The City College of New York

CSC 59866-E: Senior Project I

AI Agents for Decision Making in the Real World

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Deep Learning, Deep Reinforcement Learning (RL) & Multi-Agent Deep Reinforcement Learning (MARL): Training/Finetuning AI Models, Transformers, Q Learning, Deep Q Networks and the Bellman Equation

Logistics

Recent Milestone: Coding Assignment 1 is released!

- Due March 8, 2025 11:59 PM EST
- Take a look at the assignment early on so that you can ask me questions e.g. about using Google Colab, How to Use a GPU runtime, etc.

Next Goal: We will be finalizing Project Groups and Project Topics this week!

Our AI Agents Journey So Far

Lecture 4: We learned Tabular Q-Learning and the Bellman Equation.

Lecture 5: We discussed Reward Modeling and how agents learn to "hack" bad rewards.

Lecture 6 & 7: We covered Distributed Processing, Modalities, and physical network constraints (Latency vs. Bandwidth).

Today: We unite these concepts. How do we scale the Bellman Equation using Deep Learning to solve real-world complexities?

Today's Agenda

Deep Learning & Transformers

- Self-Attention, Encoders, and Decoders

Deep Reinforcement Learning

- Deep Q Networks

Multi-Agent Deep Reinforcement Learning

- Centralized Training Decentralized Execution

Deep Learning & Transformers

Deep Learning Refresher

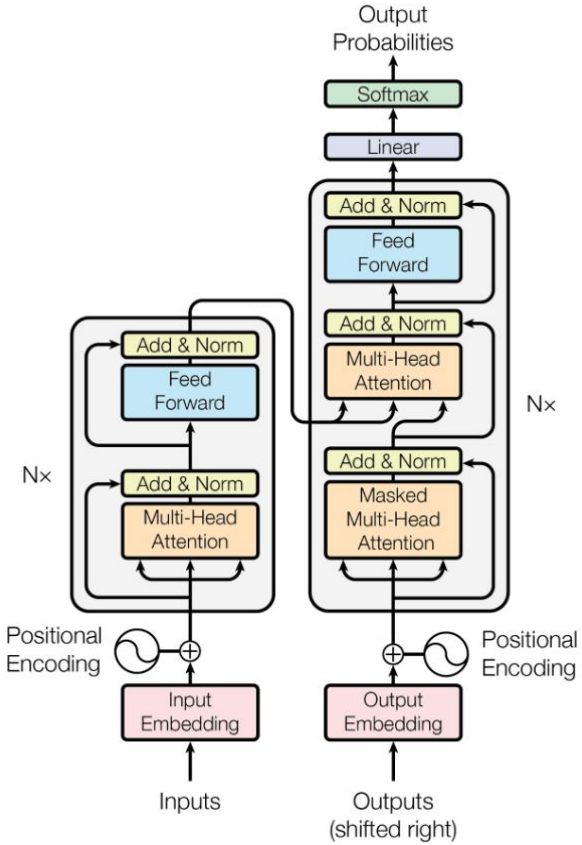
- **The Concept:** Instead of memorizing explicit rules or tables, Deep Learning uses multi-layered artificial neural networks to learn representations of data.
- **Why "Deep"?** Multiple hidden layers allow the model to learn hierarchical features (e.g., Layer 1 learns edges, Layer 2 learns shapes, Layer 3 learns a car).
- **Inference:** A forward pass through the network (computationally fast, great for Edge deployment!).
- **Training:** Backpropagation and Gradient Descent (computationally heavy).

Transformers

Before 2017, Recurrent Neural Networks (RNNs) read data sequentially. Transformers read everything at once.

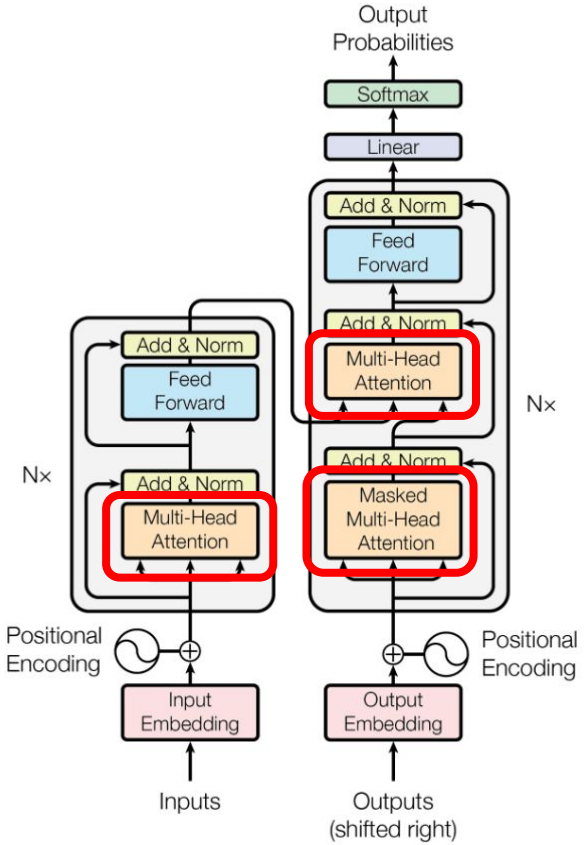
Self-Attention: The mechanism that allows the model to weigh the importance of every part of the input data simultaneously.

Relevance to AI Agents: Transformers aren't just for text (LLMs). They are now the backbone of Multi-Modal Agents (Vision-Language Models) and are actively used to process sequences of actions/states in RL (Decision Transformers).



Self-Attention

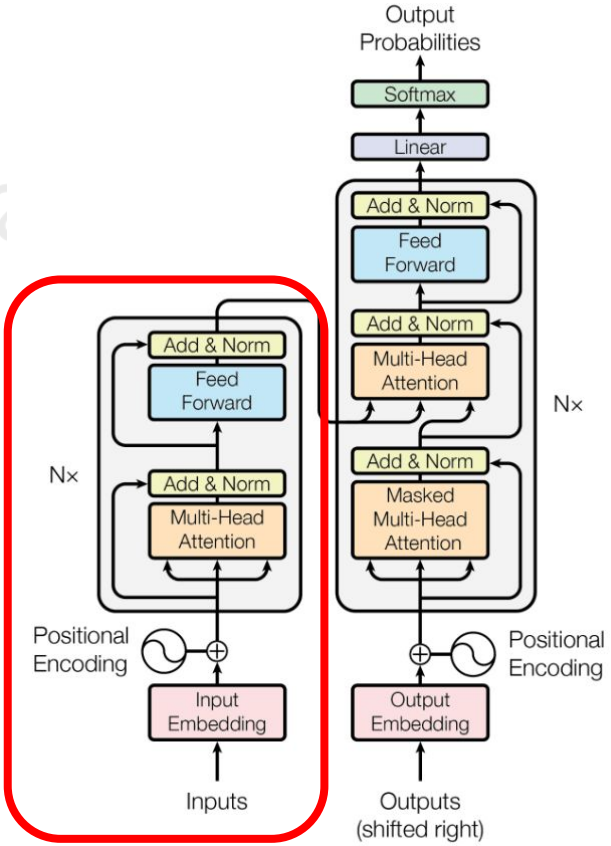
- The fundamental innovation is the **Multi-Head Attention** block.
- Instead of processing a sequence one step at a time, it computes how relevant *every* element in the sequence is to *every other* element simultaneously.
- *In the Diagram:* This is the orange block that allows the network to "attend" to different parts of its own input before moving on.



The Encoder (Left Block)

Reads input data and build a rich, contextual representation.

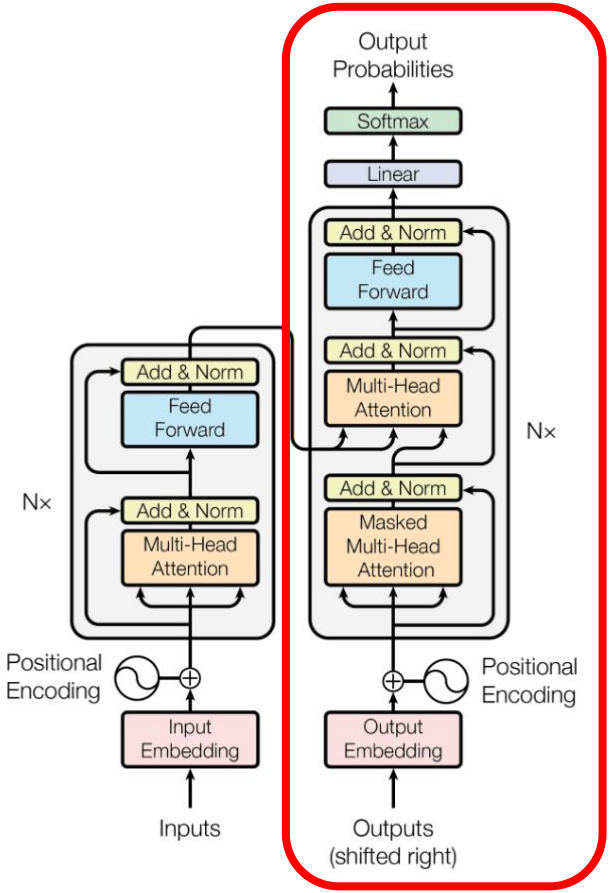
- **Input Embedding & Positional Encoding:** Turns raw data (e.g., words or pixels) into vectors and injects information about order (since the model isn't sequential).
- **Attention Block:** Allows the model to weigh the relationship between different inputs.
- **Feed Forward Block:** A standard neural network layer that processes the output of the attention block.
- **Normalization & Residual Connections (Add & Norm):** Crucial for training deep networks stably.



The Decoder (Right Half)

Goal: Generate the final output based on the Encoder's understanding.

Key Difference: It has **Masked** Attention. When generating the *next* item in a sequence, it can't be allowed to "peek ahead" at the future. It can only attend to past outputs and the full input from the encoder.



Training vs. Fine-Tuning

- **Pre-Training (The Foundation):** Training a massive model from scratch on huge datasets (e.g., the entire internet). Costs millions of dollars.
- **Fine-Tuning (The Adaptation):** Taking a pre-trained model and updating its weights on a small, specific dataset.
    - *Example:* Fine-tuning a generic LLM on medical textbooks so it becomes a surgical assistant.
- **Project Tip:** *Do not pre-train models from scratch in this class.* Use open-source foundation models (via HuggingFace) and fine-tune them for your specific tasks or use techniques at inference (e.g. Multi-Agent Debate).

Deep Reinforcement Learning

Recap: The Bellman Equation & The Curse of Dimensionality

The Bellman Equation: $Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_{a'} Q(s',a') - Q(s,a)]$

The Tabular Limit: In Lecture 4, we saw that a Q-Table requires an entry for every possible State-Action pair.

The Real-World Problem: If your state is a 256×256 RGB camera image, the number of possible states is $256^{256 \times 256 \times 3}$. A table cannot hold this. We call this the **Curse of Dimensionality**.

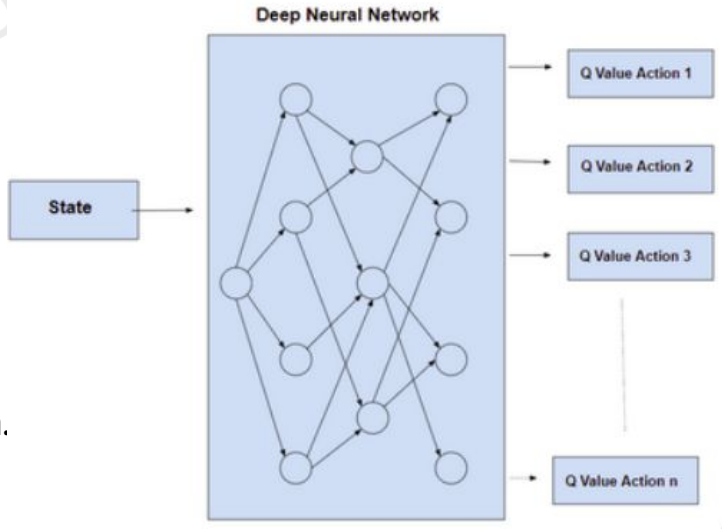
Deep Q Learning

Replace the Q-Table with a Deep Neural Network.

How it works:

- **Input:** The current state (e.g., pixels from a camera, or vector of sensor readings).
- **Network:** Processes the state to extract features.
- **Output:** A predicted Q-Value for *every* possible action.

The Breakthrough: This was the architecture DeepMind used to beat humans at Atari using raw pixels as input.



Deep Q-Learning Updates

Instead of updating a specific cell in a table, we update the *weights* of the neural network.

Target Value: $y = r + \gamma \max_{a'} Q(s', a'; \theta_{target})$

Loss Function: We minimize the Mean Squared Error (MSE) between the predicted Q-value and the Target Value (we use a *target* network here to avoid training instability).

Experience Replay: The agent stores past memories (state, action, reward, next_state) in a buffer and samples them randomly to train the network, breaking harmful correlations in sequential data.

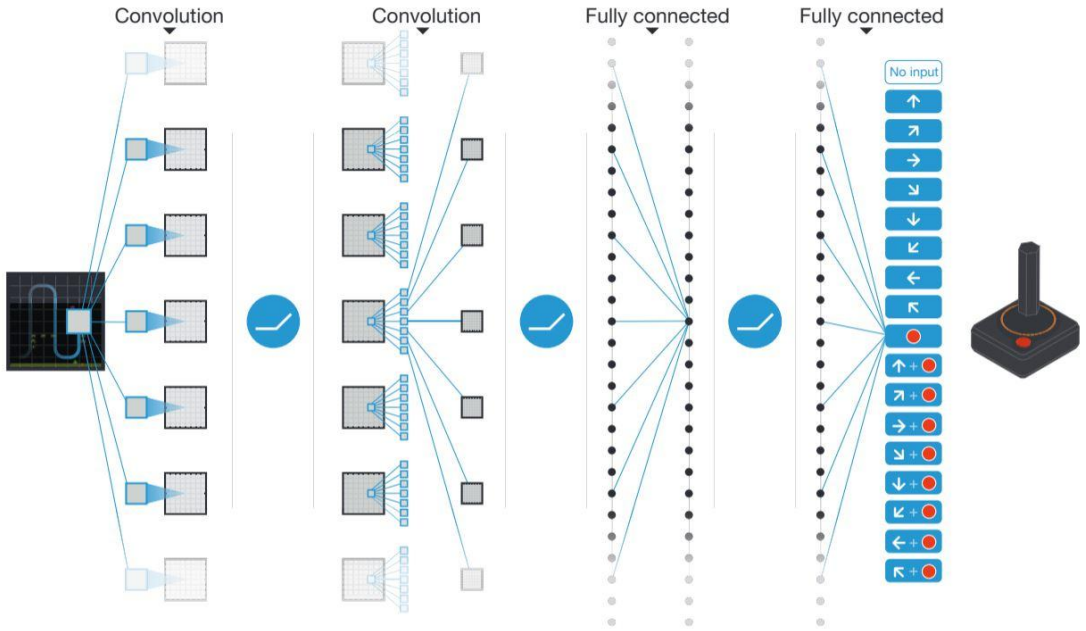
Example: Atari Games

Input: The state (last four game frames)

Network:

- Convolutional layers (useful for image data)
- Fully connected layers (normal neural network)

Output: A vector of q-values, one for each action (controller input)



Multi-Agent Deep Reinforcement Learning

Scaling to MARL

The Jump: What happens when we put multiple DQNs in the same environment?

The Non-Stationarity Problem (Revisited): From the perspective of Agent 1, Agent 2 is just part of the environment. If Agent 2's neural network updates and changes its behavior, Agent 1's environment just unexpectedly shifted.

The Consequence: Independent Deep Q-Learning (each agent learns their own DQNs without considering other agents) in multi-agent settings is notoriously unstable. The agents chase a moving target and often fail to converge.

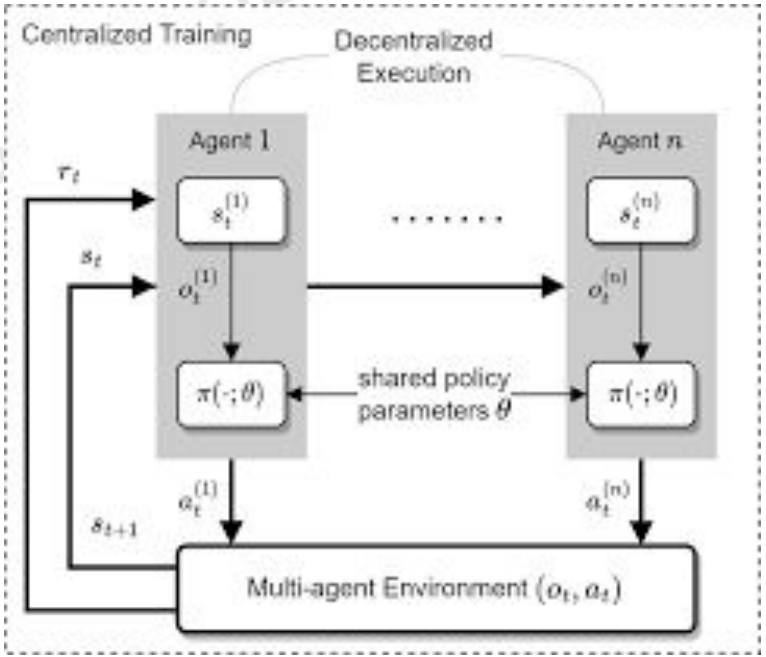
Centralized Training with Decentralized Execution

- **The Standard MARL Architecture:** The dominant paradigm for solving the non-stationarity problem in complex multi-agent environments.
- **Centralized Training (The Global View):**
  - During training in the simulator, we use a central "Critic" neural network.
  - The Critic gets to see the *Global State* (everything) and the actions of all agents. It evaluates how good the team's joint action was.
- **Decentralized Execution (The Edge):**
  - During deployment (the real world), the Central Critic is thrown away.
  - The individual agents ("Actors") only use their own local observations.
- **Relevance:** This is how most complex coordinating agents (like self-driving car fleets or drone swarms) are trained today.

Unpacking CTDE

The outer dotted boundary illustrates Centralized Training, meaning the system has full access to the global state ( ) and global rewards ( ). s_t r_t

The solid grey boxes represent Decentralized Execution, where individual agents operate independently.

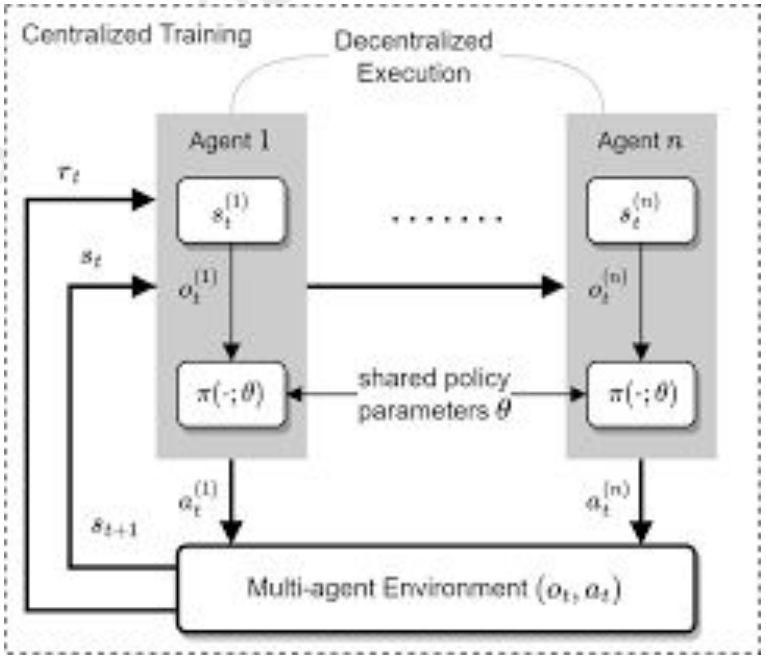


Unpacking CTDE (Cont.)

During execution, each Agent n relies on its local observation ($o_t^{(n)}$) rather than the global state.

The agents use shared policy parameters (θ) within their policy function (π) to map observations to actions ($a_t^{(1)}$, $a_t^{(n)}$).

These individual actions are fed into the Multi-agent Environment, which then advances to the next state (s_{t+1}).



Summary & Next Steps

- **Deep Learning** allows us to approximate the world rather than memorizing it.
- **DQNs** map complex, high-dimensional states to optimal actions using the Bellman Equation as a loss function.
- **CTDE** is the architectural trick we use to train cooperative multi-agent teams without requiring them to share infinite bandwidth in the real world.
- **Next Class:** Exploring Open-Source Tools and simulation environments (JaxMARL, Gymnasium, PettingZoo) to actually build these networks.

Questions?