YOLO Notes

R-CNN (Region-based Convolutional Neural Network) was a landmark model that brought deep learning into the world of **object detection**. Before YOLO and SSD, R-CNN was **the** go-to approach for combining region proposals with CNN-based classification.

Let's walk through **how R-CNN works**, step by step:

🔍 Problem R-CNN Solves

> How do you **detect** and **classify** multiple objects in an image — not just *what* is in the image, but also *where*?

🧠 R-CNN: Core Idea

Instead of scanning the image like a sliding window (which is slow and inefficient), **R-CNN** first **proposes regions**(likely to contain objects), and then **classifies each region** using a CNN.

🧱 Step-by-Step Breakdown of R-CNN

1. Region Proposal (Selective Search)

- R-CNN starts by generating **~2000 region proposals** from the input image using a traditional computer vision technique called **Selective Search**.
- These proposals are **bounding boxes** that are *likely* to contain objects.
- It's fast and class-agnostic (not deep learning-based).

📷 Example: An image might yield regions like:

- [100, 200, 300, 400] → possible dog face
- [50, 80, 200, 180] → possible cat body

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2. Warp Each Region to a Fixed Size

- Each of the 2000 proposed regions (which can be of different sizes) is **cropped** from the image and **resized**(warped) to a fixed size (e.g., `224x224` pixels).
- This resizing is necessary because CNNs (like AlexNet) need **fixed-size input**.

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3. Feature Extraction using a CNN

- Each resized region is passed through a **pretrained CNN** (e.g., AlexNet or VGG16).
- The CNN extracts **feature vectors** from the image patch.

So now, each proposal is converted into a **feature vector** that represents the visual content of that region.

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4. Classification using SVM

- For each region's feature vector, a **Support Vector Machine (SVM)** classifier is used to:
  - Predict the **class label** of the object (e.g., "dog", "car", etc.)
  - Classify it as **background** if it doesn't contain any object

5. Bounding Box Regression

- Even though selective search proposes bounding boxes, they're not always perfectly aligned.
- So R-CNN also trains a **regressor** (a small linear model) to fine-tune the position and size of each bounding box to better fit the object.

🔁 Summary Flowchart of R-CNN:

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```
Input Image
   ↓
Selective Search → ~2000 region proposals (bounding boxes)
   ↓
Crop & Resize each region → 224x224
   ↓
Pass through CNN (e.g., AlexNet) → Feature vector
```

```
    ↓
SVM classifier → Class label (or background)
    ↓
Bounding Box Regressor → Adjust bounding box coords
```

⚠️ Limitations of R-CNN

While accurate, R-CNN is **slow and inefficient**:

- It runs the CNN **2000 times per image** — once for each region proposal! 😱
- Separate stages for:
    - Region proposal (Selective Search)
    - CNN feature extraction
    - SVM classification
    - Bounding box regression
- Not end-to-end trainable — each stage is trained independently.

Let's dive into **Selective Search** — the classical computer vision technique that powers the region proposal stage in **R-CNN**.

🎯 What Is Selective Search?

Selective Search is a **region proposal algorithm** used to generate potential object locations (bounding boxes) in an image — **without using deep learning**.

Instead of exhaustively searching every possible window (like sliding windows do), it cleverly groups similar regions based on hand-crafted features like **color, texture, size, and shape**.

🧠 Intuition Behind It

Think of selective search as:

> “Start with many small regions (superpixels) and keep merging similar ones to get larger, object-like regions.”

The assumption is: **objects are made up of similar pixels grouped together**, so merging them gradually will uncover the likely object boundaries.

🧱 Step-by-Step: How Selective Search Works

1. Image Segmentation (Oversegmentation)

- Use a **superpixel segmentation algorithm** (typically **Felzenszwalb’s algorithm**) to divide the image into **many small regions** (called **superpixels**).
  Superpixels are groups of neighboring pixels with similar color or texture.
  Example: Sky, cat fur, tree leaves — all segmented into small uniform patches.

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2. Feature Extraction for Each Region

For each segmented region, extract the following features:

- **Color histogram** (RGB or HSV)
- **Texture histogram** (gradient-based)
- **Size** of the region
- **Shape / bounding box**

These features are used to determine how **similar** two regions are.

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3. Region Merging (Hierarchical Grouping)

- Start merging the **most similar neighboring regions** based on a similarity function.
- Continue merging until the whole image becomes one region.

At **every step** of merging, the **new region** formed is **added to the region proposal list** (i.e., it's a candidate bounding box).

This creates a **hierarchical tree of region proposals —** from tiny parts (e.g., cat ear) up to full objects (e.g., whole cat).

🚀 What Is Fast R-CNN?

Fast R-CNN is an improved version of **R-CNN** introduced by Ross Girshick in 2015. It **solves the speed and inefficiency problems** of R-CNN by sharing computation and combining classification and bounding box regression into a **single deep network**.

📌 Quick Recap of R-CNN Problems

R-CNN was:

- **Slow**: It runs the CNN **2000 times per image**, once per region proposal
- **Multi-stage**: You need to train the CNN, then train SVMs, then train regressors
- **Storage-heavy**: Feature vectors from all regions were saved to disk

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💡 Fast R-CNN: Key Ideas

Fast R-CNN makes **one major change**:

> Instead of feeding 2000 cropped regions through the CNN one at a time, **run the CNN once on the whole image**, then extract features for all regions from a **shared feature map**.

🧱 Step-by-Step: How Fast R-CNN Works

1. Input: Full Image + Region Proposals

- You start with:
    - The **full input image**
    - ~2000 **region proposals** (bounding boxes), usually generated by **Selective Search** (same as R-CNN)

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2. Run CNN Once on Full Image

- Pass the **entire image** through a deep CNN (e.g., VGG16)
- This produces a **feature map** for the whole image

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3. Region of Interest (RoI) Pooling

- For each region proposal, you **extract a corresponding region** from the feature map
- These regions may vary in size — so you use **RoI Pooling** to convert each one to a **fixed size** (e.g., 7×7)

> 📦 Think of RoI Pooling as "zooming in" on parts of the feature map for each proposed box.

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4. Fully Connected Layers

- The output of each RoI pooling is flattened and passed through a couple of **fully connected (FC) layers**, like a classifier head.

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5. Two Output Branches (Multitask Loss)

From the FC layers, two outputs are predicted for each RoI:

1. **Softmax classification**: Probabilities over object classes (plus background)
2. **Bounding box regression**: 4 numbers to fine-tune the box coordinates

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🧠 Training (End-to-End)

Fast R-CNN is trained end-to-end with a **multi-task loss**:

- **Classification loss** (cross-entropy)
- **Bounding box regression loss** (Smooth L1)

Everything is trained together — one network, one training stage. 🎯

🎯 Visual Flow

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```
Input Image
   ↓
Deep CNN (e.g., VGG16)
   ↓
Shared Feature Map
   ↓
[Apply RoI Pooling to each region proposal]
   ↓
FC Layers
   ↓
 ┌─────────────┬──────────────┐
 │ Classifier │ Box Regressor│
 └─────────────┴──────────────┘
```

🚀 Benefits of Fast R-CNN

Feature	Benefit
Single CNN run per image	Much faster than R-CNN

End-to-end training	One network to train — simpler and more powerful
Better accuracy	Less overfitting, better bounding box refinement
No need to save features to disk	More memory-efficient

The phrase “framed the classification problem as a regression problem” in the context of the YOLO (You Only Look Once) paper refers to how the object detection task is approached in a fundamentally different way compared to traditional classification + localization pipelines.

Let’s break it down:

🧠 Traditional Object Detection (Before YOLO)

Object detection was typically done in **two stages**:

1. **Region Proposal**: Identify *where* objects might be (e.g., using Selective Search).
2. **Classification + Bounding Box Regression**: For each proposed region, classify the object and refine the bounding box.

Here, classification and localization were *separate* tasks:

- Classification → assigns a class label (discrete output).
- Bounding Box → is a regression problem (continuous coordinates).

🚀 What YOLO Does Differently

YOLO treats the entire object detection task — classification *and* localization — as a **single regression problem**:

- The input is the image.
- The output is a vector of predictions: bounding box coordinates (x, y, width, height), **objectness score**, and **class probabilities — all at once**, as continuous values.

So instead of:

- “Is there a dog in this box?” → **classification**
- “Where is the box?” → **regression**

YOLO says:

- “Given this grid cell, regress the **entire set of outputs** (coordinates + class probs) from the image directly.” → **unified regression**

📦 What Does “Regression” Mean Here?

In this context, “regression” just means **predicting continuous outputs** (e.g., real numbers), including:

- Bounding box coordinates.
- Object confidence score.
- Even the class probabilities (before applying softmax or argmax).

> YOLO regresses *from pixels to bounding boxes and class probabilities directly*.

🔁 Why This Is Cool

- It’s **super fast** — one single neural network pass.
- It avoids the need for region proposal networks or intermediate steps.
- It’s end-to-end trainable on just the final loss.

Let’s break down the **difference between confidence scores and class probabilities** as used in the YOLOv1 loss:

🧠 First, What Are These Two Terms?

Confidence Score
This represents **how confident** the model is that **an object exists** in a predicted bounding box, and how well the box fits the object.
Mathematically:
ini

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```
Confidence = P(object) × IOU(predicted_box, ground_truth_box)
```

1.
    - `P(object)` is the probability that there's any object in the box.
    - `IOU` is how well the predicted box overlaps the actual object.
    - So even if there's an object, if the box is off, the confidence will be low.

Class Probabilities
These are the **conditional probabilities** of each class **given that there is an object**:
csharp
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```
P(class_i | object)
```

2.

🧪 In the Loss Function

The YOLOv1 loss function has **5 parts**, and you're referring to these:

🔹 Term 3 & 4: Confidence Score Loss

- These penalize errors in the **confidence score** prediction.
- One term for when an object *is* present (`P(object) = 1`) — should match IOU.
- Another for when there's *no* object (`P(object) = 0`) — should be close to 0.

This ensures:

- High confidence for correct boxes.
- Low confidence for false positives.

🔹 Term 5: Classification Loss

- Only computed if there *is* an object in the cell.
- It penalizes the error between the predicted class probabilities and the ground truth class.

This term teaches the network **what the object is**, given that it knows **there is an object**.

🔍 So What's the Key Difference?

Concept	Confidence Score	Class Probabilities
What it tells you	Is there an object? Is the box accurate?	What *kind* of object is it?
When it's computed	For every bounding box, always	Only if an object exists in the grid cell
Affects	Objectness + localization quality	Object classification
Type of value	Single scalar per box	Vector (1 per class)

🚨 Important Detail:

In inference, the final class-specific confidence score is:

java
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```
P(class_i) × IOU(pred_box, truth) = P(class_i | object) × P(object) ×
IOU = confidence × class_prob
```

This is used to filter and rank predictions.

✅ Ground Truth Confidence: How YOLOv1 Computes It

During training, for each **bounding box predictor** in a **grid cell**, we set the **ground truth confidence** as:

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```
Confidence_target = IOU(pred_box, ground_truth_box)    if predictor is
"responsible"
Confidence_target = 0                                   otherwise
```

✅ How Is the Ground Truth `P(class)` for a Cell Calculated?

For each grid cell:

- If the cell **contains the center** of a ground truth object:

Set the class probability vector to a **one-hot encoding** of the object's class:
csharp
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```
P(class_i | object) = 1 for the correct class
P(all other classes) = 0
```

  -
- If there is **no object** in the cell:
  - The class prediction **is not used** in the loss (it's ignored).

💡 Only grid cells that contain an object participate in **classification loss**.

⚙️ How YOLOv2 Uses Anchor Boxes (Step-by-Step)

1. Anchor Box Setup

Before training:

- Run **k-means clustering** on the training set bounding boxes to find **k anchor boxes** (e.g., 5).
- Each anchor box has a fixed width and height (`w_anchor`, `h_anchor`).

2. Each Grid Cell Predicts k Boxes

For every grid cell:

- The network predicts **k bounding boxes**, each based on one of the **k anchors**.

For each box, the network outputs:
kotlin
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```
tx, ty, tw, th, confidence, class probabilities
```

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3. Predicted Box Computation

From the predicted values and the anchor box, YOLOv2 **reconstructs** the final bounding box:

python
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```
bx = sigmoid(tx) + cx     # cx = x-offset of the grid cell
by = sigmoid(ty) + cy
bw = w_anchor * exp(tw)
bh = h_anchor * exp(th)
```

Why these formulas?

- `sigmoid(tx)` ensures the offset stays in [0,1] (keeps the box within the cell).
- `exp(tw)` ensures the width/height are always positive and scale relative to the anchor box.

🧠 Why Anchor Boxes?

YOLOv1 struggled with predicting boxes of **varied shapes and aspect ratios** because:

- It had to predict all box sizes from scratch.
- It had limited flexibility (2 boxes per grid cell).

Anchor boxes help by:

- Letting the network **specialize** each anchor to certain object shapes (e.g., tall, wide, square).
- Increasing the variety of box shapes it can detect.

🎯 Responsibility Assignment

During training:

- Each ground truth object is assigned to the **best-matching anchor box** (highest IOU) in the **grid cell where the object's center lies**.
- That anchor box becomes **responsible** for predicting that object.
- The rest are trained to output `confidence = 0`.

🖼️ Quick Visualization (in words):

- Grid size: 13x13
- Anchor boxes: 5
- Output tensor shape: `13 x 13 x (5 x (5 + num_classes))`
    - Each of the 5 boxes predicts 5 values + class probs:
        - `(tx, ty, tw, th, objectness) + class_probs`