Project 9

Computer Vision - A.Y. 2024/2025

Advanced Out-of-Distribution Detection for Multi-Class Classification

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Outline

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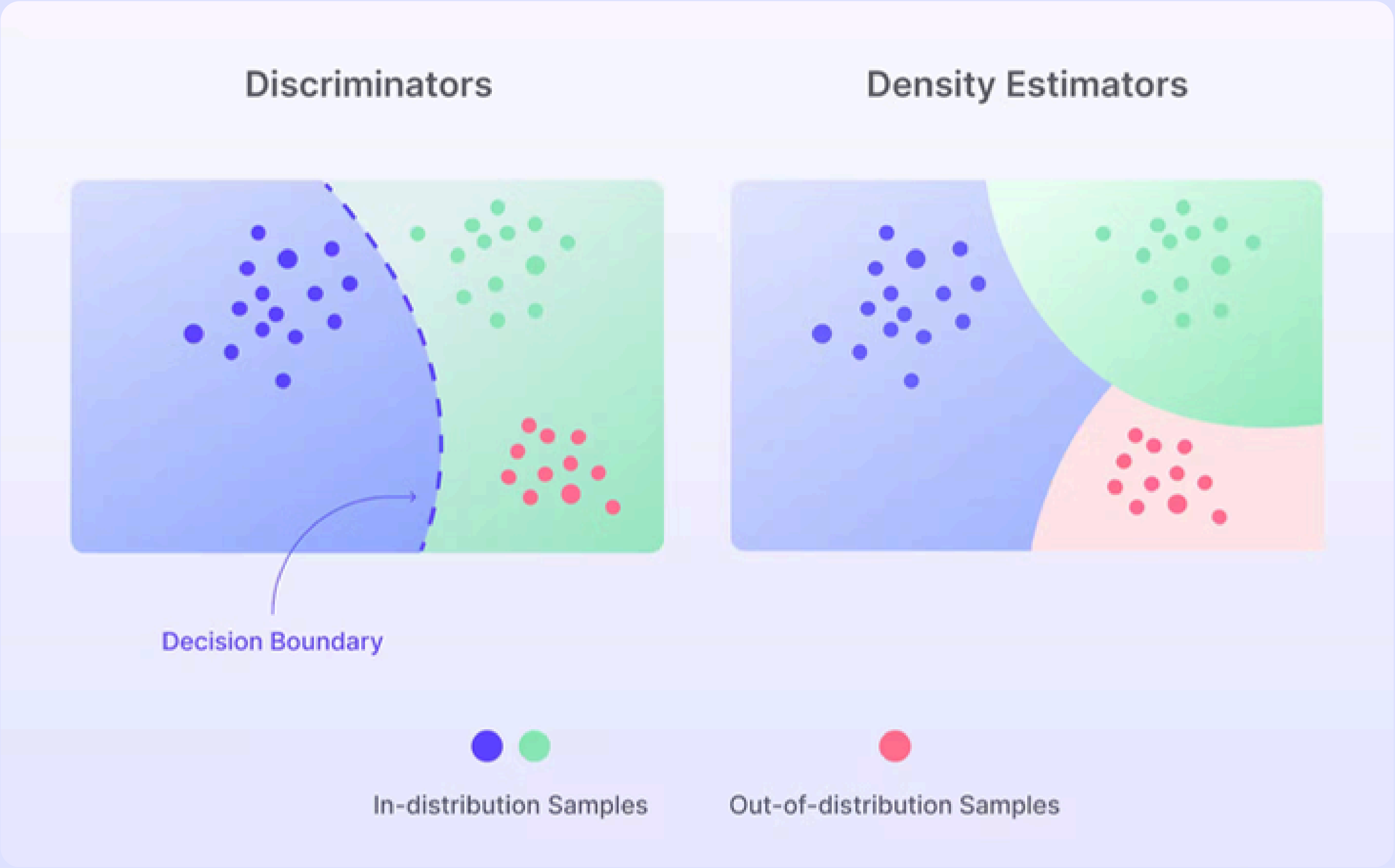
What is the challenge?

Classification models often encounter **out-of-distribution (OOD)** data, i.e., data that differs from the training distribution.
These inputs can lead to incorrect and unreliable predictions.

The goal of the project is to develop a system that can:

- Recognize known data (in-distribution, Food-101)
- Effectively detect OOD data (CIFAR-100)
- Evaluate the performance of different OOD detection techniques to improve model robustness.



In-Distribution vs Out-of-Distribution

Current Solutions for OOD Detection

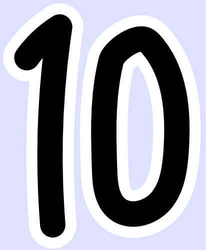
Several methods have been proposed to detect OOD inputs in deep learning models.

The main research directions include:

- **Energy-Based Models (EBMs)**: Use the model's output energy score to distinguish between in-distribution and OOD samples.
- **Gradient-Regularized Methods**: Introduce regularization terms based on gradients to improve OOD sensitivity during training.
- **Response-Based Scores**: Use neural response statistics (like activations) to compute OOD scores.

These approaches aim to improve model reliability by better separating known and unknown data distributions.

Datasets



Food-101	We have 101.000 images, 1000 images for 101 different categories of food.
SVHN	House Number Images from Google Street View, formed by digits 0-9 (10 classes).
CIFAR-100	6.000 images of natural objects for 10 different classes .

Experimental Setup: Fundamentals

Main Libraries:

- PyTorch – Core deep learning framework.
- Torchvision – Datasets, pretrained models, image transforms.
- Scikit-learn – Evaluation metrics (accuracy, precision, recall, ROC AUC, etc.).
- Matplotlib & Seaborn – Plotting and visualization.
- Google Colab + Drive – Development environment and model checkpoint storage.

Model Backbone:

- ResNet50, pretrained on ImageNet and adapted to the Food-101 dataset.
- Selective fine-tuning strategy:
  - Frozen: initial layers (low-level features).
  - Trainable: layers 2–4 + final fully connected layer.