Prathamesh Arvind Jadhav

DL QB

UNIT-4

1. Explain the difference between ML , ANN , RNN , CNN & LSTM.

Difference Between ML, ANN, CNN, RNN, and LSTM

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1. Machine Learning (ML):

- **Definition**: ML is a branch of Artificial Intelligence (AI) that enables systems to automatically learn and improve from experience without being explicitly programmed.
- **Key Concept**: Uses algorithms to find patterns in data and make decisions or predictions.
- **Types**:
  - **Supervised Learning**: Trained on labeled data (e.g., regression, classification).
  - **Unsupervised Learning**: Finds hidden patterns in unlabeled data (e.g., clustering).
  - **Reinforcement Learning**: Learns via reward-based feedback (e.g., game AI).
- **Applications**: Fraud detection, recommendation systems, weather forecasting.

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2. Artificial Neural Network (ANN):

- **Definition**: ANN is a computational model inspired by the human brain's neuron connections.
- **Structure**: Consists of an input layer, one or more hidden layers, and an output layer. Each layer has neurons connected with weighted links.
- **Function**: Learns complex relationships between input and output using activation functions and backpropagation.
- **Applications**: Handwriting recognition, customer behavior prediction, basic image classification.

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3. Convolutional Neural Network (CNN):

- **Definition**: CNN is a deep learning model specialized for processing visual data.
- **Key Feature**: Uses **convolutional layers** to automatically extract spatial features (e.g., edges, textures) from images.
- **Architecture**: Includes convolutional layers, pooling layers, and fully connected layers.
- **Advantages**: Fewer parameters and better performance on image tasks compared to regular ANN.
- **Applications**: Face recognition, medical image analysis, self-driving cars.

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4. Recurrent Neural Network (RNN):

- **Definition**: RNN is a neural network designed to handle **sequential data** where the current input depends on previous ones.
- **Key Feature**: Maintains a **memory (hidden state)** of past inputs, making it ideal for time-dependent data.
- **Limitation**: Suffers from vanishing gradients in long sequences.
- **Applications**: Text generation, speech recognition, stock market prediction.

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5. Long Short-Term Memory (LSTM):

- **Definition**: LSTM is an advanced type of RNN that can **retain long-term dependencies** using special memory cells.
- **Key Feature**: Incorporates **gates** (input, forget, output) to control the flow of information.
- **Advantage**: Solves the vanishing gradient problem, making it suitable for long sequences.
- **Applications**: Language translation, video captioning, chatbots.

Tabular Comparison:

Aspect	ML	ANN	CNN	RNN	LSTM
Data Type	Any (structured/unstructured)	Any	Spatial (e.g., images)	Sequential (e.g., time series)	Long sequential data
Memory	No memory	No memory	No memory	Short-term memory	Long-term memory
Structure	Algorithms (SVM, trees, etc.)	Input-hidden-output layers	Convolution + pooling + dense	Loops over time steps	RNN with memory cells and gates
Use Cases	Generic prediction tasks	Pattern recognition	Image/video recognition	Text, speech, time series	Long text, translation, audio analysis

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2. Explain RNN in details with real life examples.

Recurrent Neural Network (RNN) –

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1. Definition:

Recurrent Neural Network (RNN) is a type of artificial neural network designed to recognize patterns in **sequential data** (data that is ordered and dependent on previous inputs). Unlike traditional feedforward neural networks, RNNs have **loops** in their architecture, allowing information to **persist over time**.

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2. Key Characteristics:

- **Sequence Processing**: Can handle sequences of arbitrary length (text, audio, time series).
- **Memory**: Maintains a **hidden state** that captures information about previous inputs.
- **Shared Weights**: Uses the same weights for each time step, making it efficient for sequence modeling.
- **Backpropagation Through Time (BPTT)**: RNNs are trained using a special version of backpropagation that accounts for the sequential nature of inputs.

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3. Architecture:

Basic RNN Cell:

Each time step takes an input x(t) and the previous hidden state h(t-1), processes them to generate a new hidden state h(t) and optionally an output y(t).

Mathematically:

$h(t) = f(Wx * x(t) + Wh * h(t-1) + b)$

Where:

- Wx, Wh = weight matrices
- b = bias
- f = activation function (typically tanh or ReLU)

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4. Working Principle:

- The network reads one input at a time and remembers previous inputs using hidden states.
- This "memory" allows RNNs to understand context and temporal relationships.
- However, basic RNNs struggle with long-term dependencies due to the **vanishing gradient problem**, which limits learning across many time steps.

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5. Real-Life Examples of RNNs:

a) Language Modeling and Text Prediction

- Predicting the next word in a sentence.
- E.g., Autocomplete in smartphones or Google Search.

b) Speech Recognition

- Converts audio signals into text by understanding the temporal flow of spoken words.
- Used in virtual assistants like **Siri, Alexa, Google Assistant**.

c) Music Generation

- Learns from sequences of musical notes and generates new music.
- Applications in AI-based composition tools.

d) Time Series Forecasting

- Predicts future stock prices, temperature, or sales based on past trends.
- Widely used in **finance, meteorology, and retail analytics**.

e) Machine Translation

- Converts text from one language to another by processing word sequences.
- E.g., Google Translate uses RNNs in earlier versions.

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6. Advantages:

- Excellent for sequential and time-series data.
- Can model contextual relationships over time.
- Compact architecture due to shared weights.

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7. Limitations:

- **Vanishing/Exploding Gradients** in long sequences.
- Difficult to train on long-term dependencies.
- Slow training due to sequential nature (no parallelism).

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8. Improvements Over Basic RNNs:

To overcome RNN limitations, **variants** like:

- **LSTM (Long Short-Term Memory)** and
- **GRU (Gated Recurrent Unit)**
  were developed. They retain long-term dependencies more effectively using gating mechanisms.

3.Explain Bidirectional RNN in details with Example?

Bidirectional Recurrent Neural Network (Bi-RNN)

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1. Definition:

A **Bidirectional Recurrent Neural Network (Bi-RNN)** is an advanced type of RNN that improves performance on sequence tasks by processing the input data in **both forward and backward directions**. This allows the network to have access to **past (previous)** and **future (next)** context at every point in the sequence.

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2. Key Idea:

- Standard RNNs only use **past context** (previous inputs).
- Bi-RNNs use **two RNNs**: one processes the sequence **from start to end** (forward), and another processes it **from end to start** (backward).
- The final output at each time step is a **combination** of both directions, allowing the model to understand full context.

3. Working:

1. Input sequence is fed **forward** to one RNN and **backward** to another.
2. Both RNNs independently compute hidden states.
3. Outputs from both RNNs are **merged** to get the final output at each time step.

This helps the model understand context from **before and after** each word, frame, or data point.

---

3. Architecture:

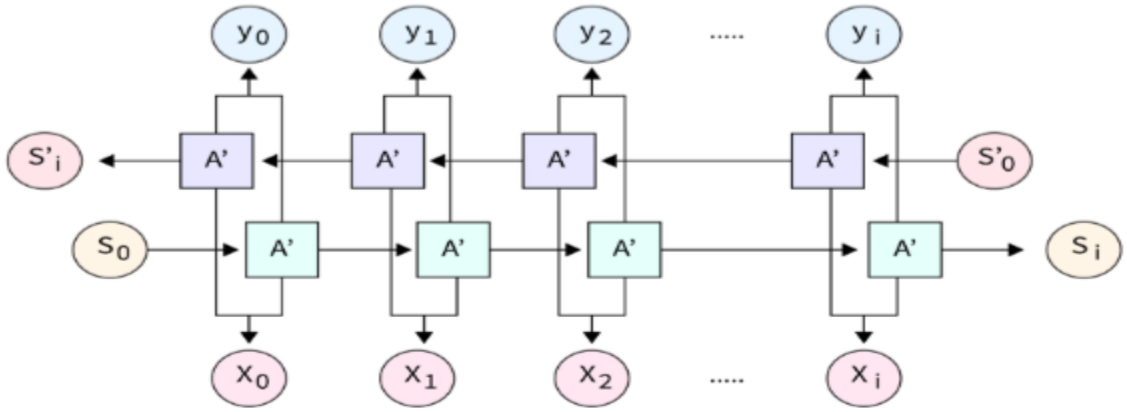
Each input is passed through:

- **Forward RNN:** $\overrightarrow{h_t} = f(W_x^f x_t + W_h^f \overrightarrow{h_{t-1}} + b^f)$
- **Backward RNN:** $\overleftarrow{h_t} = f(W_x^b x_t + W_h^b \overleftarrow{h_{t+1}} + b^b)$

Final output at time `t`:

$$y_t = g(\overrightarrow{h_t}, \overleftarrow{h_t})$$

Where `g` is a function to combine both hidden states (e.g., concatenation or summation).



4. Real-Life Example:

Named Entity Recognition (NER):

- Task: Identify names of people, places, organizations in text.
- Input: "Sachin Tendulkar played for India."
- For the word "played", Bi-RNN considers:
  - **Past**: "Sachin Tendulkar"
  - **Future**: "for India"
- This full context helps in correctly tagging "Sachin Tendulkar" as a **person** and "India" as a **location**.

---

5. Applications:

- **Natural Language Processing (NLP)**:
  - Part-of-speech tagging
  - Machine translation
  - Question answering
- **Speech Recognition**:
  - Understands complete audio context for better transcription.
- **Bioinformatics**:
  - Gene sequence analysis.

---

6. Advantages:

- Understands **both past and future** context.
- Improves accuracy in tasks where **contextual meaning** is important.
- Enhances performance over unidirectional RNNs in many sequence-based applications.

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7. Limitations:

- Requires **full input sequence** beforehand, so not ideal for real-time streaming tasks.
- Computationally **more expensive** than standard RNNs.
- Cannot be used for causal tasks (e.g., real-time prediction).

4. Explain sequence-to-sequence architecture with example in details?

Sequence-to-Sequence (Seq2Seq) Architecture –

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1. Definition:

Sequence-to-Sequence (Seq2Seq) is a **neural network architecture** used to transform one sequence into another. It is especially useful when the **input and output sequences are of different lengths**.

- Example: Translating the sentence "How are you?" into French "Comment ça va ?"

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2. Key Components:

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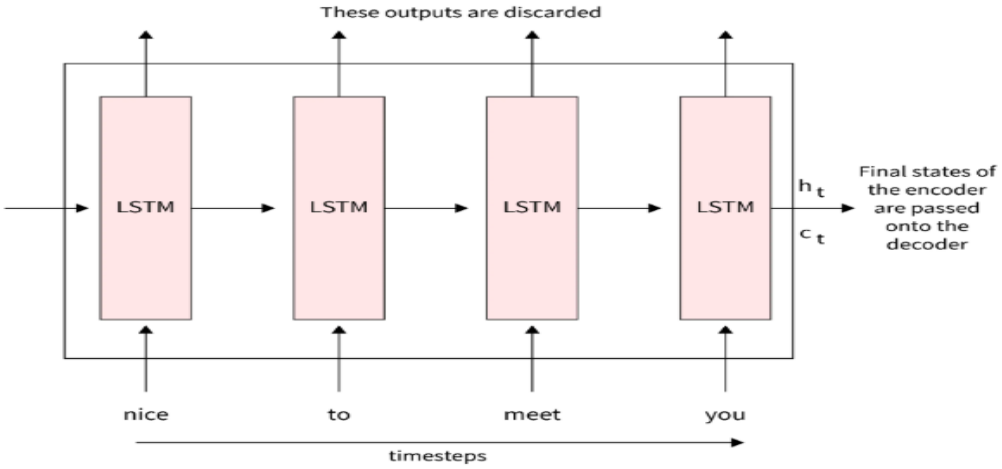
The Seq2Seq architecture consists of two main parts:

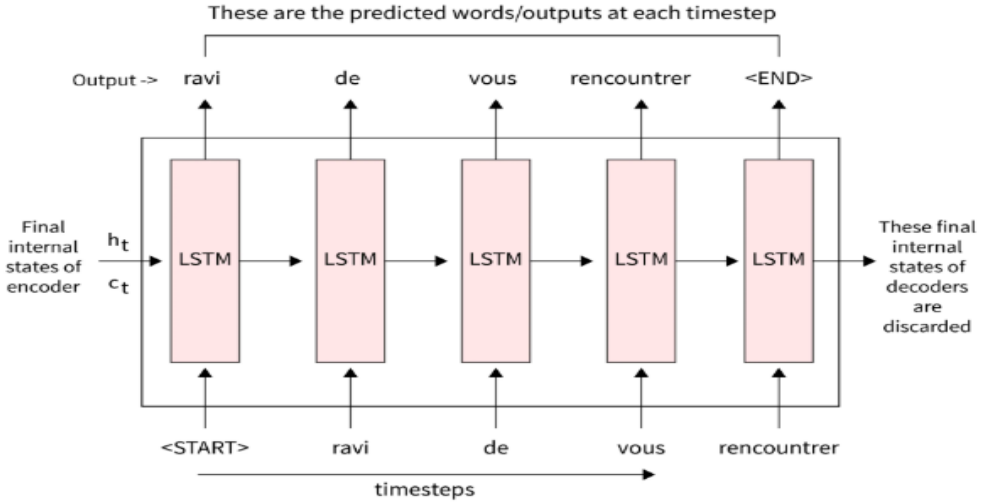
a) Encoder:

- Takes the input sequence (e.g., a sentence in English).
- Processes it and converts it into a fixed-size **context vector** (also called thought vector) that summarizes the information.
- Typically built using RNN, GRU, or LSTM cells.



b) Decoder:

- Takes the context vector from the encoder.
- Generates the output sequence one element at a time (e.g., a sentence in French).
- Also built using RNN/GRU/LSTM, with output from previous step fed as input to the next.



3. Working Principle:

Step-by-Step:

1. Input sequence: "How are you?" → fed word by word into the encoder.
2. Encoder processes and outputs a final hidden state (context vector).
3. Decoder receives this context and begins generating the output sequence "Comment ça va ?" word by word.
4. Decoder stops when an end-of-sequence token <EOS> is produced.

---

4. Example: Machine Translation

Input (English): "I love programming"

Output (French): "J'aime la programmation"

- **Encoder** processes: ["I", "love", "programming"]
- **Context Vector**: A hidden state summarizing the sentence.
- **Decoder** generates: ["J'", "aime", "la", "programmation"]

---

5. Applications of Seq2Seq:

Domain	Use Case
NLP	Machine translation (e.g., Google Translate)
Chatbots	Dialogue generation
Text Summarization	Extractive/abstractive summaries
Speech Recognition	Converting audio to text
Code Generation	Converting natural language to code

---

6. Enhancements over Basic Seq2Seq:

- **Attention Mechanism**:
    - Instead of relying on a single context vector, attention allows the decoder to **focus on different parts of the input** at each decoding step.

  - This improves translation quality, especially for long sentences.
- **Beam Search Decoding**:
  - Improves output by exploring multiple decoding paths instead of greedy selection.

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7. Advantages:

- Handles **variable-length** input and output sequences.
- Effective in many real-world NLP tasks.
- Easily extendable with attention for better performance.

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8. Limitations:

- Without attention, context vector may **lose information** for long sequences.
- Training is **computationally expensive**.
- Decoder must wait for the **entire input sequence** to be processed (not suitable for real-time applications).

5. Explain Deep recurrent networks with examples?

Deep Recurrent Networks (DRNNs) –

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1. Definition:

A **Deep Recurrent Neural Network (DRNN)** is an extension of a basic RNN, where **multiple recurrent layers are stacked** on top of each other to form a **deep architecture**. This allows the network to **learn hierarchical temporal representations** of sequential data.

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2. Motivation:

- **Basic RNNs** have limited capacity to learn complex patterns due to shallow structure (single layer).
- **DRNNs** increase depth by stacking RNN layers, allowing the model to **capture both short- and long-term dependencies** more effectively.

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3. Architecture:

DRNN Structure:

- Input is passed through **multiple RNN layers** sequentially.
- The hidden state output of each layer is used as the input for the next layer.

Example with 3 layers:

Input x → RNN Layer 1 → h1 → RNN Layer 2 → h2 → RNN Layer 3 → Output

Each layer has its own weights and learns different levels of abstraction:

- Lower layers learn low-level features (e.g., sounds, characters)
- Higher layers learn high-level patterns (e.g., words, meaning)

---

4. Working:

1. At each time step, the input is passed to the first RNN layer.
2. The hidden state is calculated and passed to the next RNN layer.
3. This continues through all layers until the final output is produced.
4. The process is repeated across time steps using **Backpropagation Through Time (BPTT)**.

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5. Real-Life Examples:

a) Speech Recognition:

- DRNNs process raw audio signals at lower layers and extract phonemes/words at higher layers.
- Used in tools like **Google Voice, Apple Siri**.

b) Text-to-Speech (TTS):

- Converts text into natural-sounding speech by learning phonetic and temporal relationships.

c) Video Analysis:

- Frames are treated as sequences; DRNNs capture movement patterns across time.

d) Handwriting Recognition:

- Learns temporal stroke sequences to identify characters/words.

---

6. Advantages:

Feature	Benefit
Depth	Learns complex features across multiple time scales
Hierarchical Representation	Lower layers learn simple patterns, higher layers learn abstract features
Improved Accuracy	Outperforms shallow RNNs in tasks with complex sequences

---

7. Limitations:

- **Higher computational cost** due to more layers and parameters.
- **Vanishing gradient problem** still exists (though mitigated using LSTM or GRU cells).
- Requires **large training data** to avoid overfitting.
- **Slower training** due to depth and recurrence.

---

8. Variants of DRNNs:

- **Deep LSTM**: Uses stacked LSTM layers instead of vanilla RNNs.
- **Bidirectional DRNNs**: Processes input in both forward and backward directions across layers.
- **GRU-based DRNNs**: Uses Gated Recurrent Units for better performance on fewer resources.

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6.Explain AutoEncode and Bidirectional Encoder Representation From Transformation.

Autoencoders & BERT –

PART A: Autoencoders

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1. Definition:

An **autoencoder** is a type of **unsupervised neural network** used to learn **efficient data representations (encodings)** by compressing and reconstructing input data. It consists of two main components: **encoder** and **decoder**.

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2. Architecture:

- **Encoder**: Compresses the input into a **latent (bottleneck) representation**.
- **Decoder**: Reconstructs the original input from the compressed representation.

Example:

Input: Image of digit "5" → Encoder compresses it → Decoder reconstructs the same image.

Input → [Encoder] → Compressed Representation → [Decoder] → Output (Reconstructed Input)

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3. Working:

- Autoencoders learn to **minimize the reconstruction error**, i.e., the difference between input and output.
- Used for tasks like **denoising**, **dimensionality reduction**, and **anomaly detection**.

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4. Types of Autoencoders:

- **Denoising Autoencoder**: Learns to remove noise from corrupted input.
- **Sparse Autoencoder**: Uses sparsity constraints to learn meaningful features.
- **Variational Autoencoder (VAE)**: Learns a distribution over latent variables (used in generative models).

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5. Applications:

- Image compression and reconstruction.
- Feature extraction and pretraining.
- Anomaly detection in finance and cybersecurity.
- Recommendation systems.

PART B: BERT (Bidirectional Encoder Representations from Transformers)

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1. Definition:

BERT is a **pretrained deep learning language model** developed by Google. It is based on the **Transformer architecture** and is designed to understand the **context of words in a sentence bidirectionally**.

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2. Key Concept – Bidirectionality:

- Traditional models (like RNNs) read text **left-to-right** or **right-to-left**.
- **BERT reads in both directions simultaneously**, giving it a **deep understanding of context**.

---

3. Architecture:

- Built entirely with **Transformer encoder blocks** (no decoder).
- Inputs are tokenized and passed through multiple self-attention layers to capture relationships between all words in a sentence.

---

4. Pretraining Tasks:

BERT is pretrained on two main tasks:

- **Masked Language Modeling (MLM)**:
    - Random words are masked, and the model predicts them.

    - E.g., “The cat sat on the [MASK].” → Predict: “mat”
- **Next Sentence Prediction (NSP)**:
    - The model learns relationships between pairs of sentences.
    - Useful in question answering and dialogue systems.

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5. Applications:

- **Question Answering** (e.g., SQuAD)
- **Text Classification**
- **Sentiment Analysis**
- **Named Entity Recognition (NER)**
- **Text Summarization**
- Used in tools like **Google Search**, **chatbots**, and **virtual assistants**.

---

6. Advantages of BERT:

- Deep bidirectional understanding of text.
- Pretrained on large corpus (Wikipedia + BooksCorpus).
- Can be fine-tuned for specific NLP tasks with high accuracy.
- Replaces traditional NLP pipelines with a unified model.

---

7. Comparison: Autoencoder vs BERT

Feature	Autoencoder	BERT
Type	Unsupervised neural network	Pretrained transformer-based language model
Focus	Data compression and reconstruction	Language understanding and prediction
Architecture	Encoder + Decoder	Only Encoder (Transformer)
Use Case	Feature extraction, anomaly detection	NLP tasks (QA, classification, NER, etc.)

7. Difference Between BRNN and Recurrent Neural Network?

Direction of Processing	Processes input **only in forward direction** (past → future)	Processes input in **both forward and backward directions**
Architecture	Single RNN layer (unidirectional)	Two RNN layers: one forward, one backward
Context Captured	Captures **only past (previous)** information	Captures **both past and future** context
Accuracy (in NLP tasks)	Lower, due to lack of future context	Higher, due to full sentence understanding
Real-time Usage	Suitable for **real-time/streaming** applications	**Not suitable** for real-time (needs full input sequence)
Complexity	Simpler, fewer computations	More complex and computationally expensive
Use Cases	Time series prediction, speech generation	Machine translation, Named Entity Recognition, QA systems
Example	Predicting next word using previous words only	Predicting word meaning using **both previous and next** words

---

Example:

Input Sentence: "He went to the bank to deposit money."

- **RNN**: When reading the word "bank", it only uses the **previous words** ("He went to the").
- **BRNN**: It also looks at the **future words** ("to deposit money") to understand that "bank" refers to a financial institution (not a riverbank).

UNIT-5

1. Explain GAN in detail with example?

Generative Adversarial Networks (GANs) –

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1. Definition:

A **Generative Adversarial Network (GAN)** is a type of deep learning model consisting of two neural networks — a **Generator** and a **Discriminator** — that are trained together using **adversarial training**.

- The **Generator** creates fake data.
- The **Discriminator** tries to distinguish between real and fake data.

Both networks are locked in a game where the generator improves to fool the discriminator, and the discriminator improves to detect fakes.

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2. Architecture:

GAN consists of two parts:

Component	Function
Generator	Takes random noise as input and generates data similar to real data.
Discriminator	Takes real and generated data and predicts whether it is real or fake.

Both networks are trained simultaneously in a loop.

---

3. Working of GAN:

1. **Input random noise** (usually a vector of random numbers) is passed to the **Generator**.
2. Generator produces **fake data** (e.g., a fake image).
3. The **Discriminator** receives both:
    - Real data from the dataset.
    - Fake data from the Generator.
4. Discriminator tries to **classify** whether the input is real or fake.
5. **Losses are calculated**:
    - Generator is penalized if the fake data is easily detected.
    - Discriminator is penalized if it fails to detect fake data.
6. Both networks are updated via backpropagation.
7. Process continues until **Generator creates highly realistic data**.

---

4. Real-Life Example: Image Generation

Scenario: Creating fake human faces

- **Generator**: Creates images of human faces that don’t actually exist.
- **Discriminator**: Tries to tell whether a face is real (from dataset) or fake (from Generator).
- After many iterations, the Generator produces images so realistic that even humans can't distinguish them.

GAN-generated faces are used in websites like **thispersondoesnotexist.com**.

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5. Applications of GANs:

Domain	Application
Computer Vision	Image generation, super-resolution, inpainting
Healthcare	Generating synthetic medical images
Entertainment	Creating art, music, cartoons
Gaming	Realistic environment creation
Security	Deepfake videos and facial animation
Data Augmentation	Creating more training data for ML models

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6. Advantages:

- Can generate **high-quality, realistic data**.
- Useful for tasks where real data is **scarce or sensitive**.
- Improves **data diversity** for machine learning training.

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7. Limitations:

- **Training is unstable**: GANs are hard to train due to adversarial setup.
- May suffer from **mode collapse**: Generator produces limited variety of outputs.
- Can be **misused** for fake media (e.g., deepfakes).

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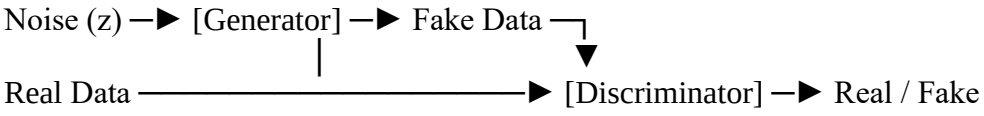
8. Diagram :



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2. Explain Boltzmann Machine with Example?

Boltzmann Machine –

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1. Definition:

A **Boltzmann Machine (BM)** is a type of **stochastic recurrent neural network** that can learn complex probability distributions over its inputs. It is a **generative model** that uses energy-based learning to represent and sample from data distributions.

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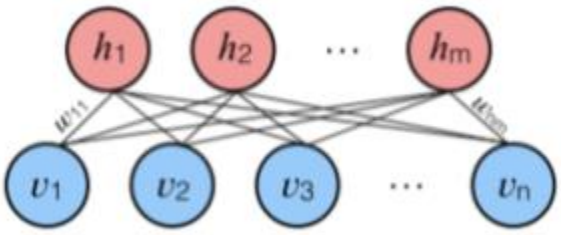
2. Architecture:

- Composed of **neurons (nodes)** arranged in layers or fully connected network.
- Each neuron is a **binary unit** (can be ON or OFF).
- Connections between neurons are **symmetric** (weights are the same in both directions).
- There are **visible units** (represent observed data) and **hidden units** (capture dependencies).



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3. Working Principle:

- The network learns by minimizing an **energy function**, which corresponds to the probability of the system's state.
- Each state of the network has an associated **energy**; lower energy states correspond to more probable data configurations.
- The network undergoes **stochastic updates** where units switch ON or OFF based on probabilities computed from current weights and states.
- Through iterative sampling (like Gibbs sampling), it eventually models the input data distribution.

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4. Example:

Suppose we want to model the pattern of handwritten digits:

- **Visible units** correspond to pixels of the digit images.
- **Hidden units** capture the latent features like strokes or curves.
- After training, the Boltzmann Machine can **generate new digit images** by sampling from the learned distribution.

---

5. Training Boltzmann Machines:

- Use **contrastive divergence** or **Markov Chain Monte Carlo (MCMC)** methods to approximate gradients.
- Adjust weights to reduce the difference between observed data distribution and model distribution.

---

6. Applications:

Domain	Use Case
Feature Learning	Extract latent features in data
Dimensionality Reduction	Compress high-dimensional data
Collaborative Filtering	Recommendation systems (e.g., Netflix)
Image Recognition	Learn representations of image data

---

7. Advantages:

- Can model **complex distributions** with hidden layers.
- **Generative capabilities** allow synthesis of new data.
- Foundation for **Deep Belief Networks (DBNs)** and other deep models.

---

8. Limitations:

- Training is **computationally expensive** and slow.

- Sampling requires many iterations to converge.
- Difficult to scale to very large datasets.

3. Explain Deep Belief Network with example?

Deep Belief Network (DBN) –

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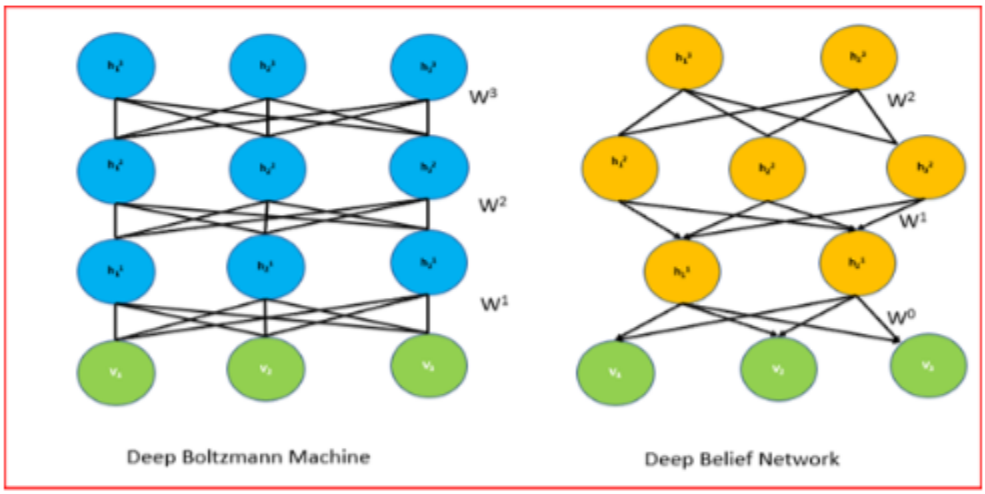
1. Definition:

A **Deep Belief Network (DBN)** is a type of **deep neural network** composed of multiple layers of **Restricted Boltzmann Machines (RBMs)** stacked together. It is a **generative probabilistic model** that learns to represent complex data distributions in an unsupervised way and can be fine-tuned for supervised tasks.



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2. Architecture:

- DBN consists of **multiple layers of RBMs**.
- Each RBM layer learns to model the features or representations of the layer below.
- The first layer takes the raw input data, and each subsequent layer learns a higher-level representation.
- After pretraining with RBMs, the whole network can be **fine-tuned using supervised learning** (e.g., backpropagation).

---

3. How it works:

- **Layer-wise pretraining:**
  Each RBM is trained individually to learn features from its input (either raw data or hidden layer output from previous RBM).
- **Stacking:**
  The hidden layer of one RBM becomes the visible layer for the next RBM.
- **Fine-tuning:**
  After pretraining, the entire network can be fine-tuned on a specific task like classification.

---

4. Example: Handwritten Digit Recognition

- Input: Images of handwritten digits (like MNIST dataset).
- The first RBM learns low-level features (edges, strokes).
- The second RBM learns higher-level features (digit shapes).
- After pretraining, the DBN is fine-tuned with labeled digits to classify images into digits 0-9.
- This hierarchical learning improves accuracy over shallow networks.

---

5. Advantages of DBN:

- Can **learn complex data representations** in a hierarchical manner.
- Helps with **unsupervised pretraining**, which reduces the problem of training deep networks from scratch.
- Improves performance when labeled data is limited.
- Efficient in **dimensionality reduction** and feature extraction.

---

6. Applications:

- Image recognition and classification.
- Speech recognition.
- Dimensionality reduction and feature learning.
- Anomaly detection.

4. Difference between Autoencoders & RBMs?

Difference Between Autoencoders and RBMs

Feature	Autoencoders	Restricted Boltzmann Machines (RBMs)
Type of Model	Deterministic neural network	Probabilistic graphical model
Architecture	Encoder + Decoder neural network	Bipartite network with visible and hidden units
Training Objective	Minimize reconstruction error (e.g., MSE loss)	Maximize likelihood of data via energy-based model
Units	Usually continuous activations (ReLU, sigmoid)	Binary or probabilistic binary units
Learning Method	Backpropagation	Contrastive Divergence or Gibbs Sampling
Data Handling	Works well with continuous and real-valued data	Typically models binary or discrete data
Generative Ability	Can reconstruct input but not inherently probabilistic	Can generate new samples from learned distribution
Interpretability	Less probabilistic, more black-box	Based on energy function, interpretable in probabilistic terms
Applications	Dimensionality reduction, denoising, feature extraction	Collaborative filtering, feature learning, pretraining deep networks
Complexity	Usually simpler and faster to train	Training can be slower due to sampling and probabilistic inference

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UNIT-6

1. Explain Dynamic Programming with the help of example (Robot in a grid world)?

Dynamic Programming in Reinforcement Learning –

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1. Definition:

Dynamic Programming (DP) in reinforcement learning is a class of methods used to compute **optimal policies** by breaking a problem into **simpler overlapping sub-problems** and solving them **recursively**. It assumes **complete knowledge** of the environment in the form of a **Markov Decision Process (MDP)**.

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2. Requirements:

DP methods are applicable **only** when:

- The environment's **transition probabilities** and **reward function** are known.
- The problem is formulated as an **MDP** with well-defined:
  - States (S)
  - Actions (A)
  - Rewards (R)
  - Transition probabilities (P)

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3. Key Algorithms in DP:

 Policy Evaluation:

- Computes the **value function** V(s)V(s)V(s) for a **given policy**.
- It estimates the **expected cumulative reward** from each state.
- Done **iteratively** until value estimates **converge**.

 Policy Iteration:

- Alternates between two steps:
  1. **Policy Evaluation** – Evaluate current policy.
  2. **Policy Improvement** – Update the policy using current value function.
- Continues until the policy becomes **stable and optimal**.

Example: Robot in a Grid World (3x3)

 Scenario:

- A robot is in a 3x3 grid (total of 9 states).
- The goal is to reach the **bottom-right corner**.
- **Reward:**
  - +1 for reaching the goal
  - -1 for every step taken (to encourage efficiency)
- The robot can move **Up, Down, Left, Right**.
- It may **slip** into adjacent cells due to uncertainty.

 How DP Works in This Example:

Step	Description
1. **Initialize Values**	Assign initial random values to all 9 states, usually 0.
2. **Policy Evaluation**	Use the **Bellman Expectation Equation** to update each state's value based on reward + expected value of next state (weighted by transition probability). Repeat until convergence.
3. **Policy Improvement**	For each state, choose the action that leads to the highest-valued neighbor. Update the policy accordingly.
4. **Repeat**	Iterate steps 2 and 3 until the value function and policy do not change.

 Result:

- The robot learns the **shortest and safest path** to the goal.
- It avoids inefficient routes that take too many steps or involve risk.
- The final policy guides the robot optimally from any cell.

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4. Advantages of DP in RL:

- Guarantees **optimal policy** if MDP is known.
- **Systematic** and **stable** approach.

- Forms the **foundation** for other RL algorithms like Q-learning.

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5. Limitations:

- Requires **complete knowledge** of the environment.
- **Computationally expensive** in large state spaces.

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6. Why DP Matters in DL

- **Reduces redundant computation** in sequence models.
- Helps in building efficient **temporal models** like RNNs and LSTMs.
- Plays a vital role in **policy optimization** in intelligent agents.

2. Explain Markov Decision Process with the help of Robot in grid world example?

Markov Decision Process (MDP) – Explained with Robot in Grid World Example

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1. What is a Markov Decision Process (MDP)?

A **Markov Decision Process (MDP)** is a mathematical framework used for modeling **decision-making** where outcomes are partly **random** and partly **under the control of an agent**. MDPs are fundamental in **Reinforcement Learning (RL)**.

An MDP is defined by a 5-tuple:

MDP = (S, A, P, R, γ)

Where:

- S = Set of **states**
- A = Set of **actions**
- P(s'|s,a) = **Transition probability** from state s to s' using action a
- R(s,a) = **Reward** received for taking action a in state s
- γ = **Discount factor** ($0 \leq \gamma \leq 1$), determines the importance of future rewards

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2. Robot in a Grid World – MDP Example

Imagine a robot placed in a 4x4 grid world. It can move:

- **Up**, **Down**, **Left**, or **Right**

The goal is to reach a **destination cell** while **avoiding obstacles** and **maximizing reward**.

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3. Defining MDP Components:

Component	Example from Grid World
States (S)	Each grid cell (e.g., (0,0), (0,1), ..., (3,3))
Actions (A)	{Up, Down, Left, Right}
Transition (P)	Probability of moving to a new cell (can include slipping/stochastic moves)
Reward (R)	+10 for reaching goal, -10 for hitting obstacle, -1 per move (to encourage shortest path)
Discount (γ)	Usually 0.9 (to prioritize immediate rewards slightly more than distant ones)

---

4. Example:

Grid:

S . . G
. X . .
. . X .
. . . .

- **S** = Start state (0,0)
- **G** = Goal state (0,3), reward = +10
- **X** = Obstacles, reward = -10
- . = Empty cells, each move gives reward = -1

Task:

The robot needs to find the best path from S to G while avoiding obstacles.

---

5. Solving the MDP:

MDPs are solved using algorithms like:

- **Value Iteration** (updates value of each state iteratively)
- **Policy Iteration** (improves policy based on value estimates)
- **Q-Learning** (used in RL when transition/reward models are unknown)

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6. Why Use MDP in Deep Learning?

- Used in **Reinforcement Learning (RL)** agents.
- Applied in robotics, game playing (like AlphaGo), and path planning.
- Helps train agents to make decisions over time with **uncertain outcomes**.

3. Explain Deep Reinforcement Learning with Tic-Tac-Toe game Example?

Deep Reinforcement Learning (Deep RL) – Explained with Tic-Tac-Toe Game Example

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1. What is Deep Reinforcement Learning?

Deep Reinforcement Learning (Deep RL) is a combination of:

- **Reinforcement Learning (RL):** An agent learns to make decisions by interacting with an environment to maximize cumulative rewards.
- **Deep Learning (DL):** Neural networks are used to approximate value functions, policies, or Q-values when the state/action space is large or continuous.

So, **Deep RL = RL + Deep Neural Networks**

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2. Components of RL (applied to games like Tic-Tac-Toe):

Term	Description
Agent	The AI playing the game (X or O)
Environment	The game board (Tic-Tac-Toe grid)
State	Current board configuration

Term	Description
Action	Placing an X or O in one of the empty cells
Reward	+1 for win, 0 for draw, -1 for loss
Policy	Strategy of selecting the next move

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3. How Deep RL Works in Tic-Tac-Toe

□ The Deep Q-Network (DQN) Approach:

1. **Q-Learning** is a popular RL algorithm where the agent learns a Q-table:
   Q(s, a) = expected reward of taking action a in state s.
2. In **Deep RL**, instead of a Q-table, we use a **Deep Neural Network** to estimate Q-values.
3. The **inputs** to the neural network are the board state (e.g., 3×3 grid → 9 inputs).
4. The **outputs** are the Q-values for each possible move (9 values, one per cell).

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4. Training the Agent:

- The agent plays thousands of games against itself or a random opponent.
- After each move:
  - It gets a **reward** based on the outcome.
  - It **updates its network** to better predict Q-values using the Bellman equation:

    $$Q(s,a) \leftarrow r + \gamma * \max(Q(s',a'))$$

  - Where γ is the discount factor for future rewards.

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5. Example Flow (Game Simulation):

1. **Initial state:** Empty board
2. **Agent selects action:** Places X in center
3. **Opponent reacts** (random or another agent)
4. Game continues until win/loss/draw
5. **Agent receives reward** and updates network accordingly

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6. Why Use Deep RL for Games Like Tic-Tac-Toe?

- Tic-Tac-Toe has only ~26,000 states → can be solved using traditional RL.
- But in **more complex games** (like Chess, Go), the number of states is **too large**, so **Deep RL is essential**.
- Deep RL generalizes better to **large, high-dimensional** state spaces.

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7. Applications of Deep RL:

Field	Use Case
Gaming	AlphaGo, AlphaZero, Atari games
Robotics	Path planning, grasping objects
Healthcare	Personalized treatment strategies
Finance	Automated trading agents

4. Explain Deep Reinforcement Learning?

Deep Reinforcement Learning (DRL) –

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1. Definition:

Deep Reinforcement Learning (DRL) is a powerful Artificial Intelligence (AI) technique that combines:

- **Reinforcement Learning (RL):** An agent learns by interacting with an environment to maximize cumulative rewards.
- **Deep Learning (DL):** Uses neural networks to approximate functions and learn from high-dimensional sensory data.

Together, DRL allows agents to **learn complex behaviors** and **decision-making policies** from raw inputs like images, states, or signals.

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2. Core Components of DRL:

Component	Description
Agent	Learner or decision-maker interacting with environment
Environment	External system providing feedback (reward or penalty)
State	Current situation or condition of the environment
Action	A move made by the agent to change the state
Reward	Numeric feedback from the environment after an action
Policy	Strategy that maps states to actions
Value Function	Estimates future cumulative reward from a given state
Model	(Optional) Predicts the environment's response to actions
Exploration-Exploitation	Trade-off between trying new actions and using known successful ones
Learning Algorithm	Learns policy or value function (e.g., Q-learning, Policy Gradient)
Deep Neural Networks	Approximates functions like policy or value for high-dimensional input
Experience Replay	Stores past experiences to improve learning stability

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3. How Deep RL Works (Workflow):

1. **Initialization:** Define agent, environment, and parameters.
2. **Interaction:** Agent takes action → gets new state and reward.
3. **Experience Storage:** Stores (state, action, reward, next state).
4. **Policy Update:** Neural network (Q-function or policy) is updated.
5. **Exploration vs Exploitation:** Agent balances exploring new actions vs. reusing best-known ones.
6. **Reward Maximization:** Gradually learns to choose actions that yield the highest cumulative reward.
7. **Convergence:** Over time, the policy becomes stable and optimal.
8. **Generalization:** Learns to apply knowledge in new, unseen states.
9. **Evaluation and Deployment:** Trained agent is tested or deployed in real-world tasks.

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4. Real-World Example: Tic-Tac-Toe Game

- **Agent**: AI player (X or O)
- **State**: Current configuration of the 3×3 board
- **Actions**: Marking an empty cell
- **Reward**:
  - +1 for winning
  - 0 for a draw
  - -1 for losing
- **Learning**: Through thousands of simulated games, the agent learns strategies to win or draw.
- **Deep Network**: Used to predict best moves in unseen board configurations.

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5. Applications of DRL:

Field	Use Case
Gaming	AlphaGo, Chess, Dota 2 – strategic gameplay AI
Robotics	Navigation, object manipulation, autonomous driving
Finance	Portfolio optimization, trading bots
Healthcare	Treatment planning, disease detection, robotic surgery
NLP	Dialogue systems, translation, sentiment analysis
Energy Management	Smart grids, load balancing, energy optimization
Recommender Systems	Personalized product/movie recommendations
Industrial Automation	Supply chain optimization, process control
Agriculture	Irrigation control, pest management, crop forecasting
Education	Adaptive learning platforms, intelligent tutoring systems

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6. Challenges in DRL:

- **Sample Inefficiency**: Requires lots of training data/interactions.
- **Exploration Complexity**: Hard to balance exploration vs. exploitation.
- **Safety and Stability**: Risk of unsafe behaviors in real-world systems.
- **Sparse Rewards**: Harder to learn when feedback is delayed or infrequent.

5. Difference between Q-Learning and Deep Q-Network (DQN).

Difference between Q-Learning and Deep Q-Network (DQN)

Aspect	Q-Learning	Deep Q-Network (DQN)
Definition	A model-free RL algorithm using Q-table	An extension of Q-learning using neural networks to estimate Q-values
State Representation	Discrete states (e.g., integers, small spaces)	High-dimensional or continuous states (e.g., images, sensor data)
Q-Value Storage	Stored in a 2D Q-table (State × Action)	Approximated using a deep neural network
Scalability	Poor for large or continuous state spaces	Scales well to large and complex environments
Function Approximation	No approximation – uses explicit table	Uses deep neural network as a function approximator
Memory Requirement	High for large state-action pairs	Lower due to model-based approximation
Experience Replay	Not used	Used to stabilize training by breaking correlations in data
Target Network	Not used	Separate target network improves stability
Use Cases	Simple environments (e.g., grid world, tic-tac-toe)	Complex tasks (e.g., Atari games, robotic control, image inputs)
Learning Input	State as index or vector	Raw pixel input or feature vectors