

❓ 1. What "Error" Means in YOLOv1

In machine learning (and YOLOv1), **error** means the **difference between the model's predictions and the ground truth** (actual labels in training data).

YOLOv1 measures this through its **loss function**, which calculates how far the predicted bounding boxes and class probabilities are from the real ones.

So, the total **error (loss)** =

Localization error + Confidence error + Classification error

❑ 2. Types of Errors in YOLOv1

There are **three major error components** in YOLOv1's working:

| Type | Description | What It Measures |
|---|--|--|
| 1. Localization Error | Error in bounding box coordinates | How far the predicted box is from the true box |
| 2. Confidence (Objectness) Error | Error in predicting whether an object exists | How sure the model is that a cell contains an object |
| 3. Classification Error | Error in identifying the correct class | Whether the object was labeled with the right category |

Let's break each of these in detail.

❑ 3. Localization Error (Bounding Box Error)

❑ What it is:

This error happens when YOLOv1 predicts a bounding box that **does not align accurately** with the true object.

❑ It involves four variables:

$bx, by, bw, b_{hb_x}, b_y, b_w, b_hbx, by, bw, bh$

Where:

- bx, by, b_{hb_x}, b_y → box center coordinates (relative to grid cell)
- bw, b_{hb_w}, b_hbw, bh → box width and height (relative to image size)

❑ The loss is calculated as:

$$\lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^B 1_{ijobj} [(b_x - \hat{b}_x)^2 + (b_y - \hat{b}_y)^2 + (b_w - \hat{b}_w)^2 + (b_h - \hat{b}_h)^2] \lambda_{coord}$$

$$\sum_{i=0}^{S^2} \sum_{j=0}^B \mathbf{1}_{ij}^{obj} \left[(b_x - \hat{b}_x)^2 + (b_y - \hat{b}_y)^2 + (\sqrt{b_w} - \sqrt{\hat{b}_w})^2 + (\sqrt{b_h} - \sqrt{\hat{b}_h})^2 \right]$$

$$\lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^B 1_{ijobj} [(b_x - \hat{b}_x)^2 + (b_y - \hat{b}_y)^2 + (b_w - \hat{b}_w)^2 + (b_h - \hat{b}_h)^2]$$

Where:

- $1_{ijobj} = \mathbf{1}_{ij}^{obj} = 1$ if an object appears in cell i and box j is responsible.
- $\hat{b}_x, \hat{b}_y, \hat{b}_w, \hat{b}_h$ are the **true** values.
- The **square roots** of width and height are used to reduce error sensitivity for large boxes.

□ Meaning:

If the predicted box is even slightly off in position or size, YOLO adds this to the localization error.

□ 4. Confidence (Objectness) Error

□ What it is:

YOLO predicts a **confidence score** (p_c) for each box, representing how sure it is that an object exists in that cell.

- $p_c = \Pr(\text{object}) \times \text{IoU}_{pred, truth}$
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 - $\Pr(\text{object})$: probability that an object is present.
 - $\text{IoU}_{pred, truth}$: overlap between predicted and true box.

□ There are two cases:

1. **If an object exists in the cell:**
 $\text{Error} = (p_c - \hat{p}_c)^2$
2. **If no object exists:**
 $\text{Error} = \text{smaller weight} \times (p_c - \hat{p}_c)^2$

So YOLO uses two terms:

$$\lambda_{noobj} \sum_{i=0}^{S^2} \sum_{j=0}^B 1_{ijnobj} (p_c - \hat{p}_c)^2 \lambda_{noobj}$$

$$\sum_{i=0}^{S^2} \sum_{j=0}^B \mathbf{1}_{ij}^{noobj} (p_c - \hat{p}_c)^2 \lambda_{noobj}$$

$$\sum_{i=0}^{S^2} \sum_{j=0}^B 1_{ijnobj} (p_c - \hat{p}_c)^2$$

and

$$\sum_{i=0}^S \sum_{j=0}^B 1_{ijobj} (p_c - \hat{p}_c)^2 \sum_{i=0}^S \sum_{j=0}^B \mathbf{1}_{ij}^{obj} (p_c - \hat{p}_c)^2$$

□ **Meaning:**

If the model says there's an object where there isn't one → **false positive (Type I error)**

If it says there's no object where there is → **false negative (Type II error)**

□ **5. Classification Error**

□ **What it is:**

Each grid cell predicts **class probabilities** (e.g., car, person, dog).

Error happens when the **predicted class distribution** does not match the **true class label**.

$$\sum_{i=0}^S \sum_{c \in \text{classes}} 1_{iobj} (p(c|object) - \hat{p}(c|object))^2 \sum_{i=0}^S \sum_{c \in \text{classes}} (p(c|object) - \hat{p}(c|object))^2$$

□ **Meaning:**

If a cell has an object but the network predicts the wrong class (e.g., dog instead of cat), this error increases.

□ **6. Total YOLOv1 Loss Function**

Combining all three error types:

$$L = \lambda_{coord} \sum_{i=0}^S \sum_{j=0}^B 1_{ijobj} [(b_x - \hat{b}_x)^2 + (b_y - \hat{b}_y)^2 + (b_w - \hat{b}_w)^2 + (b_h - \hat{b}_h)^2] + \sum_{i=0}^S \sum_{j=0}^B 1_{ijobj} (p_c - \hat{p}_c)^2 + \lambda_{noobj} \sum_{i=0}^S \sum_{j=0}^B 1_{ijnobj} (p_c - \hat{p}_c)^2 + \sum_{i=0}^S \sum_{c \in \text{classes}} 1_{iobj} (p(c|object) - \hat{p}(c|object))^2$$

$$\begin{aligned} L = & \lambda_{coord} \sum_{i=0}^S \sum_{j=0}^B \mathbf{1}_{ij}^{obj} \left[(b_x - \hat{b}_x)^2 + (b_y - \hat{b}_y)^2 + (\sqrt{b_w} - \sqrt{\hat{b}_w})^2 + (\sqrt{b_h} - \sqrt{\hat{b}_h})^2 \right] \\ & + \sum_{i=0}^S \sum_{j=0}^B \mathbf{1}_{ij}^{obj} (p_c - \hat{p}_c)^2 \\ & + \lambda_{noobj} \sum_{i=0}^S \sum_{j=0}^B \mathbf{1}_{ijnobj} (p_c - \hat{p}_c)^2 \\ & + \sum_{i=0}^S \sum_{c \in \text{classes}} \mathbf{1}_{iobj} (p(c|object) - \hat{p}(c|object))^2 \end{aligned}$$

Where:

- $\lambda_{coord}=5$ $\lambda_{coord}=5$ (more weight on box position)
- $\lambda_{noobj}=0.5$ $\lambda_{noobj}=0.5$ (less weight on background cells)

□ 7. Summary of Error Types in YOLOv1

| Error Type | Occurs When | Corresponds To | Handled By |
|-----------------------------|--------------------------------------|------------------------------|-----------------------------|
| Localization Error | Predicted box doesn't match true box | Bounding box regression loss | Coordinate loss term |
| Confidence Error | Wrongly predicts object presence | Objectness score error | Confidence loss term |
| Classification Error | Wrong object label | Misclassification | Class probability loss term |

□ 8. Analogy to Statistical Errors

| YOLO Error | Statistical Equivalent | Description |
|----------------------------------|---------------------------------------|------------------|
| Predicts object when none exists | Type I Error (False Positive) | Wrong detection |
| Misses object that exists | Type II Error (False Negative) | Missed detection |

So, in short:

YOLOv1's total error = Localization Error + Confidence Error + Classification Error

Each of these is carefully weighted in the loss function to train the model effectively.