

**Open Elective Course [OE]**

Course Code: CSO507

Winter 2023-24

Lecture#

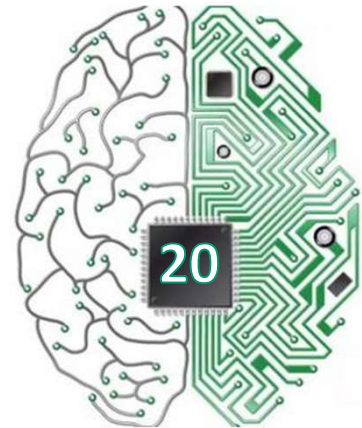
# Deep Learning

**Unit-4: Convolutional Neural Networks (Part-VIII)****Unit-5: Sequence Modeling****Course Instructor:****Dr. Monidipa Das**

Assistant Professor

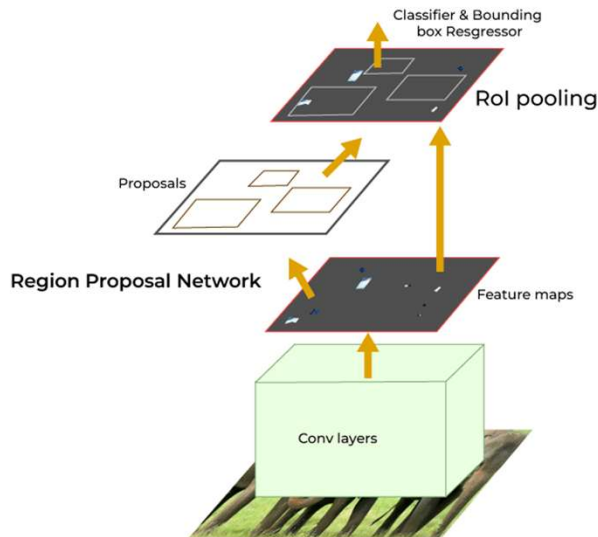
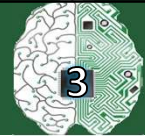
Department of Computer Science and Engineering

Indian Institute of Technology (Indian School of Mines) Dhanbad, Jharkhand 826004, India



## YOLO Model for Object Detection

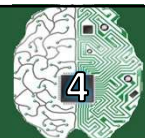
# YOLO: You Only Look Once



- The approaches that we have seen so far are two stage approaches
- They involve a region proposal stage followed by separate classification and regression stage
- Can we have an end-to-end architecture which does both proposal and classification simultaneously ?
- This is the idea behind YOLO
  - **You Only Look Once.**

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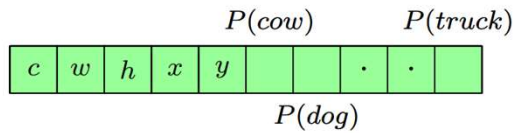
## Key Insights



- **Previous Approaches**
  - more complicated model pipeline
  - expensive computation
  - lacks contextual information for detection
- **YOLO Algorithm**
  - less complicated pipeline
  - efficient computation
  - has contextual information for detection

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# YOLO: You Only Look Once



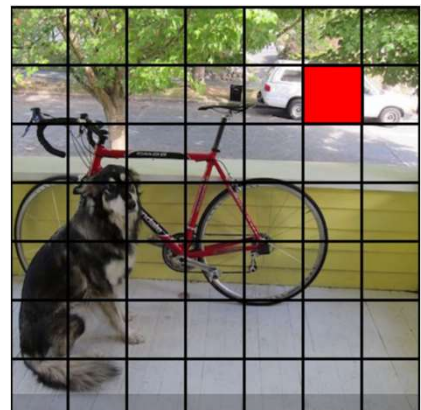
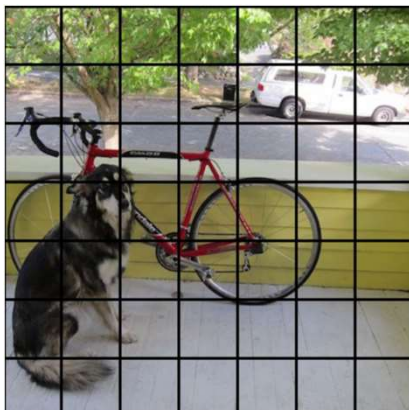
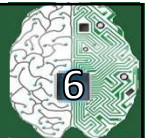
$S \times S$  grid on input

Considering only 1 bounding box per cell

- Divide an image into  $S \times S$  grids
- For each such cell we are interested in predicting  $5 + k$  quantities
  - Confidence
  - Width of the bounding box
  - Height of the bounding box
  - Center (x,y) of the bounding box
  - Probability of the object in the bounding box belonging to the k-th class (k - values)
- The output layer thus contains  $S \times S \times (5 + k)$  elements

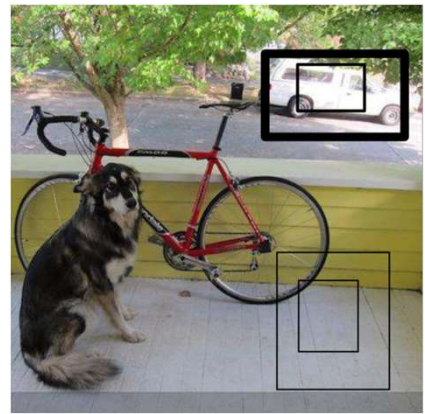
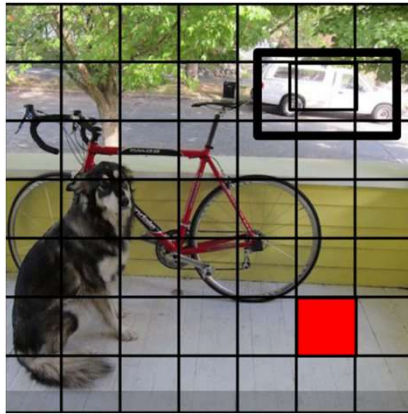
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# YOLO: You Only Look Once



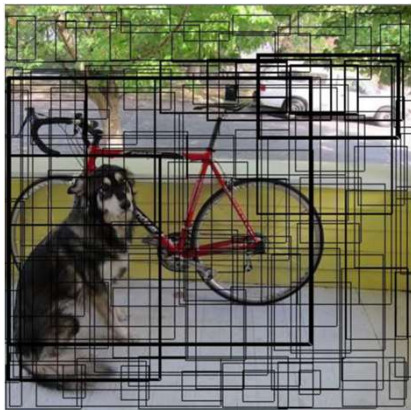
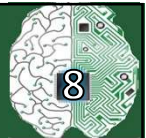
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# YOLO: You Only Look Once



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# YOLO: You Only Look Once

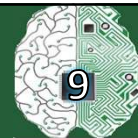


Considering  $B$   
number of bounding  
boxes per cell, the  
output layer  
dimension would be:  $S \times S \times (B * 5 + k)$

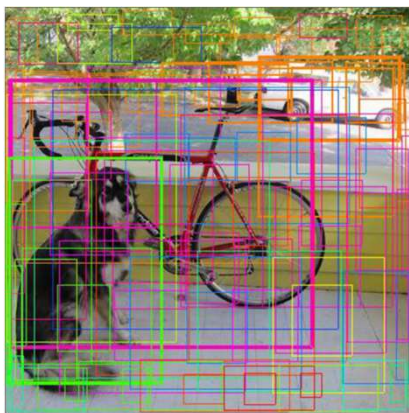
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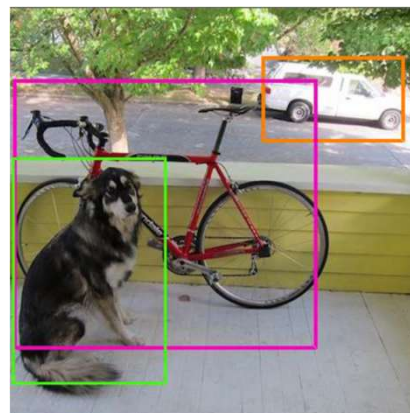
# YOLO: You Only Look Once



Class-specific Confidence



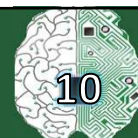
After applying Non-Maximum Suppression (NMS)



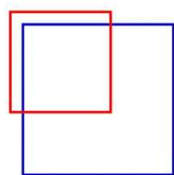
**Class-specific Confidence:**  $\Pr(\text{Class}_i | \text{Object}) * \Pr(\text{Object}) * \text{IOU}_{\text{pred}}^{\text{truth}} = \Pr(\text{Class}_i) * \text{IOU}_{\text{pred}}^{\text{truth}}$

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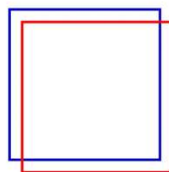
# IoU: Intersection over Union



$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$



Poor



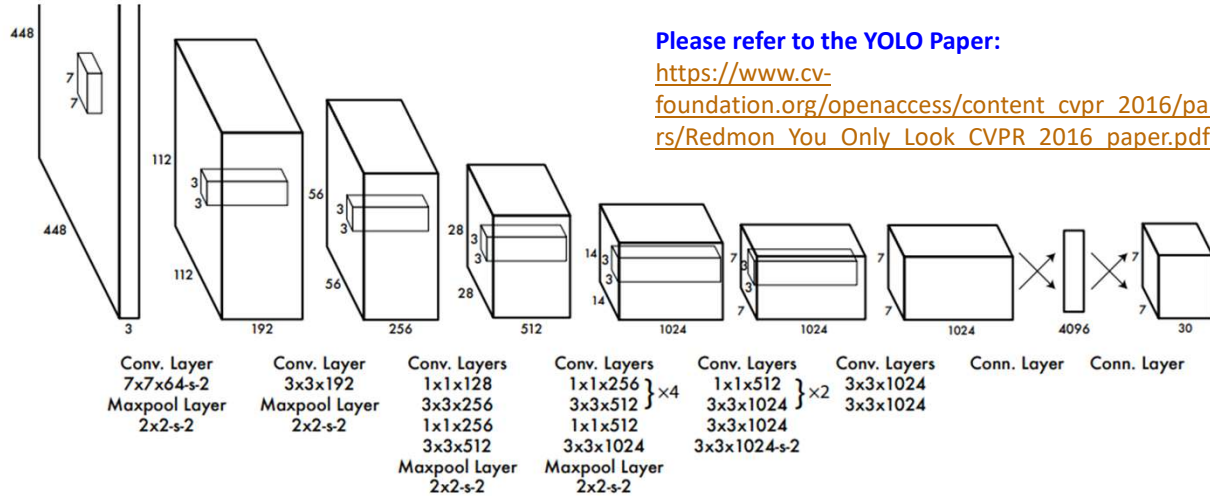
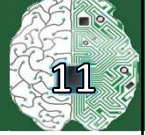
Good



Excellent

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# Network Design



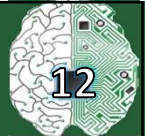
Please refer to the YOLO Paper:

[https://www.cv-foundation.org/openaccess/content\\_cvpr\\_2016/papers/Redmon\\_You\\_Only\\_Look\\_CVPR\\_2016\\_paper.pdf](https://www.cv-foundation.org/openaccess/content_cvpr_2016/papers/Redmon_You_Only_Look_CVPR_2016_paper.pdf)

Inspired from GoogLeNet, however does not use Inception layer

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# YOLO Objective Function



$$\begin{aligned}
 & \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{1}_{ij}^{\text{obj}} \left[ (x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right] \\
 & + \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{1}_{ij}^{\text{obj}} \left[ \left( \sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left( \sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right] \\
 & + \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{1}_{ij}^{\text{obj}} (C_i - \hat{C}_i)^2 \\
 & + \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{1}_{ij}^{\text{noobj}} (C_i - \hat{C}_i)^2 \\
 & + \sum_{i=0}^{S^2} \mathbb{1}_i^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2
 \end{aligned}$$

Please refer to the YOLO Paper:

[https://www.cv-foundation.org/openaccess/content\\_cvpr\\_2016/papers/Redmon\\_You\\_Only\\_Look\\_CVPR\\_2016\\_paper.pdf](https://www.cv-foundation.org/openaccess/content_cvpr_2016/papers/Redmon_You_Only_Look_CVPR_2016_paper.pdf)

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# YOLO Objective Function



$$\lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{1}_{ij}^{\text{obj}} \left[ (x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right]$$

$$+ \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{1}_{ij}^{\text{obj}} \left[ \left( \sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left( \sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right]$$

**Coordinate Loss:** Minimize the difference between  $x, y, w, h$  pred and  $x, y, w, h$  ground truth. ONLY IF object exists in grid box and if bounding box is resp for pred

$$+ \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{1}_{ij}^{\text{obj}} (C_i - \hat{C}_i)^2$$

**Confidence Loss:** Loss based on confidence ONLY IF there is object

$$+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{1}_{ij}^{\text{noobj}} (C_i - \hat{C}_i)^2$$

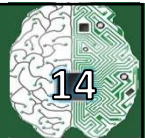
**No Object Loss:** based on confidence if there is no object

$$+ \sum_{i=0}^{S^2} \mathbb{1}_i^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2$$

**Class loss,** minimize loss between true class of object in grid box

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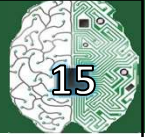
# Advantages of YOLO



- Pipeline comprised of a single network
- Learns general representation of the objects
- Extremely fast
- Reasons globally

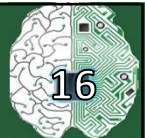
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# Drawbacks of YOLO



- More localization error
- Loss function

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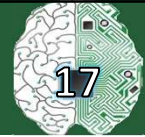


## Unit-5: Introduction (Sequence Modelling)

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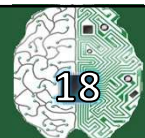
# Sequential Data Examples



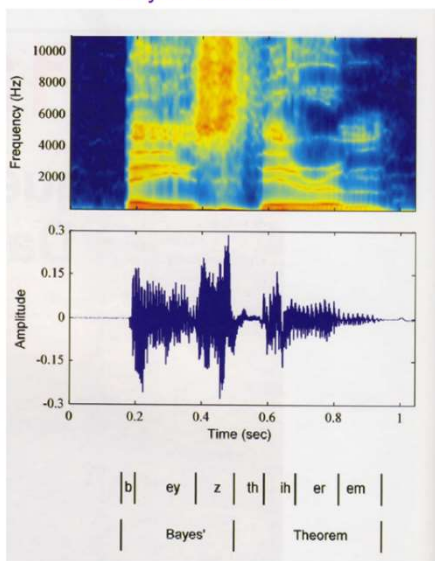
- Often arise through measurement of time series
  - Acoustic features at successive time frames in speech recognition
  - Sequence of characters in an English sentence
  - Parts of speech of successive words
  - Snowfall measurements on successive days
  - Rainfall measurements on successive days
  - Daily values of currency exchange rate
  - Nucleotide base pairs in a strand of DNA

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## Example



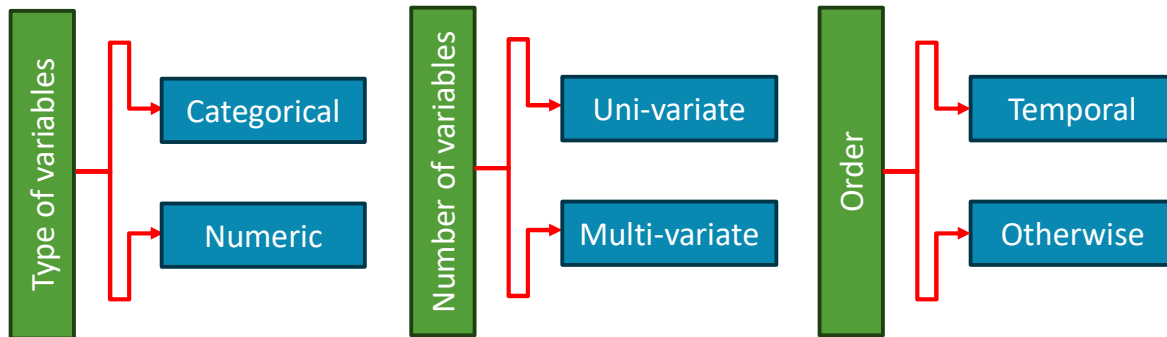
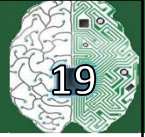
Bayes Theorem



- Decompose sound waves into frequency, amplitude using Fourier transforms
- Plot of the intensity of the spectral coefficients versus time index

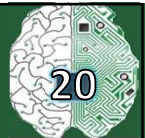
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# Types of Sequential Data



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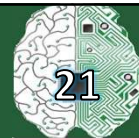
## Two common tasks with sequential data



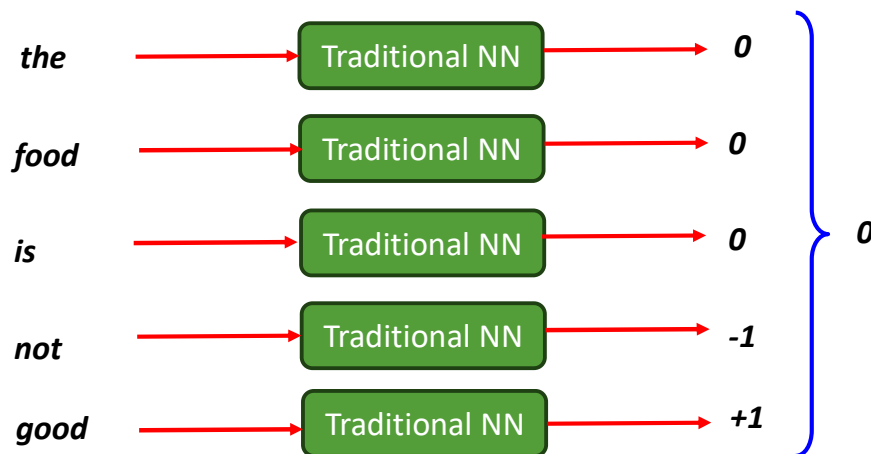
- **1. Sequence-to-sequence**
  - **Named Entity Recognition**
    - Input: Jim bought 300 shares of Acme Corp. in 2006
    - NER: [Jim]**Person** bought 300 shares of [Acme Corp.]**Organization** in [2006]**Time**
  - **Machine Translation:** Echte dicke kiste → Awesome sauce
- **2. Sequence-to-symbol**
  - **Sentiment:**
    - Best movie ever → Positive
  - **Speaker recognition**
    - Sound spectrogram → Harry

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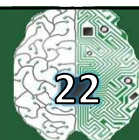
# Traditional NN & Sequence Data



- Categorizing a piece of text: ***“the food is not good”***



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## Questions?

Acknowledgement: Prof. Dr. S. K. Saha, Department of CSE, IIT (ISM) Dhanbad

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