Neural Networks

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Neural Networks

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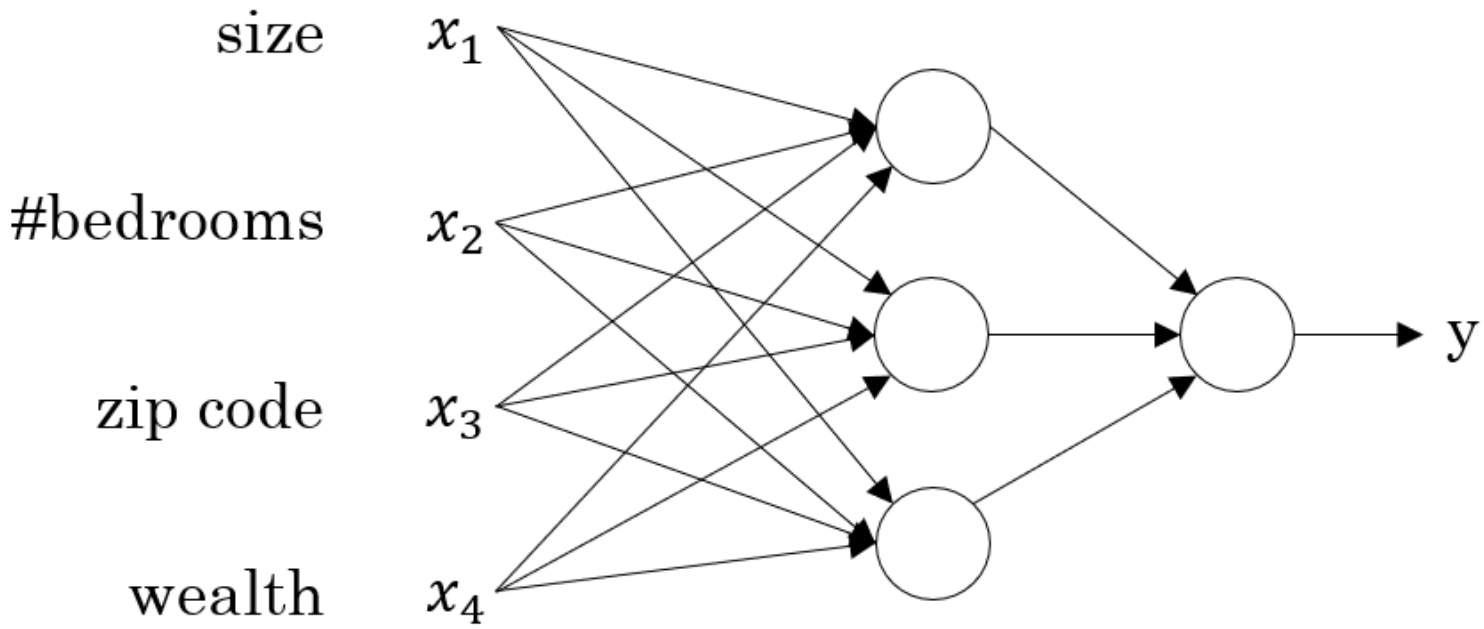
- A neural network is a function that maps input features to outputs using layers of simple units called neurons
- Each neuron computes a weighted sum of its inputs then applies a non linear activation
- Stacking layers lets the model learn complex patterns that linear models cannot capture

- **Input layer** holds the features
- **Hidden layers** learn intermediate representations
- **Output layer** produces predictions

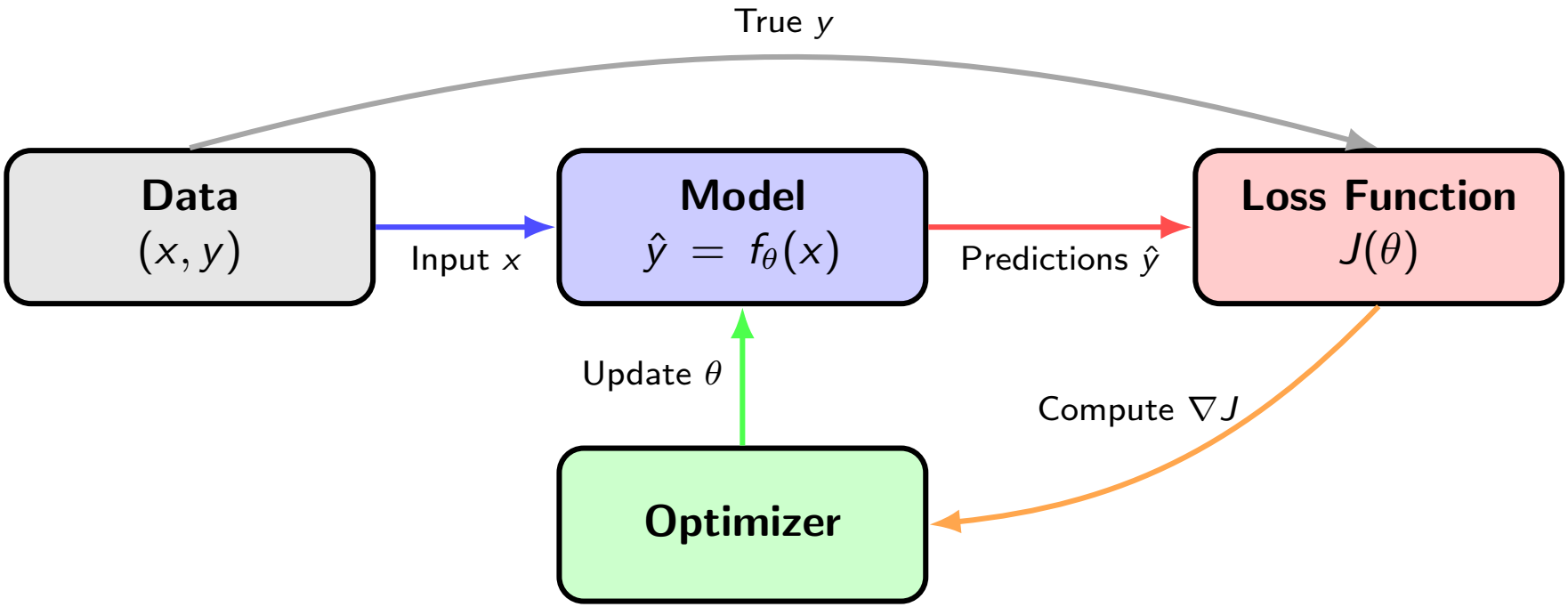
Neural Network



Neural Network as Part of the Learning System

- **Neural network model**
  - Maps input x to prediction $\hat{y} = f_\theta(x)$
  - θ are the parameters (weights and biases)
- **Loss function**
  - Measures how far predictions are from targets
  - Guides what it means to be a good model for the task
- **Optimizer**
  - Uses gradients of the loss to update θ
  - Tries to find parameters that reduce the loss on data

The Training Loop



Forward Pass:

- Data $\rightarrow$ Model $\rightarrow$ Predictions
- Compute Loss

Backward Pass:

- Calculate gradients
- Update parameters

Repeat until loss converges (model learns)!

The Forward Pass

- The forward pass starts from inputs and flows through the network
- Each layer applies a linear transformation then an activation
- At the end we compute the loss between predictions and targets

Example for one hidden layer

$$a^{(1)} = \sigma\left(W^{(1)}x + b^{(1)}\right)$$

$$\hat{y} = g\left(W^{(2)}a^{(1)} + b^{(2)}\right)$$

- $x \in \mathbb{R}^k$ input features
- $a^{(1)}$ hidden layer activations
- g is the output activation chosen for the task

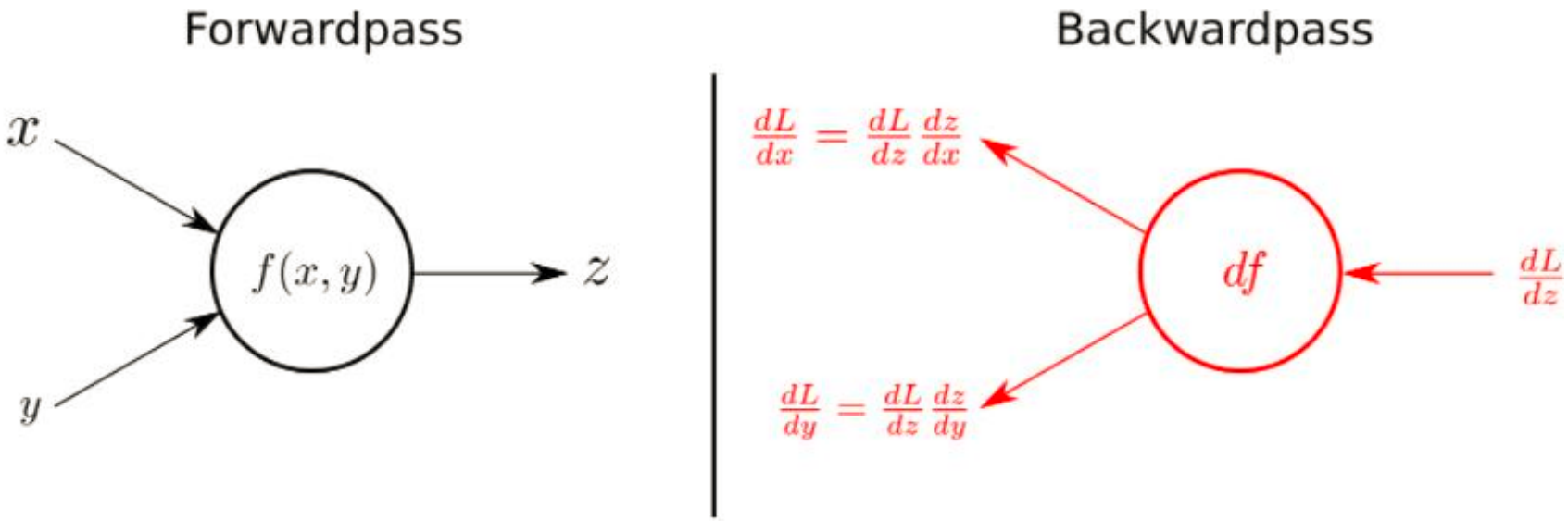
The Backward Pass

- The backward pass starts from the loss and flows backward through the network
- It uses the chain rule to compute gradients of the loss with respect to every parameter
- These gradients tell the optimizer how to change weights to reduce the loss

At a high level

- Forward pass gives $\hat{y}$ and loss $J(\theta)$
- Backward pass gives gradients $\nabla_\theta J$
- Optimizer updates parameters using these gradients

Forward and Backward Together



Single Neuron Computation

- Input features $x \in \mathbb{R}^k$
- Weights $w \in \mathbb{R}^k$ and bias $b \in \mathbb{R}$

$$z = w^\top x + b \quad , \quad a = \sigma(z)$$

- z is the pre activation (linear part)
- σ is an activation function
- a is the neuron output that feeds the next layer or the loss

Why We Need Activation Functions

- If we only stack linear layers without activations we still get a linear function
- Non linear activations let the network approximate complex functions
- They introduce bends and thresholds that help separate classes and model non linear trends

Common Activation Functions

ReLU

$$\sigma(z) = \max(0, z)$$

- Simple and works well in deep nets
- Keeps positive values and drops negatives

Sigmoid

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

- Outputs values in $(0, 1)$
- Used for probabilities in binary classification

Tanh

$$\sigma(z) = \tanh(z)$$

- Outputs values in $(-1, 1)$
- Often used in recurrent networks

Softmax for Multiclass Outputs

- For multiclass classification the output layer gives scores $z \in \mathbb{R}^C$ for C classes
- The softmax function turns scores into a probability distribution

$$\text{softmax}(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}$$

- Each output is between 0 and 1
- All outputs sum to 1

Inputs and Outputs in Practice

- Input vector $x \in \mathbb{R}^k$
  - Example features
  - Age income number of past purchases
- Output shape depends on the task
  - Scalar for single output regression or binary classification
  - Vector for multi output regression or multiclass classification

Network Shapes for Different Tasks

Task	Input	Output of NN	Typical loss
Single output regression	$x \in \mathbb{R}^k$	$\hat{y} \in \mathbb{R}$	Mean squared error
Multi output regression	$x \in \mathbb{R}^k$	$\hat{y} \in \mathbb{R}^m$	MSE over all outputs
Binary classification	$x \in \mathbb{R}^k$	$\hat{p} \in (0, 1)$	Binary cross entropy
Multiclass classification	$x \in \mathbb{R}^k$	$\hat{p} \in \mathbb{R}^C$ softmax	Cross entropy

Examples of Heads on Top of the Same Body

- The hidden layers can be shared across tasks
- Only the last layer and the loss change
- Regression head
  - Last layer has one neuron with linear activation
  - Use mean squared error
- Binary head
  - Last layer has one neuron with sigmoid
  - Use binary cross entropy
- Multiclass head
  - Last layer has C neurons with softmax
  - Use cross entropy over classes

Optimizers: Gradient Descent

- Parameters θ are updated in the direction that reduces the loss

$$\theta_{\text{new}} = \theta_{\text{old}} - \alpha \nabla_\theta J(\theta)$$

- α is the learning rate
- $\nabla_\theta J(\theta)$ is the gradient of the loss with respect to the parameters
- In deep learning we usually use mini batch gradient descent

AdaGrad

- Keeps a running sum of squared gradients for each parameter:

$$G_t = G_{t-1} + g_t^2$$

- Update rule with parameter wise learning rate:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{G_t} + \epsilon} g_t$$

- Parameters with large accumulated gradients get smaller effective learning rates
- Works well for sparse features

RMSProp

- Uses an exponential moving average of squared gradients:

$$E[g^2]_t = \alpha E[g^2]_{t-1} + (1-\alpha) g_t^2$$

- Update rule:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{E[g^2]_t + \epsilon}} g_t$$

- Prevents the learning rate from shrinking too fast and keeps training going
- Often used as a base idea in modern optimizers

Adam

- Keeps a moving average of gradients and squared gradients:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

- Bias correction:

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}, \qquad \hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

- Update rule:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \epsilon} \hat{m}_t$$

- Combines momentum + adaptive step size and usually speeds up training

AdamW

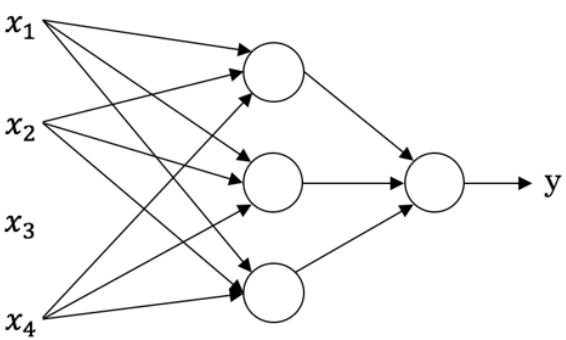
- Uses the same Adam update, plus decoupled weight decay:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \epsilon} \hat{m}_t - \eta\lambda\theta_t$$

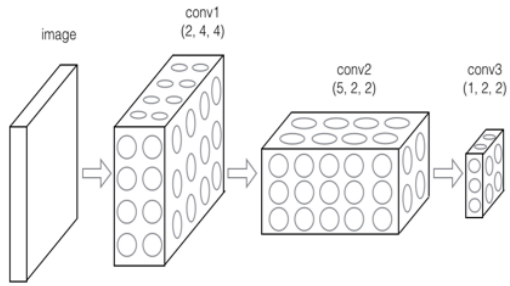
- Weight decay is applied directly to parameters instead of through the gradient
- Often used as a strong default optimizer for modern deep networks

Types of Neural Network Architectures

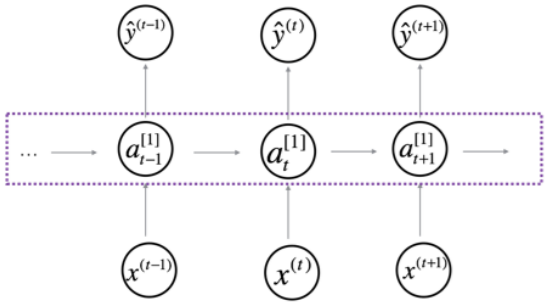
- **MLP** fully connected network for tabular data
- **CNN** convolutional neural network for images
- **RNN and variants** for sequences and time series



Standard NN



Convolutional NN

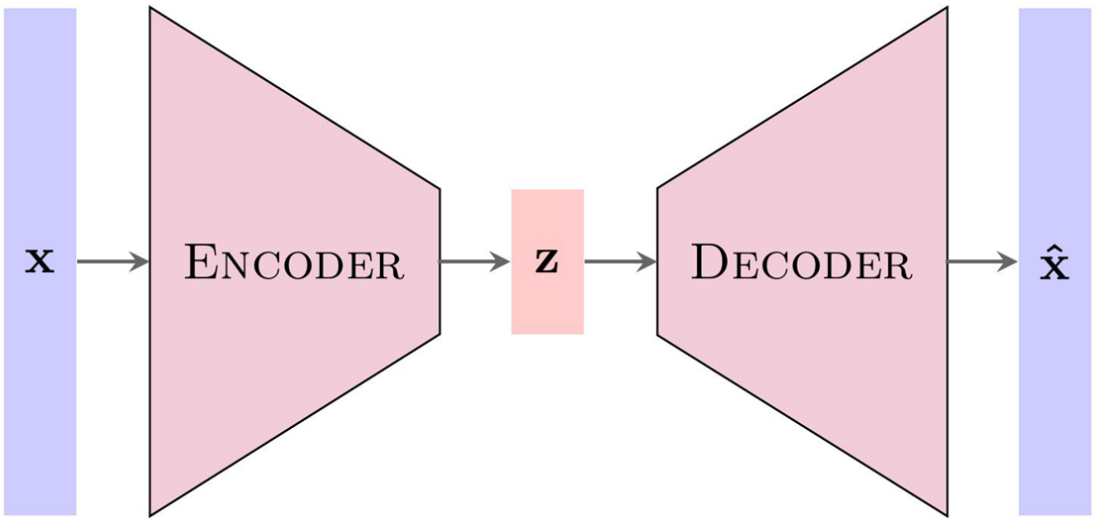


Recurrent NN

What Is an Autoencoder

- An autoencoder is a network that tries to reconstruct its input
- It has two parts
  - **Encoder** maps x to a lower dimensional code z
  - **Decoder** maps z back to a reconstruction $\hat{x}$
- The loss compares $\hat{x}$ and x usually with mean squared error

Autoencoder Diagram



The bottleneck forces the network to learn a compressed representation of the data

Autoencoder Applications

- Dimensionality reduction and visualization
- Denoising images or signals
- Anomaly detection using high reconstruction error
- As a pretraining step to learn useful representations

References

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- Ian Goodfellow Yoshua Bengio Aaron Courville, Deep Learning
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