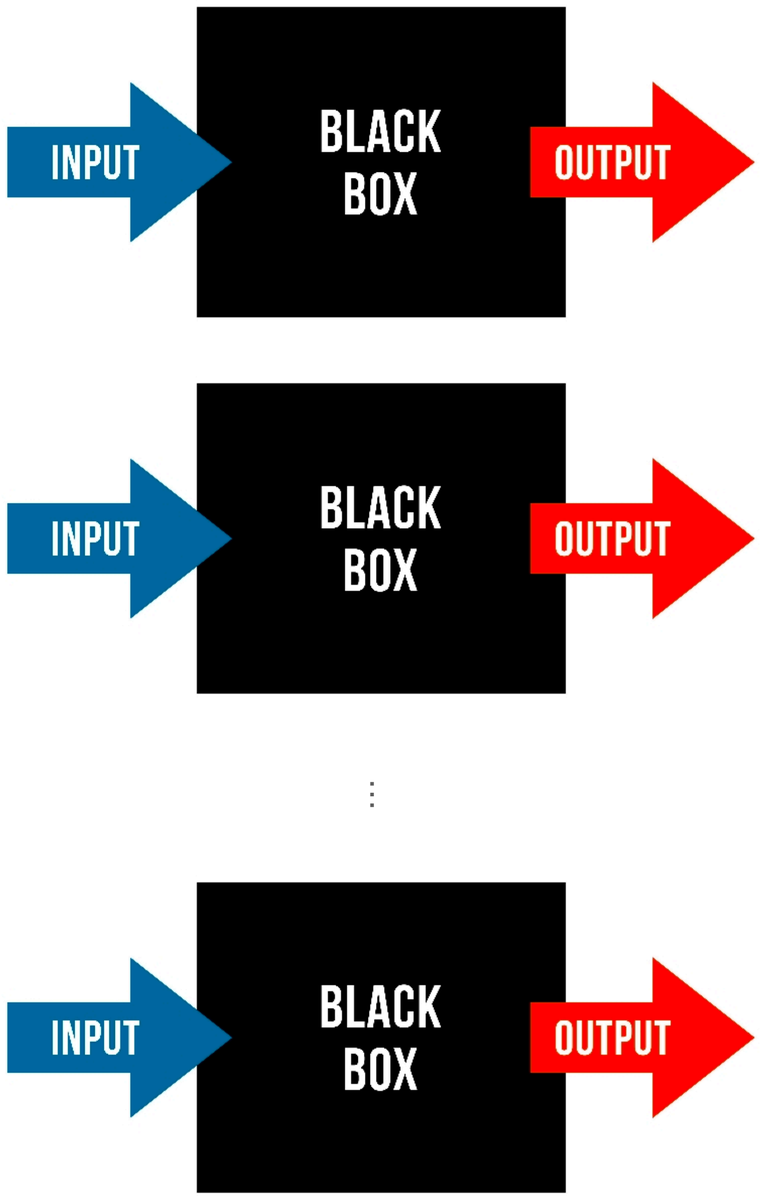
Unsupervised Aggregation of Deep Models

Amirhossein Afsharrad

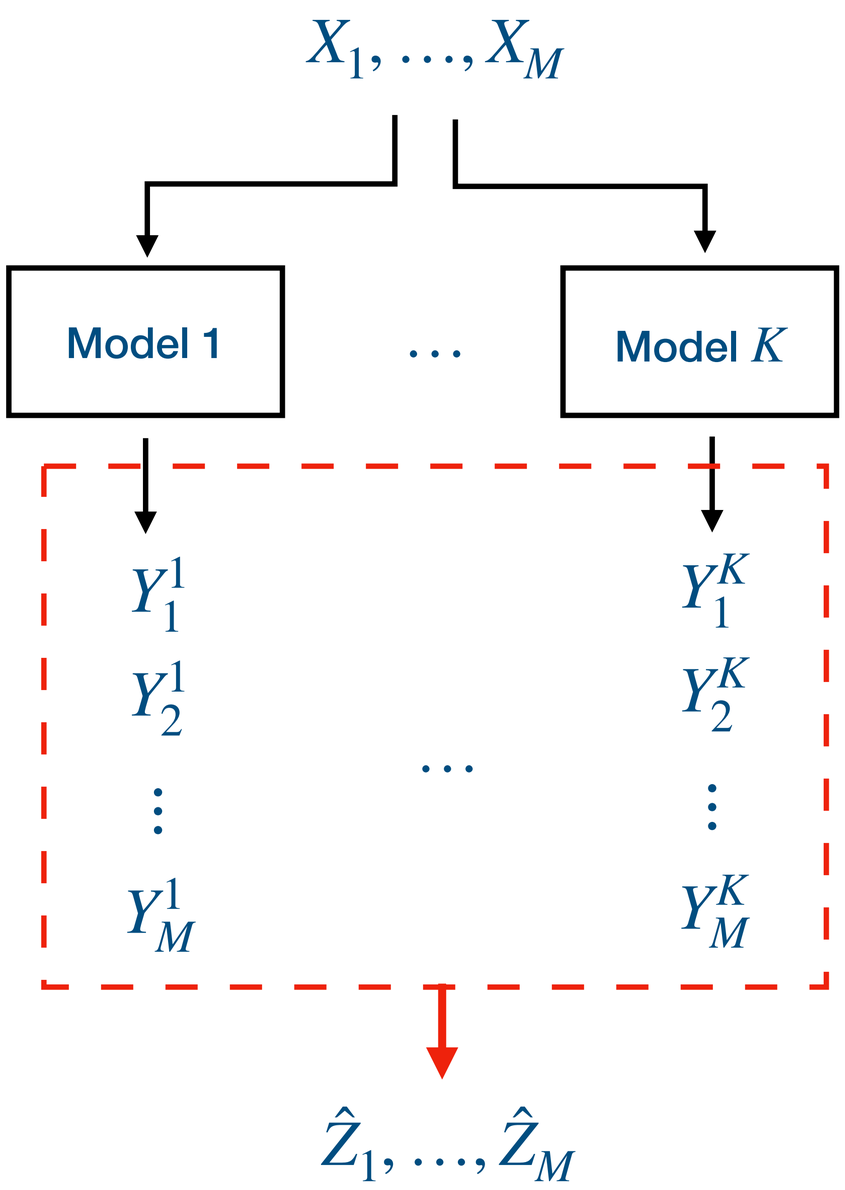
Introduction

- **Ensemble Models:** a group of algorithms focusing on aggregating multiple base learners to outperform each individual learner
- **Black-Box Models:** models that we only have access to their input-output pairs
- **Goal:** aggregation of deep black-box models in an **unsupervised** manner



Problem Statement

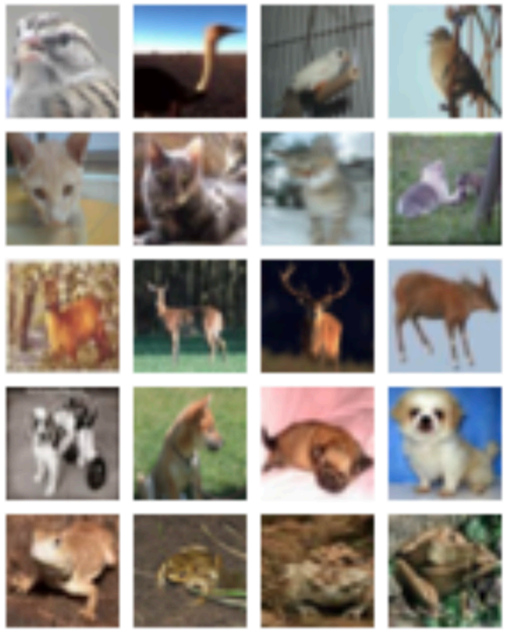
- $X_1, \ldots, X_M$: unlabelled samples (images)
- K local classifiers
- Y_m^k: label of the kth model to the mth input
- $Z_1, \ldots, Z_M$: hidden true labels
- Goal: Estimate $Z_{1:M}$ by observing $X_{1:M}$ and $Y_{1:M}^{1:K}$



Dataset

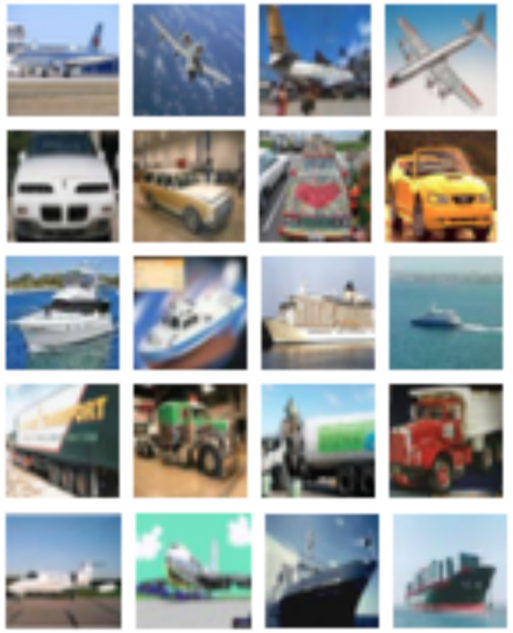
- CIFAR10
- ImageNet
- Animal and Non-Animal binary classification

Animal



$Z = 1$

Non-Animal



$Z = 0$

Mathematical Model

Model Introduction

- **Model 1: Uniform Error Model**
  - The kth model makes a prediction error with probability ϵ_k
  - Maximum Likelihood Problem:

$$\max_{Z_1,\ldots,Z_M} \sum_{k=1}^{K} \sum_{m=1}^{M} \log \mathbb{P}(Y_m^k \mid Z_m)$$

- **Model 2: Non-Uniform Error Model**
  - The kth model makes a prediction error with probability $\epsilon_k(X)$ for the input vector X
  - Maximum Likelihood Problem:

$$\max_{Z1,\ldots,Z_M} \sum_{k=1}^{K} \sum_{m=1}^{M} \log \mathbb{P}(Y_m^k \mid Z_m, X_m)$$

Mathematical Model

Problem Formulation

- **Model 1: Uniform Error Model**
  - Since we do not know ϵ_k, we jointly maximize over ϵ, $Z_{1:M}$:

$$\max_{\epsilon_1,\ldots,\epsilon_K} \max_{Z_1,\ldots,Z_M} \sum_{k=1}^{K} \sum_{m=1}^{M} \log \mathbb{P}(Y_m^k \mid Z_m)$$

  - Solving this problem is exponential in M, instead we use Expectation Maximization:

Until Convergence:
1. Fix Z, and maximize over ϵ
2. Fix ϵ, and maximize over Z

- **Model 2: Non-Uniform Error Model**
  - Since we do not know ϵ_k, we jointly maximize over ϵ, $Z_{1:M}$:

$$\max_{\epsilon_1(.),\ldots,\epsilon_K(.)} \max_{Z1,\ldots,Z_M} \sum_{k=1}^{K} \sum_{m=1}^{M} \log \mathbb{P}(Y_m^k \mid Z_m, X_m)$$

  - Solving this problem is exponential in M, instead we use Expectation Maximization:

Until Convergence:
1. Fix Z, and maximize over ϵ
2. Fix $\epsilon(\,.\,)$, and maximize over Z

Mathematical Model

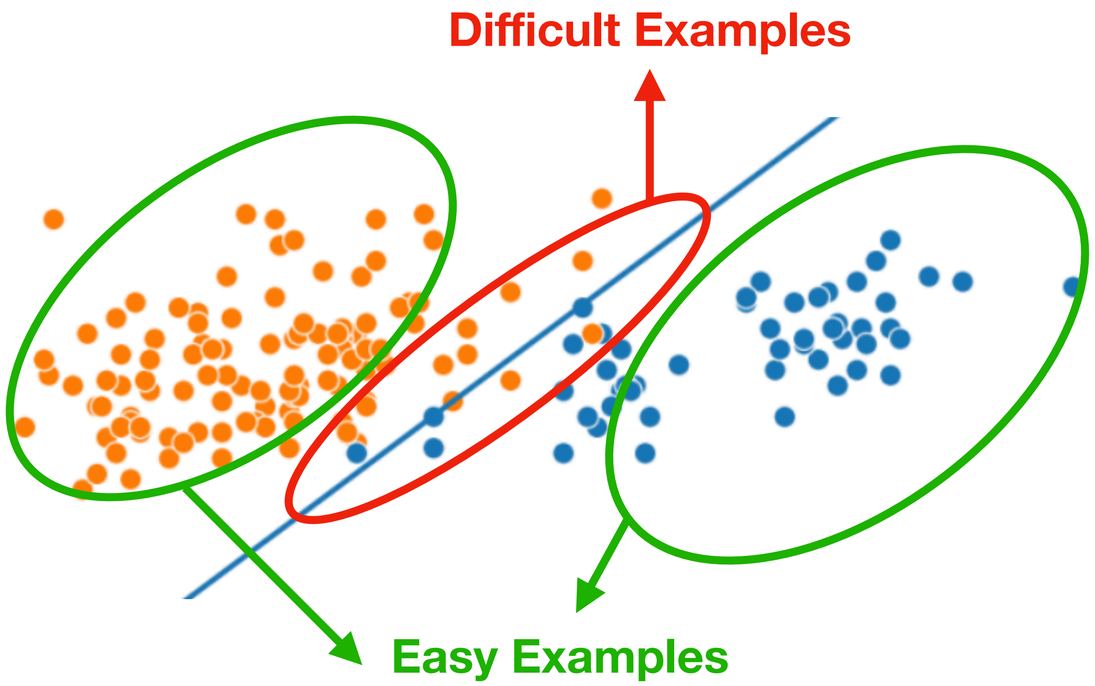
Comparing the Two Models

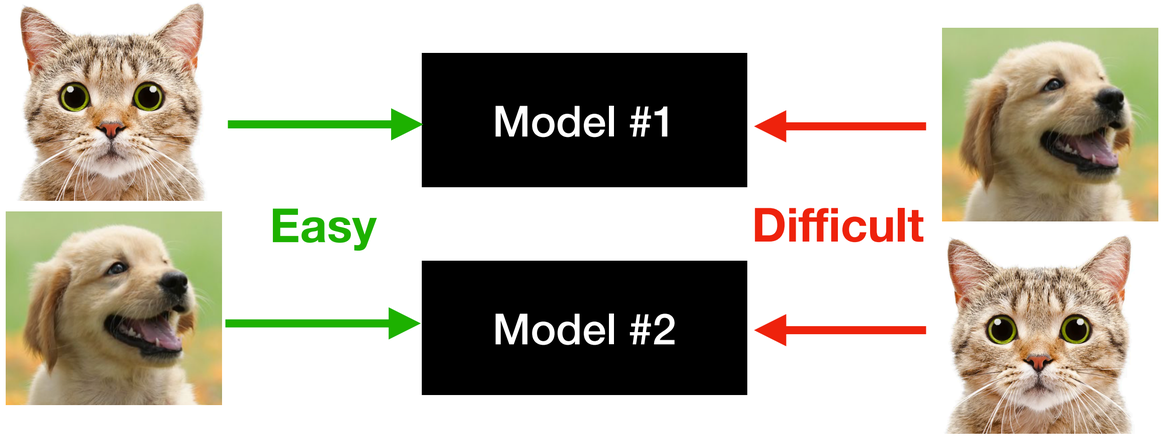
- Why do we need to introduce the non-uniform model?

  The error depends on the input

1. There are easy and hard examples

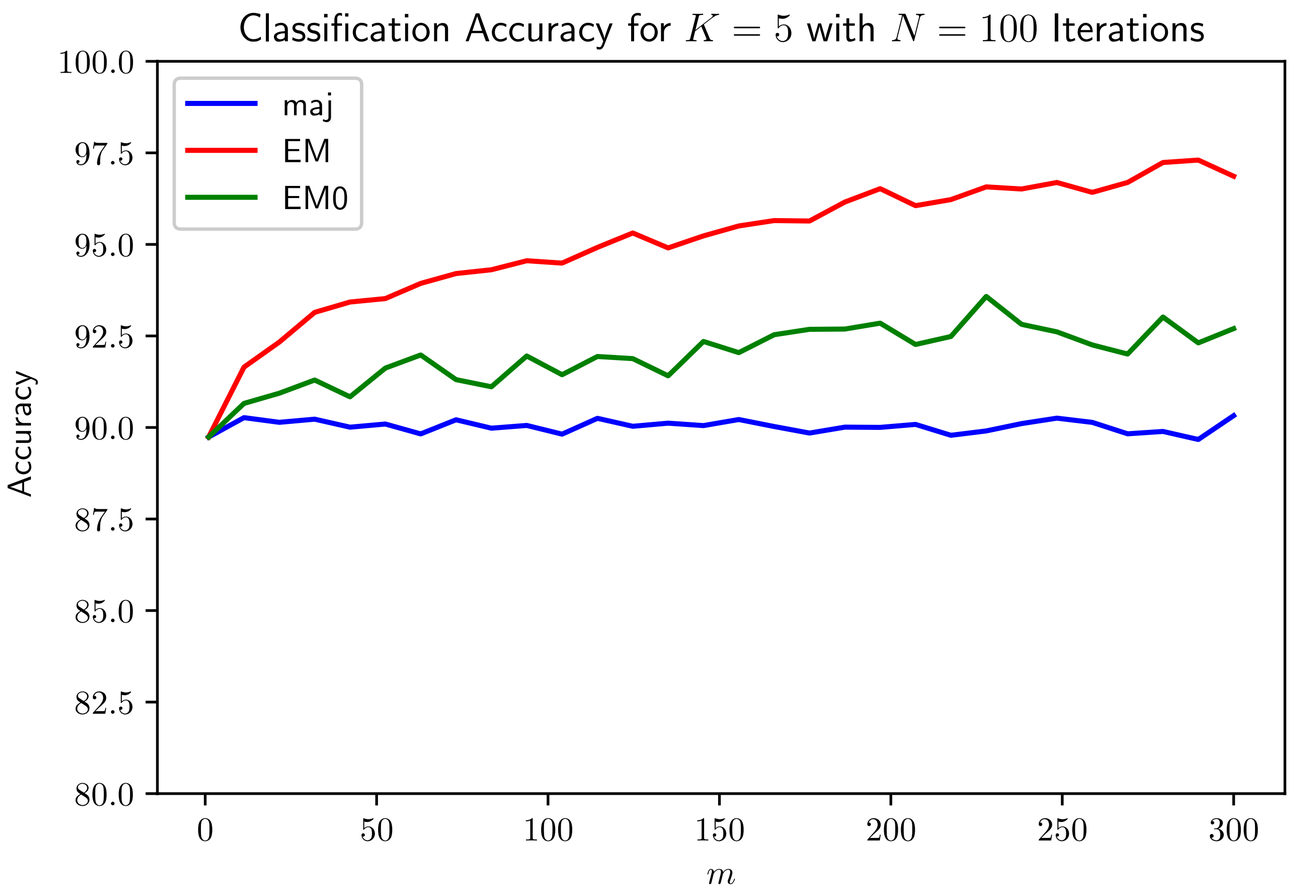
2. Models can be specialized
   A specific example can be easy for one model but difficult for another





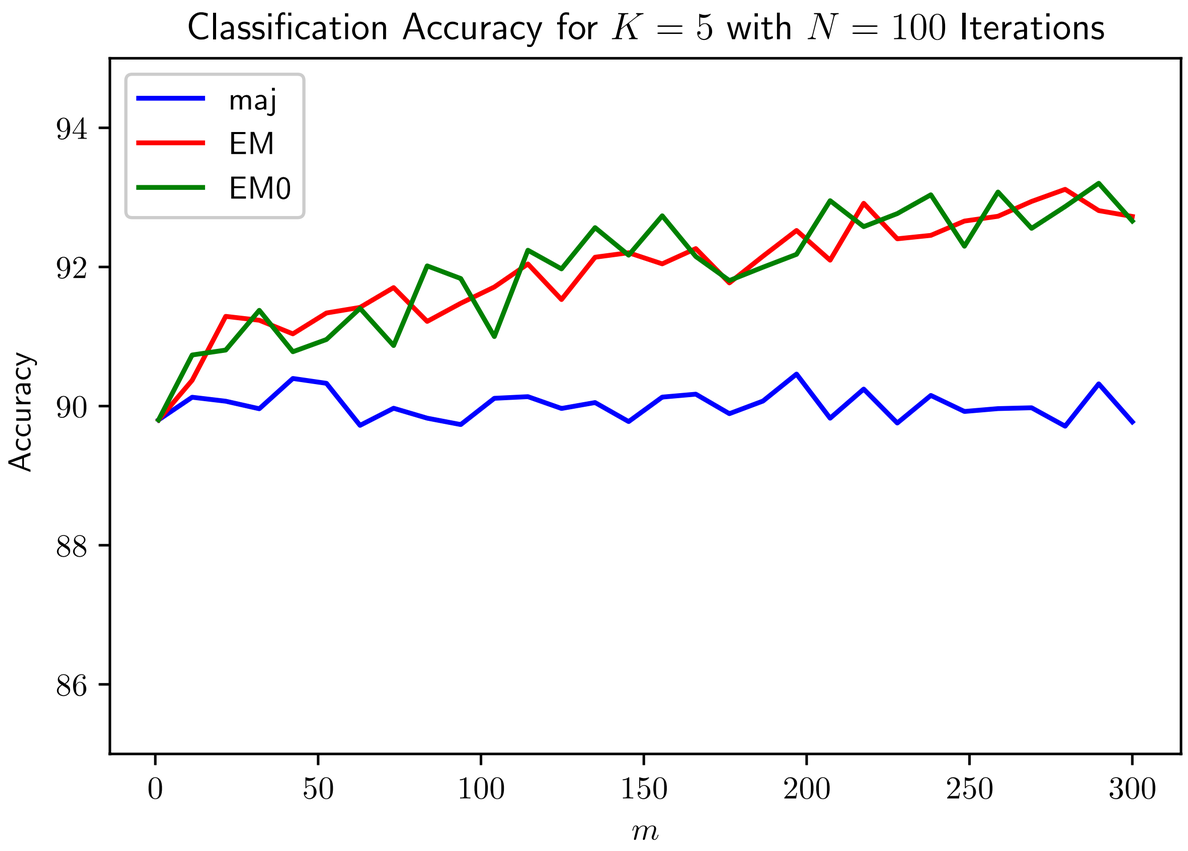
Results

- Ideal (Synthetic) Setting
- Local models having different overall accuracy
- $\epsilon_k(X)$ varies with X
    - maj: simple majority voting
    - EM0: uniform error model
    - EM: non-uniform error model



Results

- Ideal (Synthetic) Setting
- Local models having different overall accuracy
- $\epsilon_k(X)$ does not vary with X (uniform error model holds)



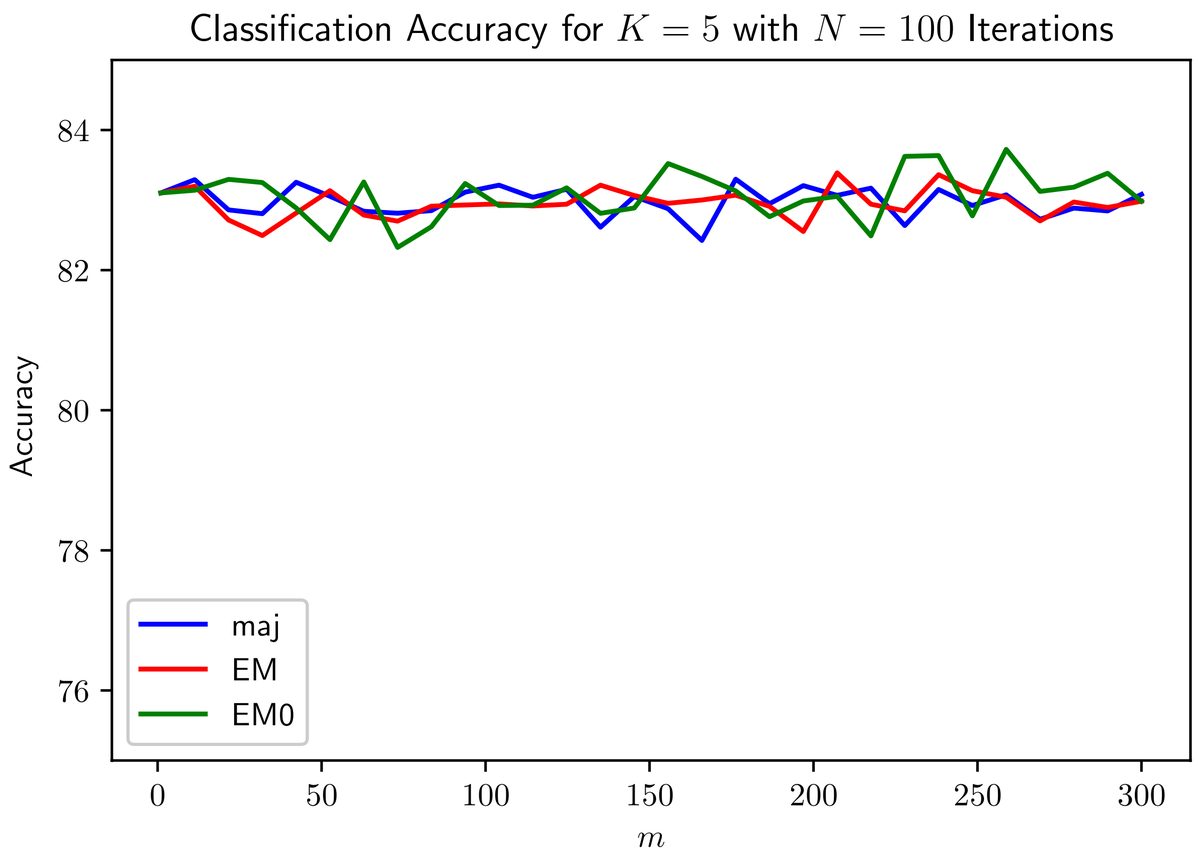
Results

- Realistic Setting
- 5 convolutional neural networks

Problem: pixel-wise distance of images is not a good measure

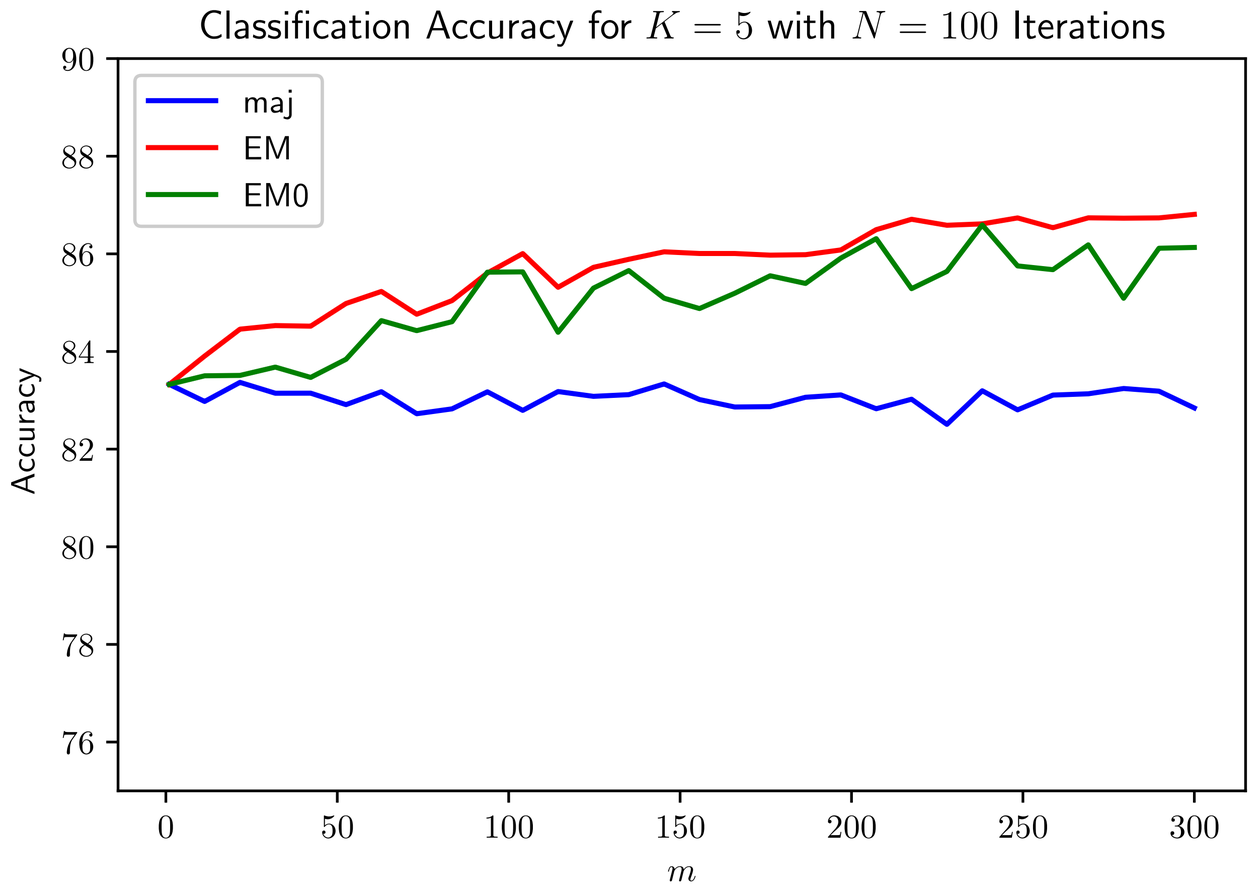
Solution:

1. Color histogram / HOG
2. Auto-Encoders



Results

- Realistic Setting
- 5 convolutional neural networks
- $\epsilon_k(X)$ varies with X
- Auto-encoders used to create $\hat{X}$ from X, then we estimate $\epsilon_k(\hat{X})$



Conclusion and Future Works

- We studied a novel approach to combine black-box deep models and outperform majority voting for model aggregation.
- Future directions:
  - Non-binary classification
  - More complicated models (RNNs)
  - Finding theoretical guarantees for the proposed algorithms