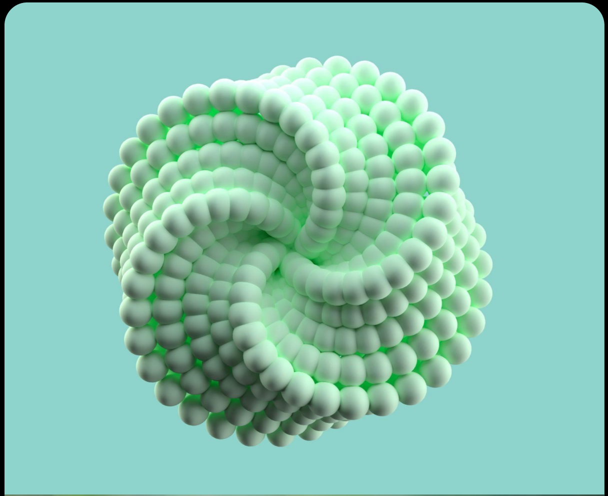


GROUP 2DEEP2LEARN – FEB 2025

Neural Networks in Nature

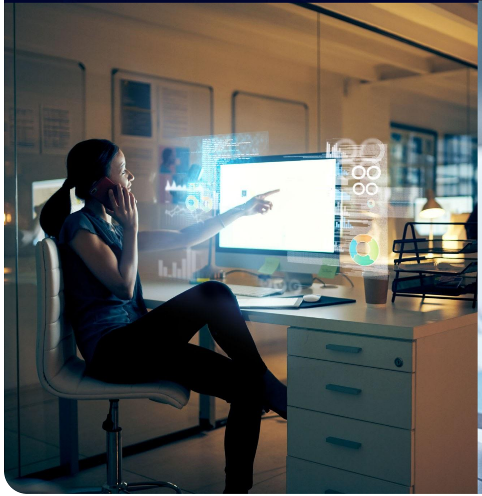
Contributors
Olugbenga Adegoroye
Jazmine Brown
Varit (Henry) Kobutra
Kimberly Navarrete
Phillip Torres

Prepared for
Prof. Patricia McManus
ITAI 2376

Agenda

01

Brief overview of biological neurons

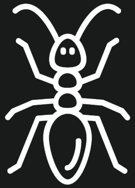

Brief Overview

Nature has been implementing neural networks long before computers existed.

Biological neural networks, found in brains and nervous systems, have inspired the artificial neural networks we use today. These networks are composed of interconnected neurons that process and transmit information through electrochemical signals, forming the basis for learning, memory, and adaptation in living organisms.

02

The Neural Network Zoo

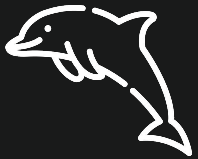


Feedforward Neural Networks

Simple, organized in layers, works in colonies like neurons

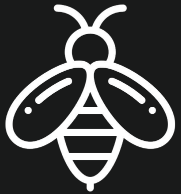
GAN

Adapts and transforms, creates convincing imitations



Transformers

Highly intelligent, processes complex sequences, excellent at communication



Self-Organizing Maps

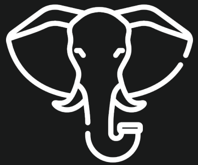
Organizes data into patterns, creates structured representations

RNN

Adaptable, processes information cyclically, has memory-like capabilities

CNN

Exceptional at pattern recognition, processes visual information hierarchically



LSTM

Superior memory retention, processes long sequences of information

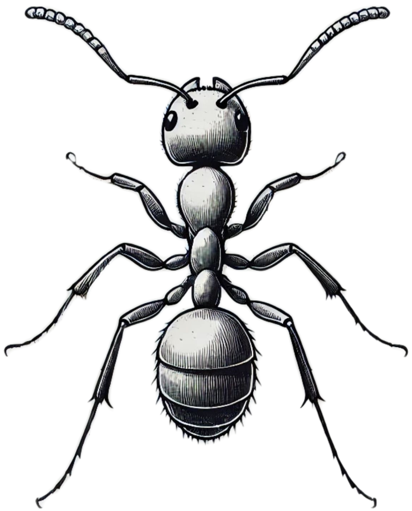
Hopfield Networks

Creates intricate webs of connections, pattern completion abilities

03

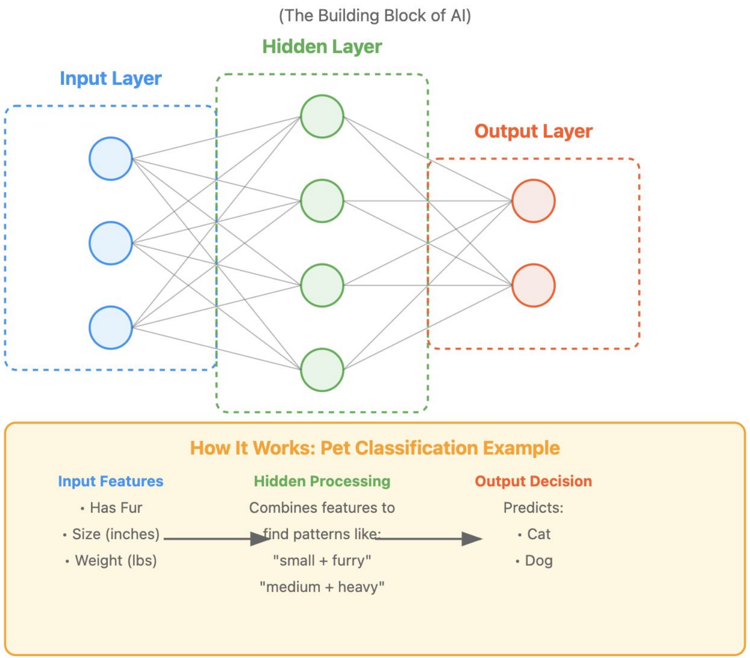
Understanding Each Neural Network

Ants

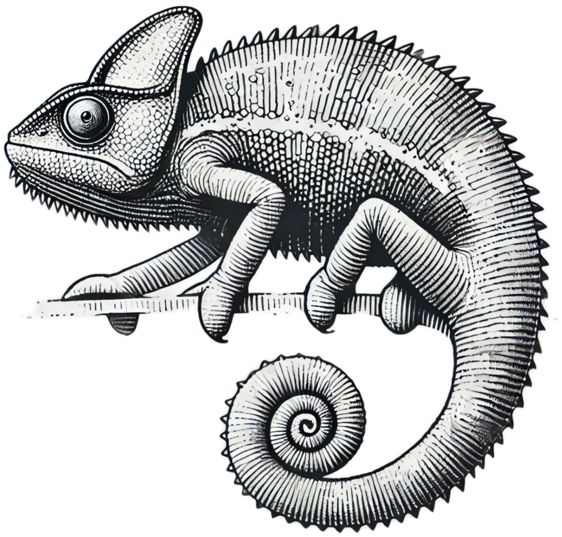


Simple, organized in layers, works in colonies like neurons

Feedforward Neural Networks

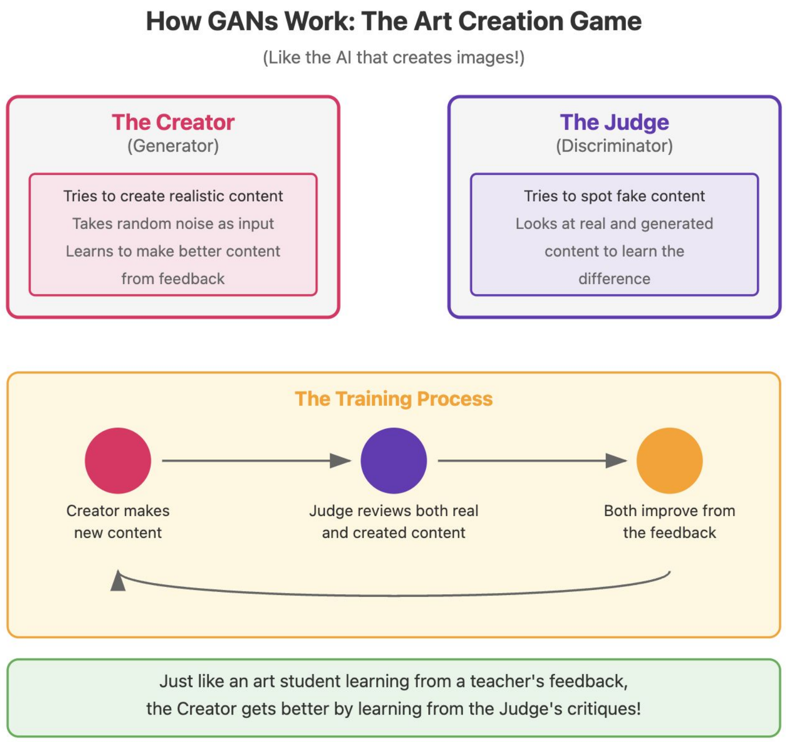


Chameleon

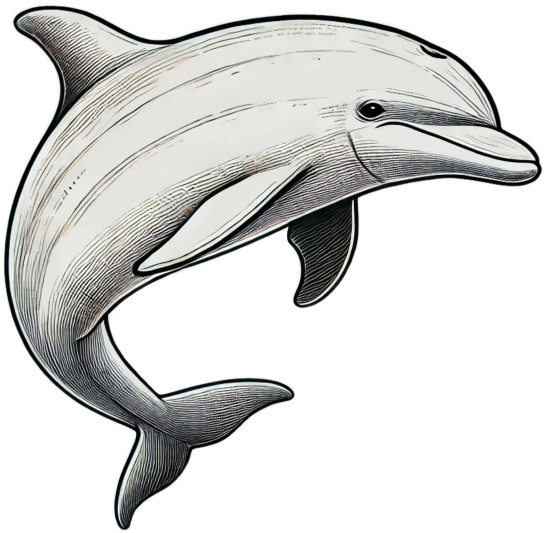


Adapts and transforms, creates convincing imitations

GAN

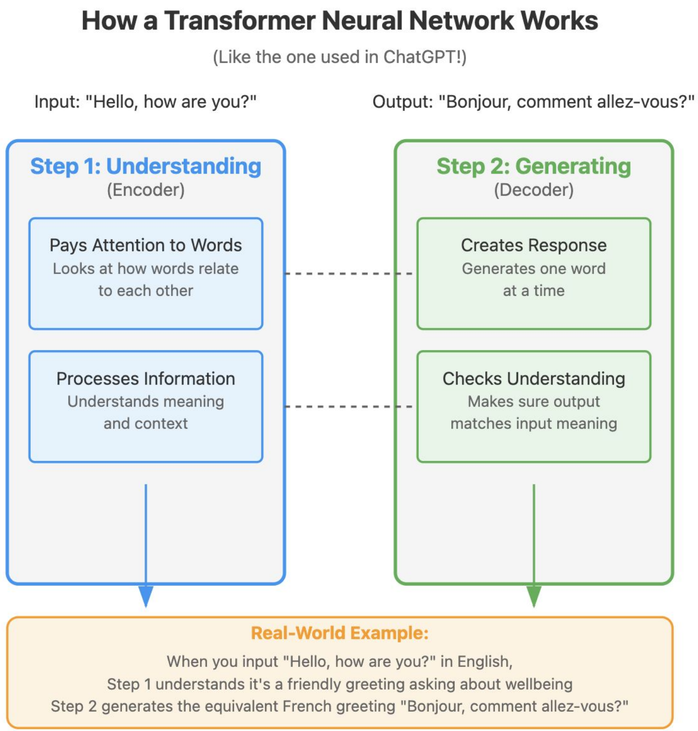


Dolphin



Highly intelligent, processes complex sequences, excellent at communication

Transformers

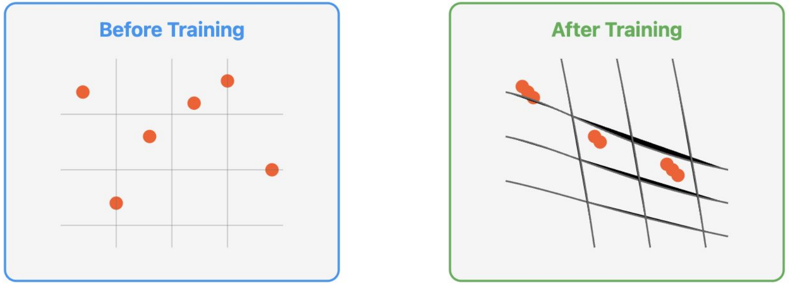


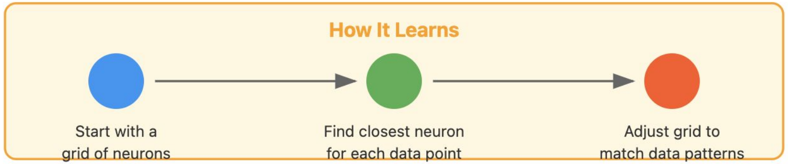
Honeybee

Organizes data into patterns, creates structured representations

Self-Organizing Maps

(How AI Organizes Data Like a Brain)

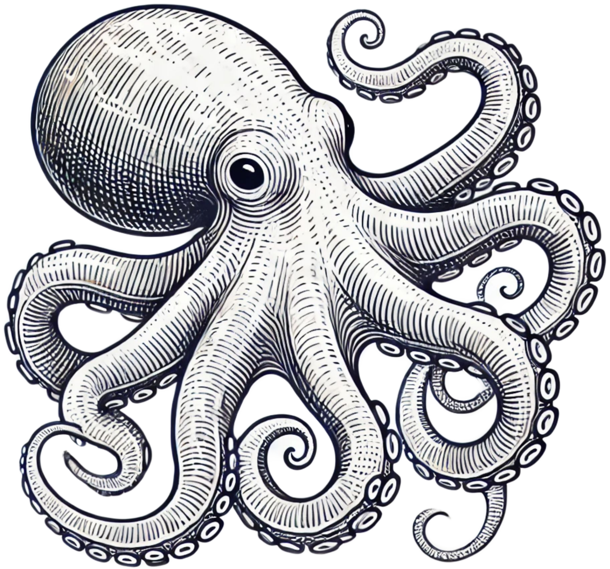




Real-World Example: Customer Segmentation

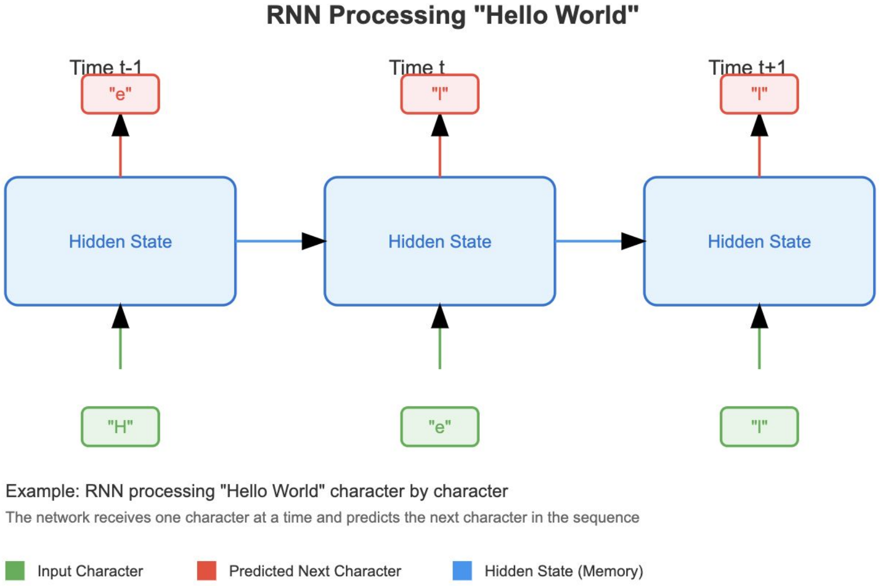
Imagine organizing customers based on their shopping habits:
Similar customers (like "luxury shoppers" or "bargain hunters")
naturally group together on the map!

Octopus



Adaptable, processes information cyclically, has memory-like capabilities

RNN



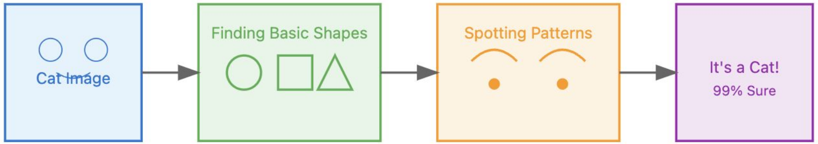
Eagle

Exceptional at pattern recognition, processes visual information hierarchically

CNN

How CNNs Look at Images

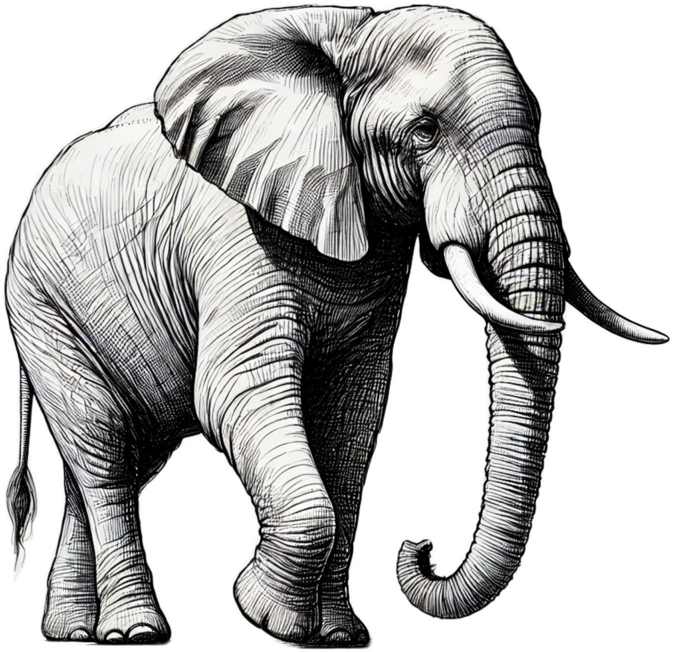
(Like Having Super-Powered Eyes!)



How It Works:

1. Looks at Image
   Like your eyes seeing a picture
2. Finds Simple Shapes
   Spots edges, circles, and lines
3. Recognizes Patterns
   Combines shapes into features (eyes, ears, whiskers)

Elephant



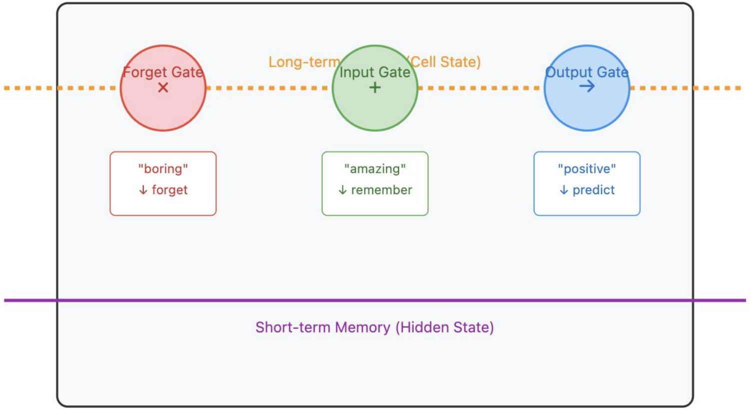
Superior memory retention, processes long sequences of information

LSTM

Understanding LSTM Memory

(Like a Smart Notepad that Remembers Important Things)

Example: Reading a Movie Review Word by Word

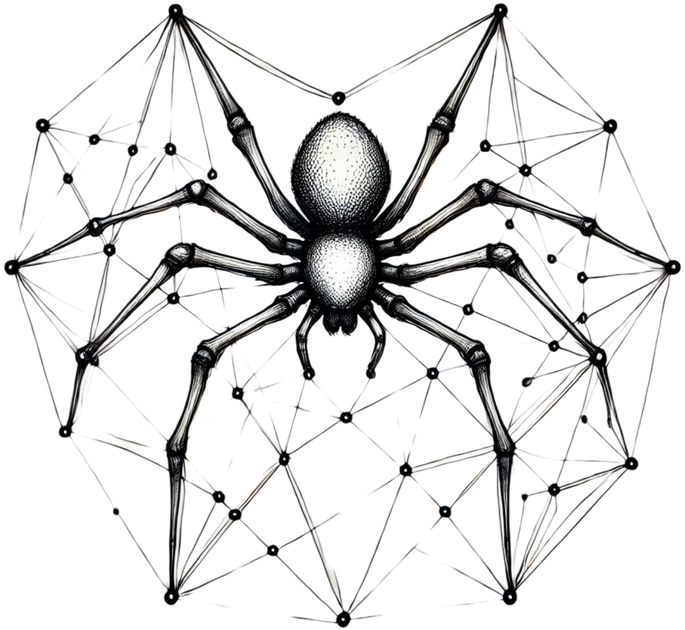


How LSTM Processes "This movie was boring but the ending was amazing!"

1. Forget Gate: Decides to forget "boring" as the ending changes the sentiment
2. Input Gate: Adds "amazing" to memory as it's more relevant for final opinion
3. Output Gate: Predicts "positive" based on remembering the amazing ending

→ The movie gets a positive rating despite mixed feelings!

Spider

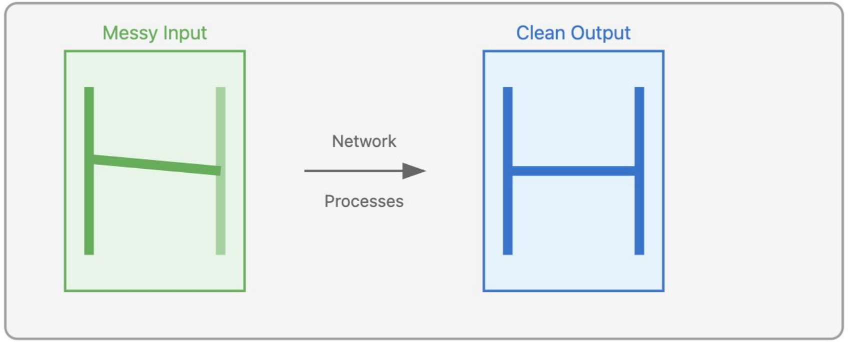


Organizes data into patterns, creates structured representations

Hopfield Networks

Like a spider's web capturing patterns, Hopfield Networks serve as content-addressable memory systems. They excel at pattern completion, taking noisy or incomplete inputs and reconstructing the complete learned pattern.

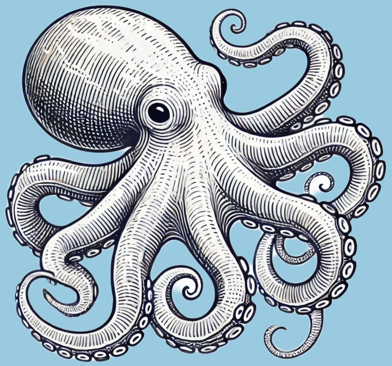
Hopfield Network: Pattern Memory



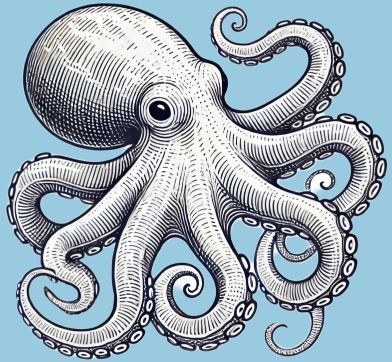
04

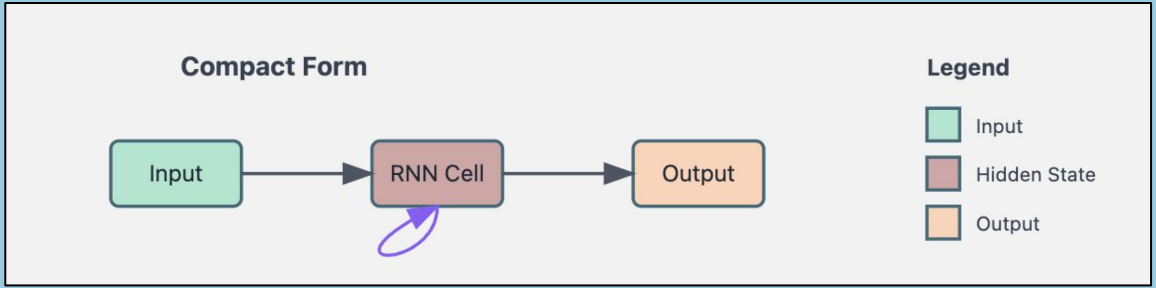
RNN Deep Dive

Recurrent Neural Networks

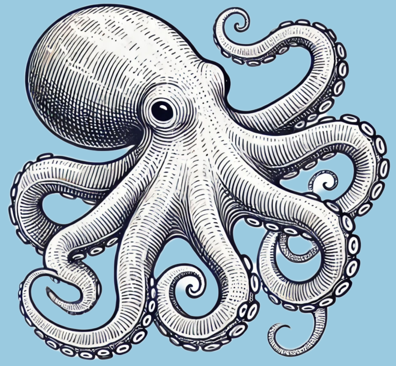


Like an octopus with its distributed neural system, RNNs process information in cycles, maintaining context through time.



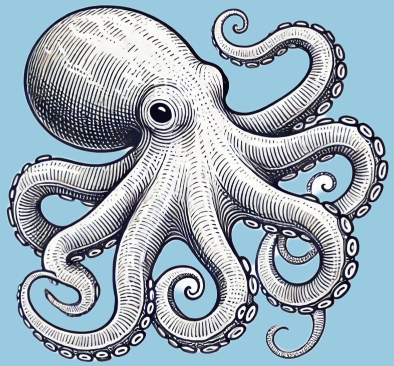


RNNs excel at sequential data processing, making them ideal for tasks like natural language processing, time series analysis, and pattern recognition in temporal data. Their ability to maintain internal state and process sequences of varying lengths makes them particularly versatile among neural network architectures.

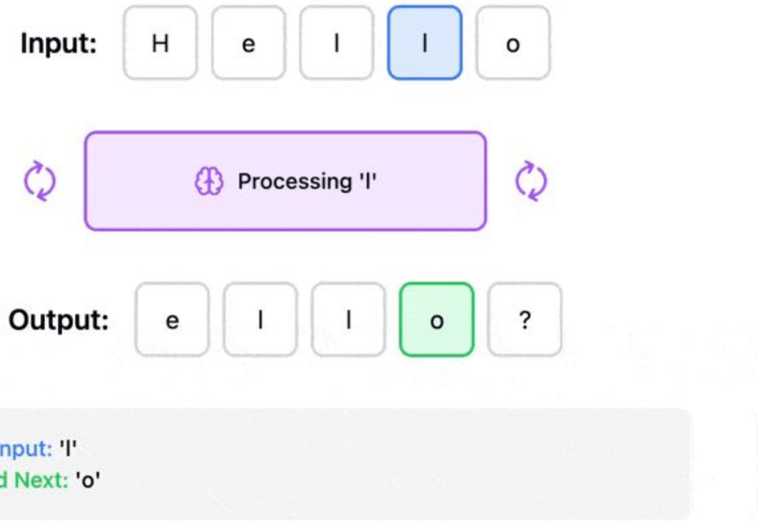


Sample (Simplified) Implementation

```python
# Define RNN model class inheriting from PyTorch's Module
class SimpleRNN(nn.Module):
    def __init__(self, input_size, hidden_size, output_size):
        super(SimpleRNN, self).__init__()

        # Core RNN layer
        # input_size: dimension of input features
        # hidden_size: number of hidden units
        self.rnn = nn.RNN(input_size, hidden_size)

        # Output layer transforms RNN output
        # to desired output dimension
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x, hidden):
        # x shape: (seq_len, batch, input_size)
        # hidden shape: (1, batch, hidden_size)

        # Process input sequence through RNN
        out, hidden = self.rnn(x, hidden)

        # Transform RNN output to final output
        out = self.fc(out)

        # Return both output and final hidden state
        # for next sequence prediction
        return out, hidden
```



RNN Processing Sequential Data



Neural networks in nature demonstrate remarkable efficiency and adaptability, having evolved over millions of years

By studying and emulating these biological systems, we continue to advance artificial neural network design and capabilities. The parallels between natural and artificial neural networks highlight the profound connection between biological intelligence and modern AI systems.

We'll now take questions