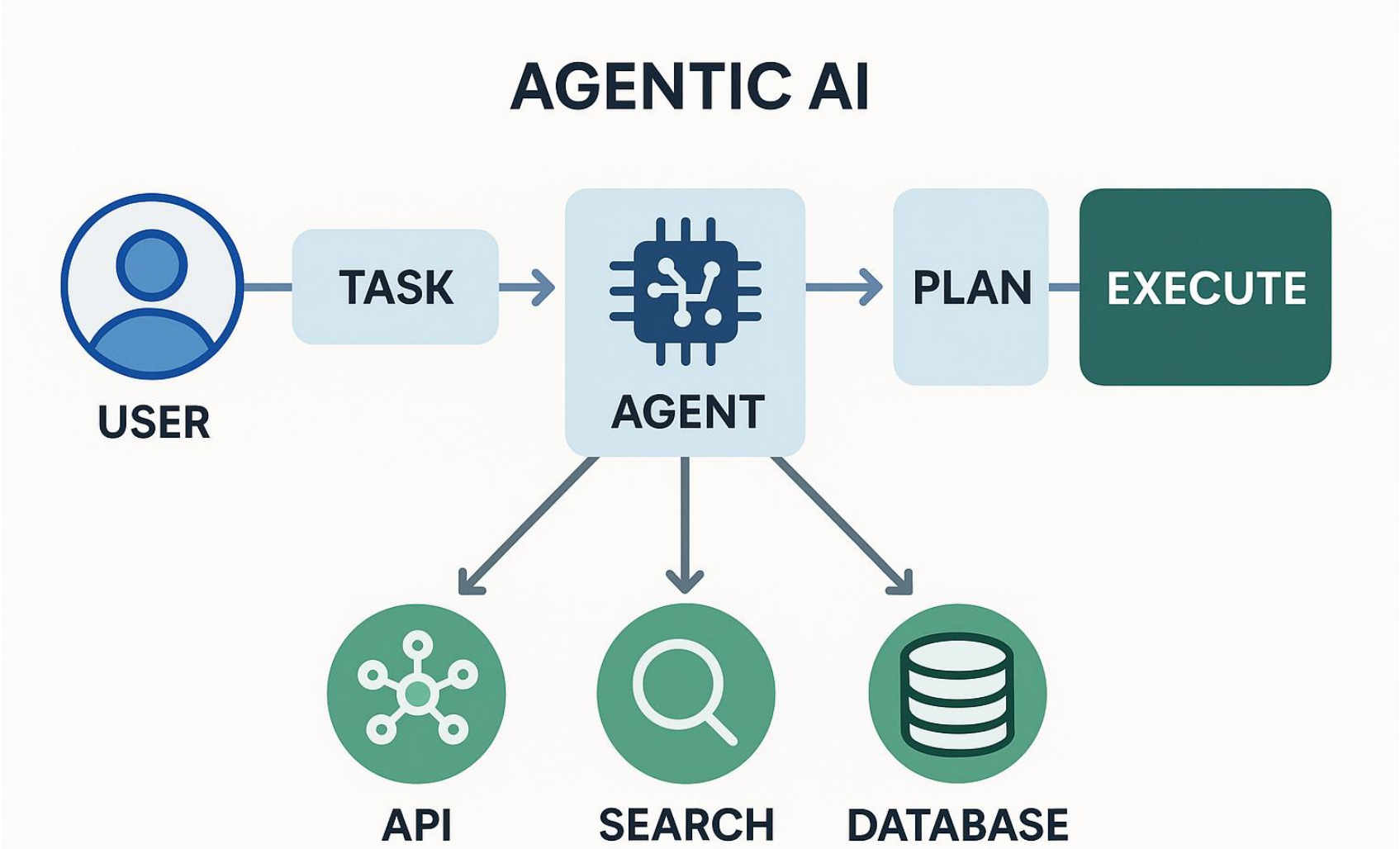
Retrieval-Augmented Generation (RAG)

- **Bridges search + generation:** Combines external knowledge retrieval with large language models (LLMs) to improve factual accuracy
- **Retriever module:** Fetches relevant documents or embeddings from a vector database or search index based on the query
- **Vector Databases:** Purpose-built for storing and searching vector embeddings
  - Enables fast similarity search and semantic retrieval to power RAG, recommendations, and multimodal AI
- **Generator module:** Conditions its response on both the input query and retrieved content, ensuring grounded outputs
- Good for **Q/A systems**, **chatbots**, & **technical documentation search**

Retrieval-Augmented Generation (RAG)



Agentic AI Workflow



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