Custom Loss Function Design

Aligning Training with Domain-Specific Objectives

💡 Why Custom Loss?

Standard loss functions may not sufficiently reflect domain-specific objectives

Align learning with business metrics or task requirements

⚙️ Key Considerations

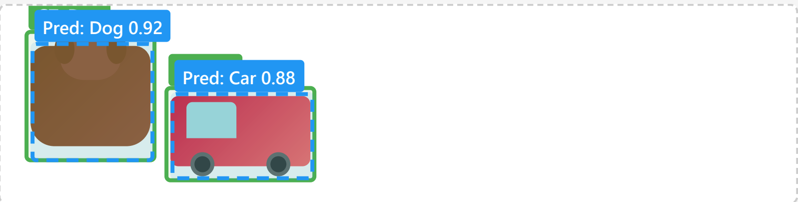
1. **Differentiability** - Ensure differentiability
2. **Computational Efficiency** - Fast computation
3. **Numerical Stability** - Avoid overflow/underflow

Multi-term Combination

$$L_{total} = w_1 \cdot L_1 + w_2 \cdot L_2 + \ldots + w_n \cdot L_n$$

🎯 Object Detection Loss Visualization

Ground Truth + Prediction



Ground Truth Prediction

📋 Design Process

1. Verify reflection of true optimization goal
2. Combine multiple loss terms with weighting coefficients
3. Validate performance improvement with held-out data

🎯 Domain Examples

Computer Vision
Perceptual Loss (Style Transfer), SSIM (Image Quality)

Object Detection
YOLO/Faster R-CNN: Classification + Localization + Objectness

Instance Segmentation
Mask R-CNN: Detection + Pixel-level segmentation losses

Medical Imaging
Diagnostic accuracy, sensitivity/specificity balance

Financial Forecasting
Risk-adjusted returns, prediction confidence intervals

NLP Tasks
Semantic similarity, contextual consistency

① **Classification Loss:** Cross-entropy for class labels `-Σ y·log(ŷ)`

② **Localization Loss:** IoU/Smooth L1 for bbox coordinates `Smooth-L1(bbox_pred, bbox_gt)`

③ **Objectness Loss:** Confidence score (0.92, 0.88) `BCE(obj_pred, obj_gt)`

Total: $L = \lambda_1 \cdot L\_cls + \lambda_2 \cdot L\_box + \lambda_3 \cdot L\_obj$