

# Deep Learning Presentation

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Explaining and Harnessing Adversarial Examples

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# Motivation & Problem Statement

## The Context:

- Neural Networks are vulnerable to **Adversarial Examples**: inputs with worst-case perturbations causing high-confidence errors [GSS14].
- This is a security risk for safety-critical applications (e.g., autonomous driving).

## Project Goals

- ① Analyze the seminal work by Goodfellow et al. (2015).
- ② Extend the analysis from Classification to Object Detection (YOLO11n).

# Theoretical Framework: The Linearity Hypothesis

## Why are deep networks vulnerable?

- *Old Hypothesis:* Overfitting or extreme non-linearity.
- *Goodfellow's Hypothesis:* Models are "**too linear**" in high-dimensional spaces.

Consider a linear activation  $\mathbf{w}^\top \mathbf{x}$ . With perturbation  $\boldsymbol{\eta}$ :

$$\mathbf{w}^\top (\mathbf{x} + \boldsymbol{\eta}) = \mathbf{w}^\top \mathbf{x} + \mathbf{w}^\top \boldsymbol{\eta} \quad (1)$$

If we set  $\boldsymbol{\eta} = \varepsilon \cdot \text{sign}(\mathbf{w})$ :

- The activation grows by  $\varepsilon mn$  (where  $n$  is dimensionality).
- Many small changes accumulate to a massive shift in output.

# The Fast Gradient Sign Method (FGSM)

FGSM is a single-shot attack designed to maximize loss under an  $L_\infty$  constraint.

## The Attack Formula

$$\eta = \varepsilon \cdot \text{sign}(\nabla_x J(\theta, x, y)) \quad (2)$$

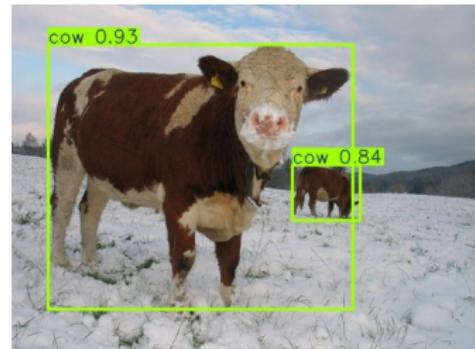
- **Efficient:** Requires only one backpropagation pass.
- **Dual Use:** Used for generating attacks and for adversarial training (regularization).
- **Constraint:**  $\|\eta\|_\infty < \varepsilon$  ensures imperceptibility.

# Our Contribution: Object Detection Setup

We extended the study to **One-Stage Detectors**.

## Experimental Setup:

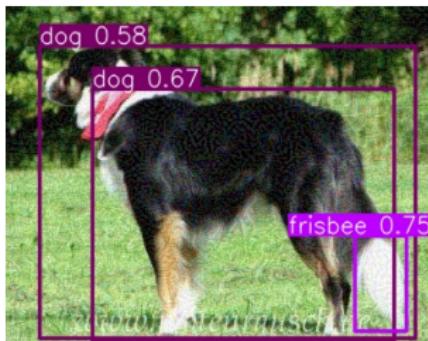
- **Target Model:** YOLOv1n (Nano) [JQ24].
- **Transfer Target:** SSDlite MobileNetV3.
- **Dataset:** Trained on COCO, Evaluated on VOC2007.
- **Metric:** Mean Average Precision (mAP) @ IoU=0.5.



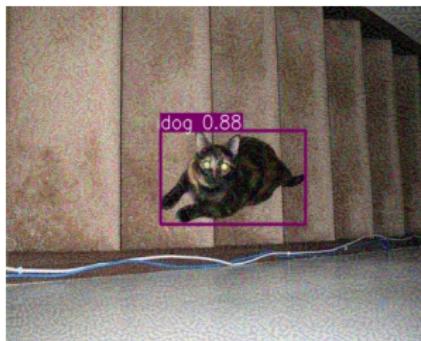
Clean Detection (Confidence 0.70)

## Attack Results: Failure Modes

FGSM successfully degrades detection performance, leading to three specific failure modes:



**Fabrication:** Detecting non-existent objects.



**Mislabeling:** Predicting wrong classes.



**Vanishing:** Valid objects erased from prediction.

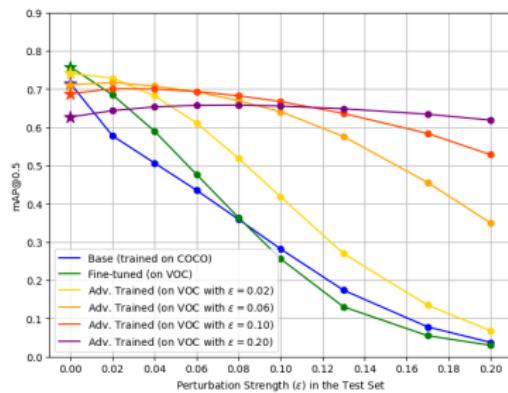
**Transferability:** Attacks generated for YOLO11n also degraded SSDlite (Black-box scenario), confirming the universality of the vulnerability.

# Adversarial Training: The Trade-off

We fine-tuned YOLO11n on adversarial examples.

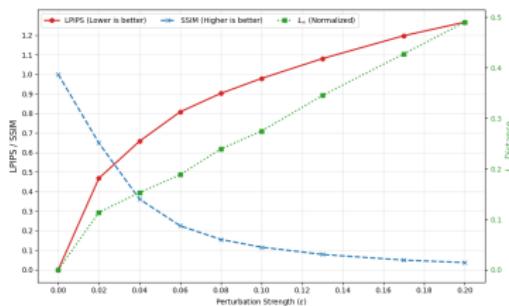
## Key Findings:

- **Trade-off:** Increasing  $\varepsilon$  improves robustness but degrades performance on clean images.
- **Low  $\varepsilon$  (0.02):** Negligible defense.
- **High  $\varepsilon$  (0.20):** Destroys clean accuracy.
- **Sweet Spot:** We identified  $\varepsilon \in [0.08, 0.10]$  as the optimal balance for this architecture.



# Critique of Imperceptibility

Is  $L_\infty$  a good proxy for human perception?



- We compared  $L_\infty$  against perceptual metrics: **SSIM** and **LPIPS**.
- **Result:** While  $L_\infty$  scales linearly with  $\epsilon$ , perceptual degradation (LPIPS) is non-linear.
- **Implication:** Future defenses should optimize against perceptual distances rather than simple pixel norms.

# Conclusion

- ① **Validation:** We confirmed Goodfellow's hypothesis that linearity is the primary cause of adversarial vulnerability.
- ② **Generalization:** We showed these vulnerabilities persist in complex Object Detection tasks (YOLO11n).
- ③ **Defense:** Adversarial Training is effective but introduces a critical trade-off between robustness and standard accuracy.
- ④ **Future Work:** Investigating patch-based attacks and integrating perceptual metrics (LPIPS) into the loss function.

# Bibliography I

- [GSS14] Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy. “Explaining and harnessing adversarial examples”. In: *arXiv preprint arXiv:1412.6572* (2014).
- [JQ24] Glenn Jocher and Jing Qiu. *Ultralytics YOLO11*. Version 11.0.0. 2024. URL:  
<https://github.com/ultralytics/ultralytics>.