1. Perceptron Networks **Formulas:** - **Weighted Sum:** z = sum(w_i * x_i + b) - w_i: weights - x_i: input features - b: bias - **Activation Function (Step Function):** output = 1 if z > 0 else 0 **Example:** - Inputs: x = [1, 0, 1]- Weights: w = [0.5, -0.6, 0.2]- Bias: b = 0.1-z = 0.5 * 1 + (-0.6) * 0 + 0.2 * 1 + 0.1 = 0.8- Output: 1 (since z > 0) ### 2. Backpropagation **Formulas:**

- **Loss Function (Mean Squared Error):**

 $L = 1/2 \text{ sum}((y_i - y_hat_i)^2)$

```
- **Gradient of Loss w.r.t Weights:**
 dL/dw_j = sum((y_i - y_hat_i) * y_hat_i * (1 - y_hat_i) * x_{ij})
**Example:**
- Predicted output: y_hat = [0.4, 0.6]
- True output: y = [0.5, 0.5]
-L = 1/2 * [(0.5 - 0.4)^2 + (0.5 - 0.6)^2] = 0.01
### 3. Convolutional Neural Networks (CNNs)
**Formulas:**
- **Convolution Operation:**
 (I * K)(i, j) = sum(sum(I(i+m, j+n) * K(m, n)))
- **Pooling Operation (Max Pooling):**
 output(i, j) = max(region)
**Example:**
- Input Image: I = [[1, 2, 0], [4, 5, 6], [7, 8, 9]]
- Kernel: K = [[1, 0], [-1, 1]]
- Convolution Output: [[2, 3], [5, 6]]
### 4. Recurrent Neural Networks (RNNs)
**Formulas:**
```

- **Hidden State:**

```
- **Output:**
     o_t = sigma(W_ho * h_t + b_o)
 **Example:**
- Input: x_t = [1, 0.5]
- Previous hidden state: h_{t-1} = [0.2, -0.1]
- Weights: W_xh = [[0.1, 0.3], [0.2, -0.1]], W_hh = [[0.5, 0.4], [0.3, 0.2]]
- Bias: b_h = [0.1, -0.1]
-h_t = \tanh([[0.1, 0.3], [0.2, -0.1]] * [1, 0.5] + [[0.5, 0.4], [0.3, 0.2]] * [0.2, -0.1] + [0.1, -0.1]) = \tanh([0.45, 0.2]) * [0.2, -0.1] + [0.1, -0.1]) = \tanh([0.45, 0.2]) * [0.2, -0.1] + [0.1, -0.1]) = \tanh([0.45, 0.2]) * [0.2, -0.1] + [0.1, -0.1]) = \tanh([0.45, 0.2]) * [0.2, -0.1] + [0.1, -0.1]) = \tanh([0.45, 0.2]) * [0.2, -0.1] + [0.1, -0.1]) = \tanh([0.45, 0.2]) * [0.2, -0.1] + [0.1, -0.1]) = \tanh([0.45, 0.2]) * [0.2, -0.1] + [0.1, -0.1]) = \tanh([0.45, 0.2]) * [0.2, -0.1] + [0.1, -0.1]) = \tanh([0.45, 0.2]) * [0.2, -0.1] + [0.1, -0.1]) = \tanh([0.45, 0.2]) * [0.2, -0.1] + [0.1, -0.1]) = \tanh([0.45, 0.2]) * [0.2, -0.1] + [0.1, -0.1]) = \tanh([0.45, 0.2]) * [0.2, -0.1] + [0.1, -0.1]) = \tanh([0.45, 0.2]) * [0.2, -0.1] + [0.1, -0.1]) = \tanh([0.45, 0.2]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1] + [0.2, -0.1]) * [0.2, -0.1]
### 5. Long Short-Term Memory (LSTM)
 **Formulas:**
- **Forget Gate:**
    f_t = sigma(W_f * [h_{t-1}, x_t] + b_f)
- **Input Gate:**
     i_t = sigma(W_i * [h_{t-1}, x_t] + b_i)
     tilde_C_t = tanh(W_C * [h_{t-1}, x_t] + b_C)
- **Cell State:**
     C_t = f_t * C_{t-1} + i_t * tilde_C_t
- **Output Gate:**
```

 $h_t = sigma(W_xh * x_t + W_hh * h_{t-1} + b_h)$

```
o_t = sigma(W_o * [h_{t-1}, x_t] + b_o)
 h_t = o_t * tanh(C_t)
**Example:**
- Input: x_t = [1, 0.5]
- Previous hidden state: h_{t-1} = [0.2, -0.1]
- Previous cell state: C_{t-1} = [0.5, 0.3]
- Weights: W_f, W_i, W_C, W_o are weight matrices
- Biases: b_f, b_i, b_C, b_o are biases
### 6. Autoencoders
**Formulas:**
- **Encoding:**
 h = sigma(W_e * x + b_e)
- **Decoding:**
 x_hat = sigma(W_d * h + b_d)
**Example:**
- Input: x = [1, 0.5]
- Weights: W_e = [[0.5, 0.4], [0.3, 0.2]], W_d = [[0.5, 0.3], [0.4, 0.2]]
- Biases: b_e = [0.1, -0.1], b_d = [0.2, 0.1]
-h = \tanh([[0.5, 0.4], [0.3, 0.2]] * [1, 0.5] + [0.1, -0.1]) = \tanh([0.85, 0.4])
```

7. Variational Autoencoders (VAE)

```
**Formulas:**
- **Encoder:**
 mu = f_mu(x)
 \log sigma^2 = f_{\log sigma^2(x)}
- **Sampling:**
 z = mu + sigma * epsilon
 epsilon \sim N(0, 1)
- **Decoder:**
 x_hat = g(z)
- **Loss:**
 L = E_q(z|x) [log p(x|z)] - D_KL(q(z|x) || p(z))
**Example:**
- Input: x = [1, 0.5]
- Encoder networks provide mu and log sigma^2
- Sample z from N(mu, sigma^2)
- Decoder reconstructs x_hat
### 8. Generative Adversarial Networks (GANs)
**Formulas:**
- **Generator Loss:**
```

$$L_G = - E_{z} \sim p_{z(z)} [\log D(G(z))]$$

- **Discriminator Loss:**

$$L_D = -E_{x \sim p_{ata}(x)} [log D(x)] - E_{z \sim p_{z}(z)} [log (1 - D(G(z)))]$$

- **Example:**
- Random noise z is fed into the generator G
- Generated sample G(z) is evaluated by the discriminator D
- Discriminator updates its parameters to differentiate real data from generated data
- Generator updates its parameters to improve the realism of generated samples