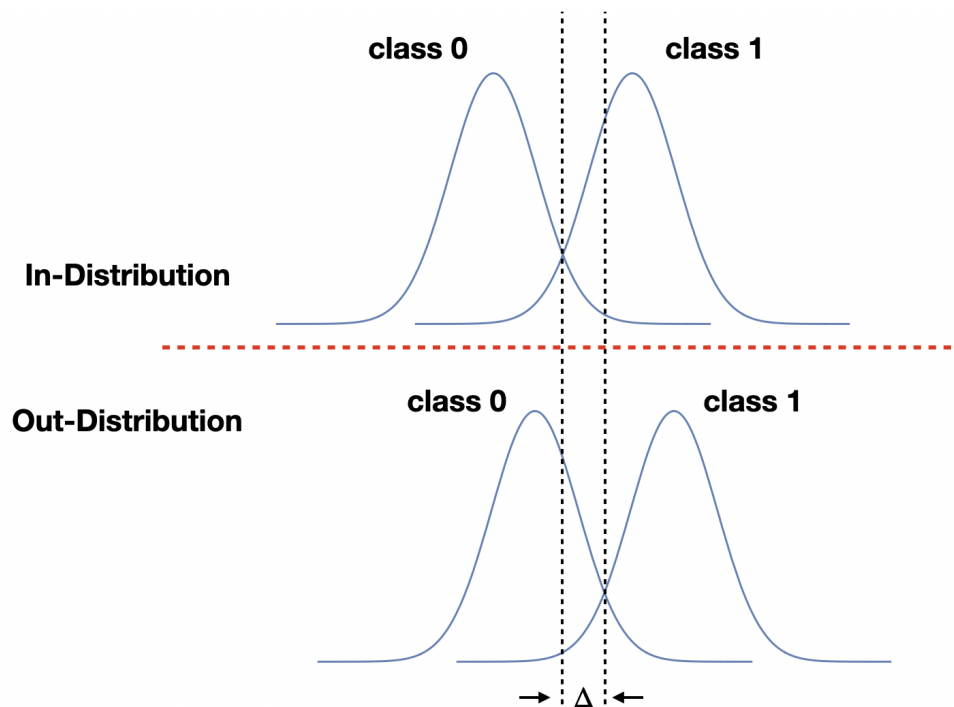


# Out-of-Distribution Learning

# Gaussian Tasks Experiment

- Consider an in-distribution task that consists of two class conditional gaussians.
- Now, consider an out-of-distribution task similar to the above task, but whose center is displaced by an amount  $\Delta$ .
- The amount  $\Delta$  reflects the "similarity" between the two tasks.



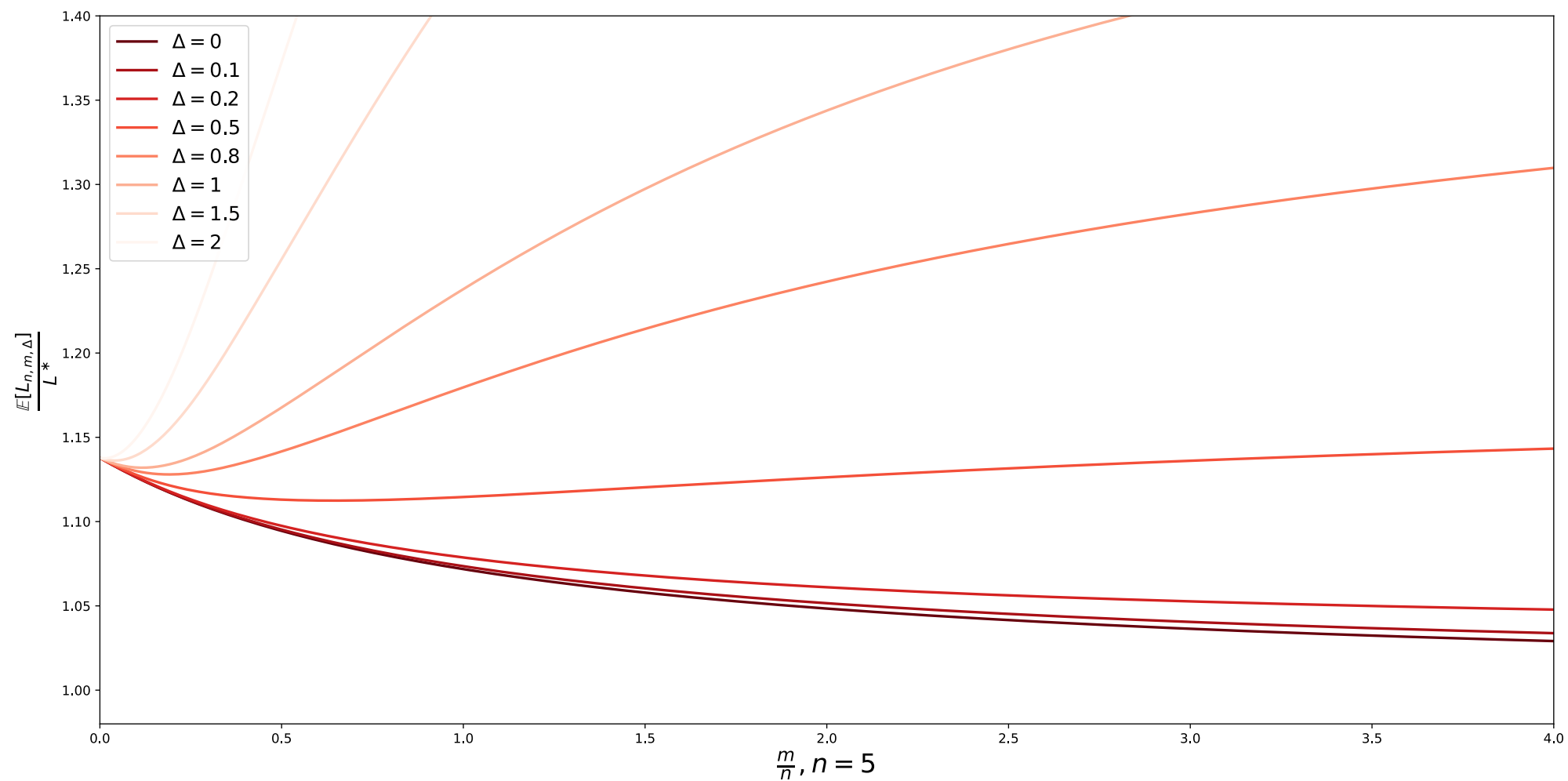
# Gaussian Tasks Experiment

- We have access to  $n$  samples from the in-distribution task, and  $m$  samples from the out-of-distribution task.
- Using both the in-distribution and out-of-distribution samples, we train a classifier  $h$  aimed at the in-distribution classification task.
- Let's denote the classification error of  $h$  by  $\mathbb{E}[L_{n,m,\Delta}]$ .

# Gaussian Tasks Experiment

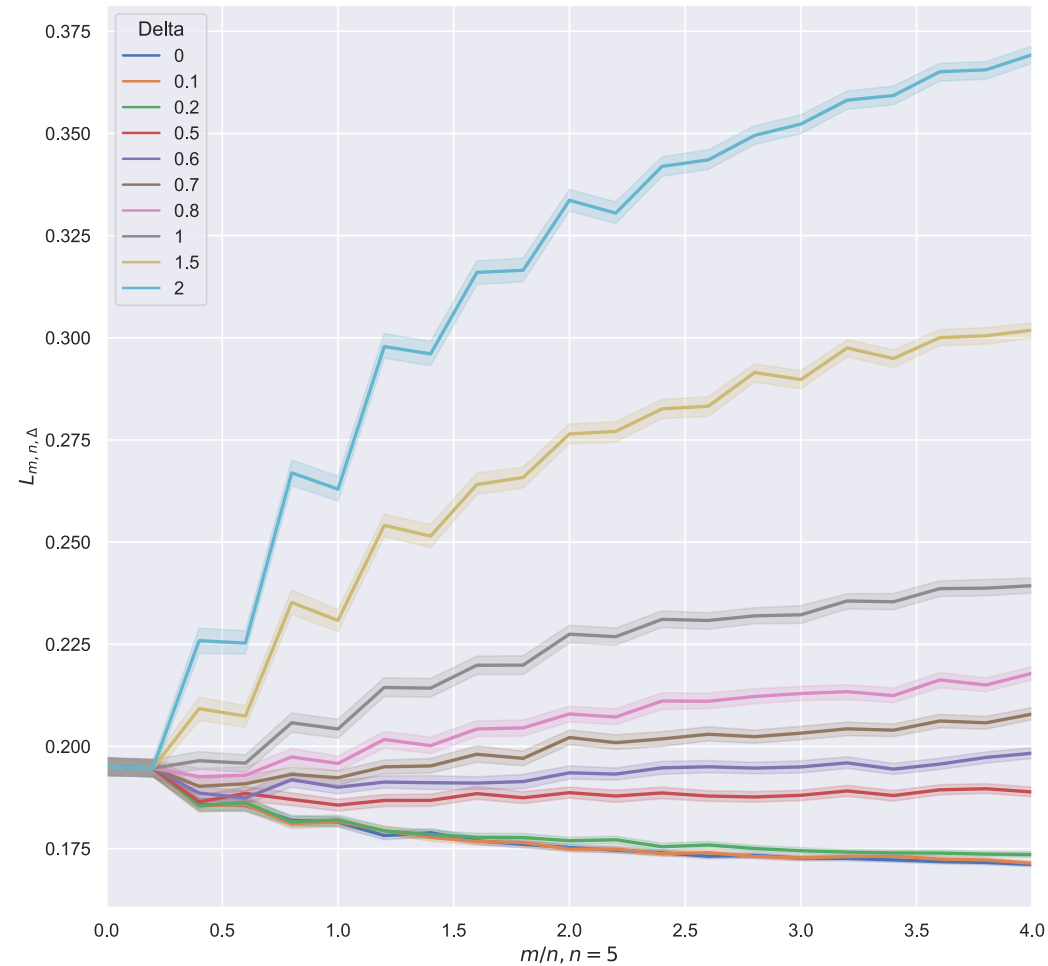
- Let  $n$  be a small fixed constant. We hypothesize that,
  - For very small  $\Delta$ , as we add more out-of-distribution data (as  $m$  increases) the  $\mathbb{E}[L_{n,m,\Delta}]$  would decrease.
  - For moderately large  $\Delta$ , as we add more out-of-distribution data (as  $m$  increases) the  $\mathbb{E}[L_{n,m,\Delta}]$  would initially decrease and start increasing later. The initial decrease is due to the reduction in the variance of  $h$ . The later increase is due to the increase in bias of  $h$  caused by the out-of-distribution samples.
  - For very large  $\Delta$ , as we add more out-of-distribution data (as  $m$  increases) the  $\mathbb{E}[L_{n,m,\Delta}]$  would keep increasing.

# Gaussian Tasks Experiment



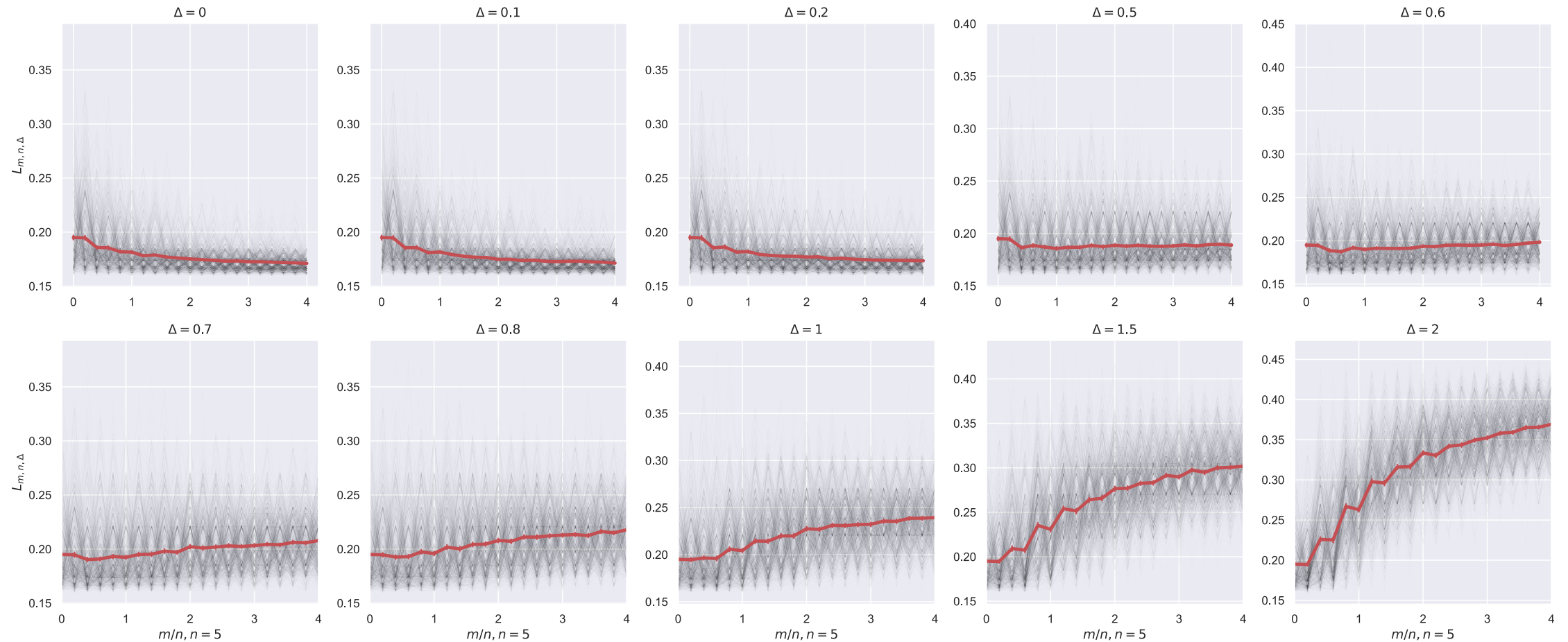
# Gaussian Tasks Experiment

- Number of replicates: 1000



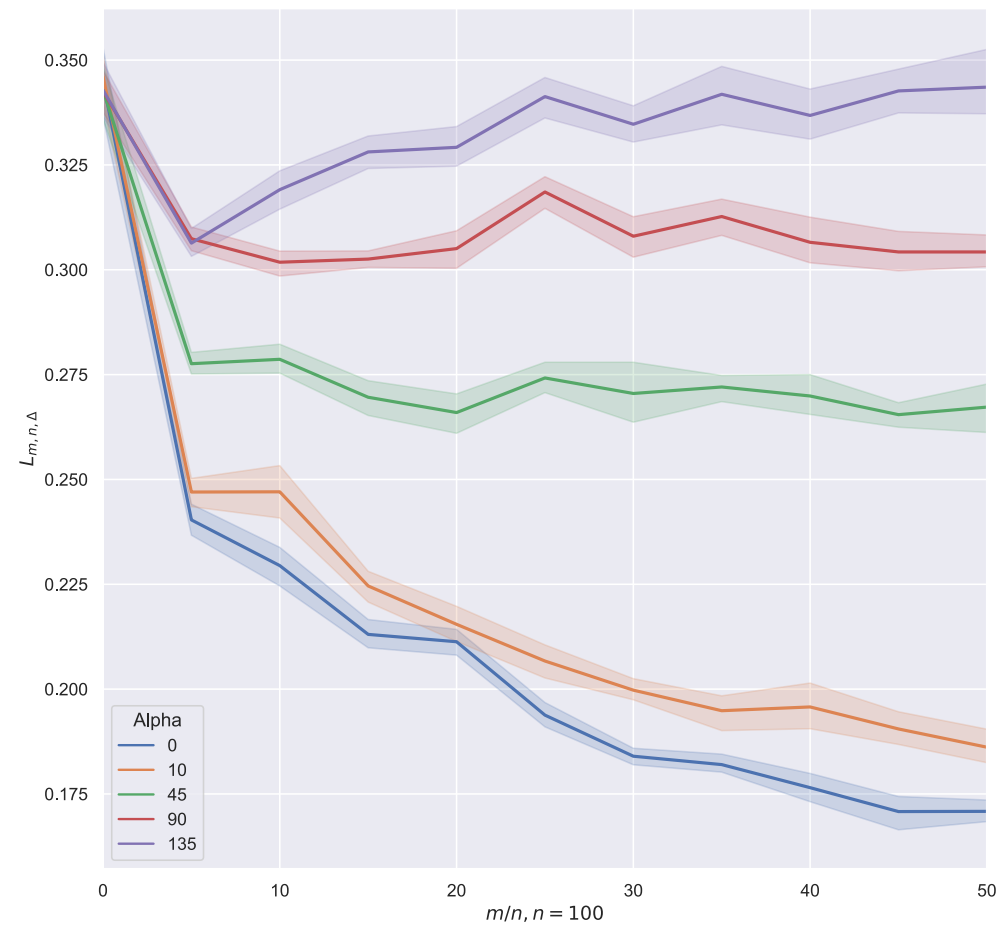
# Gaussian Tasks Experiment

- Number of replicates: 1000



# Bird vs. Cat & $\alpha$ -Rotated Bird vs. Cat (Single-Head Network)

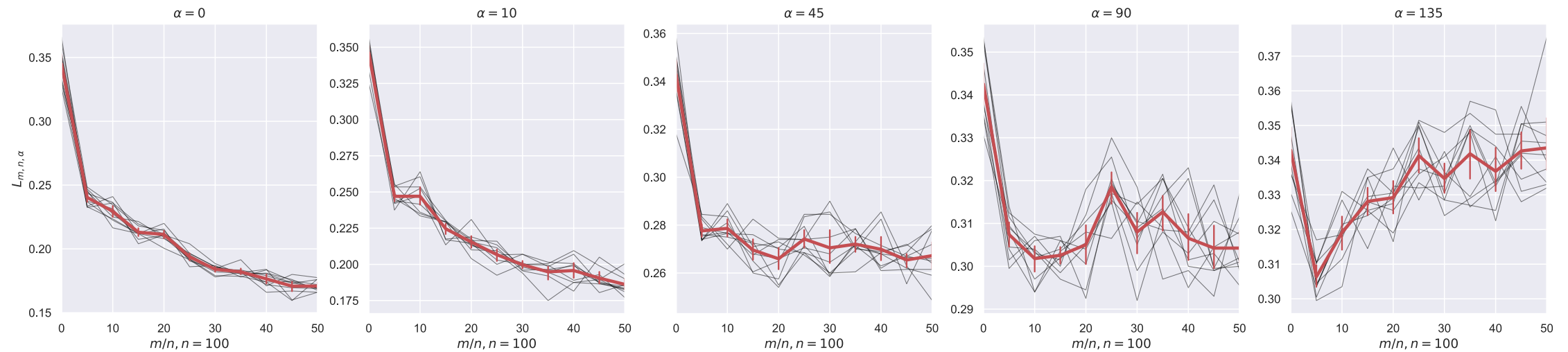
- Number of replicates: 10, Network: SmallConv





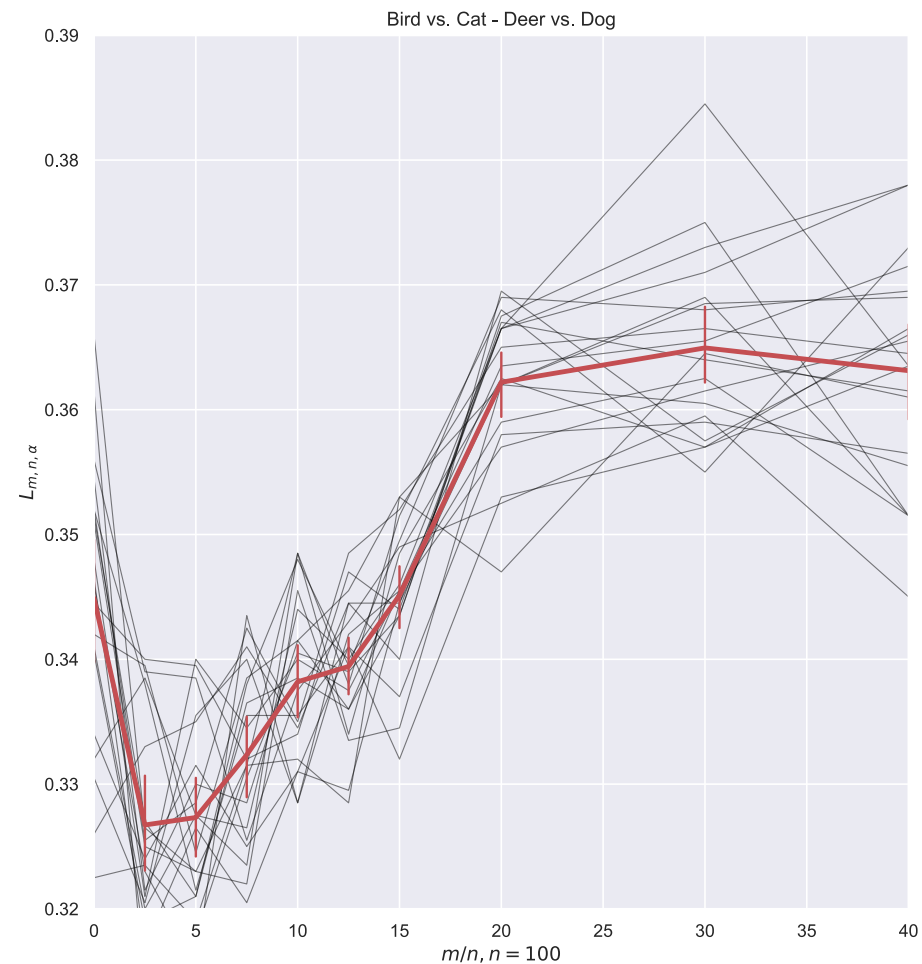
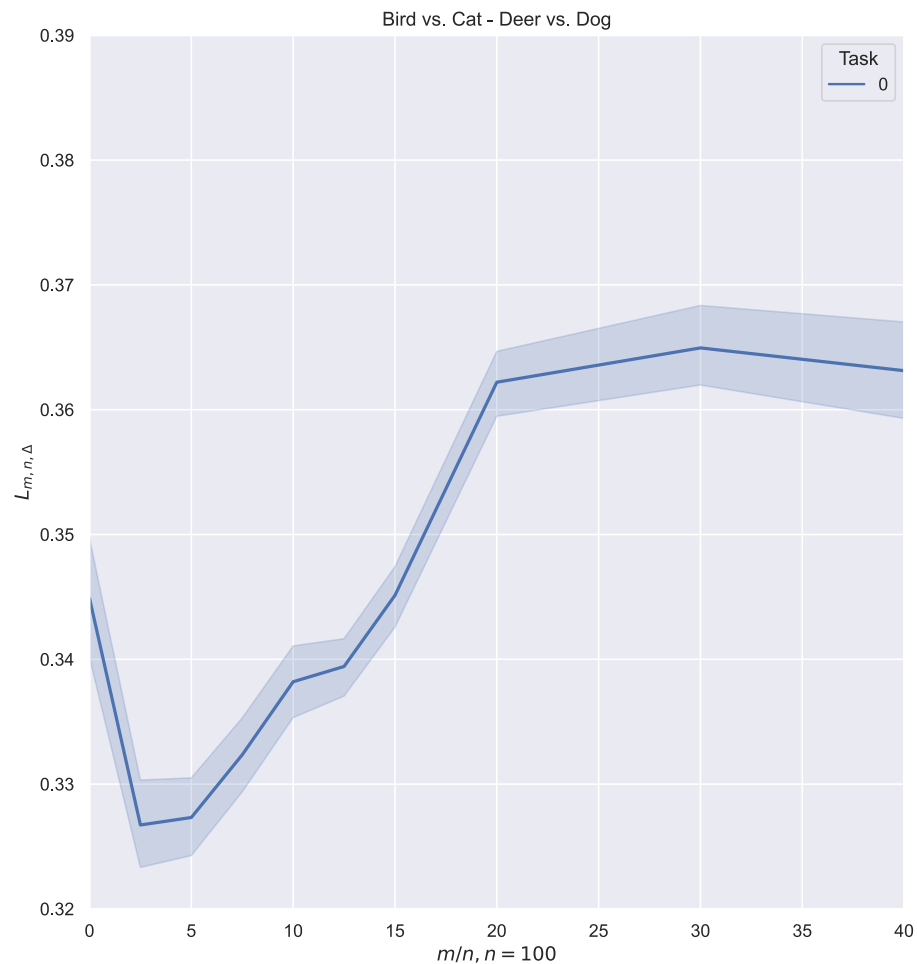
# Bird vs. Cat & $\alpha$ -Rotated Bird vs. Cat (Single-Head Network)

- Number of replicates: 10, Network: SmallConv



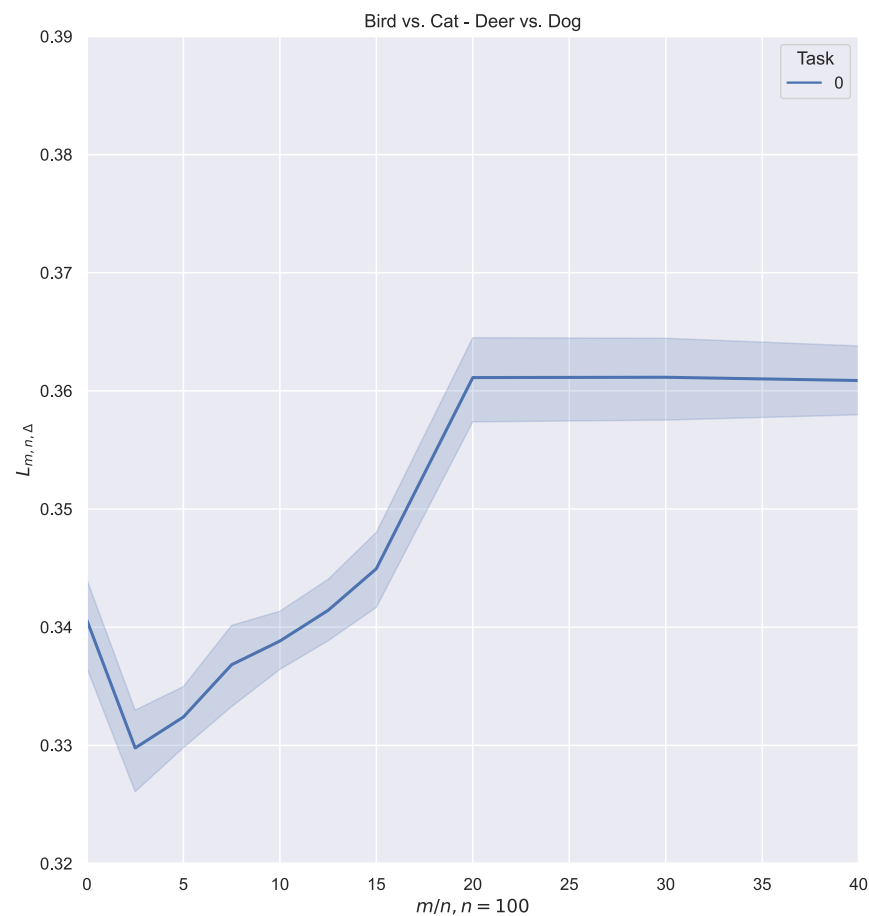
## Task 2: Bird vs. Cat & Task 3: Deer vs. Dog (Single-Head Network)

- Number of replicates: 20, Network: SmallConv



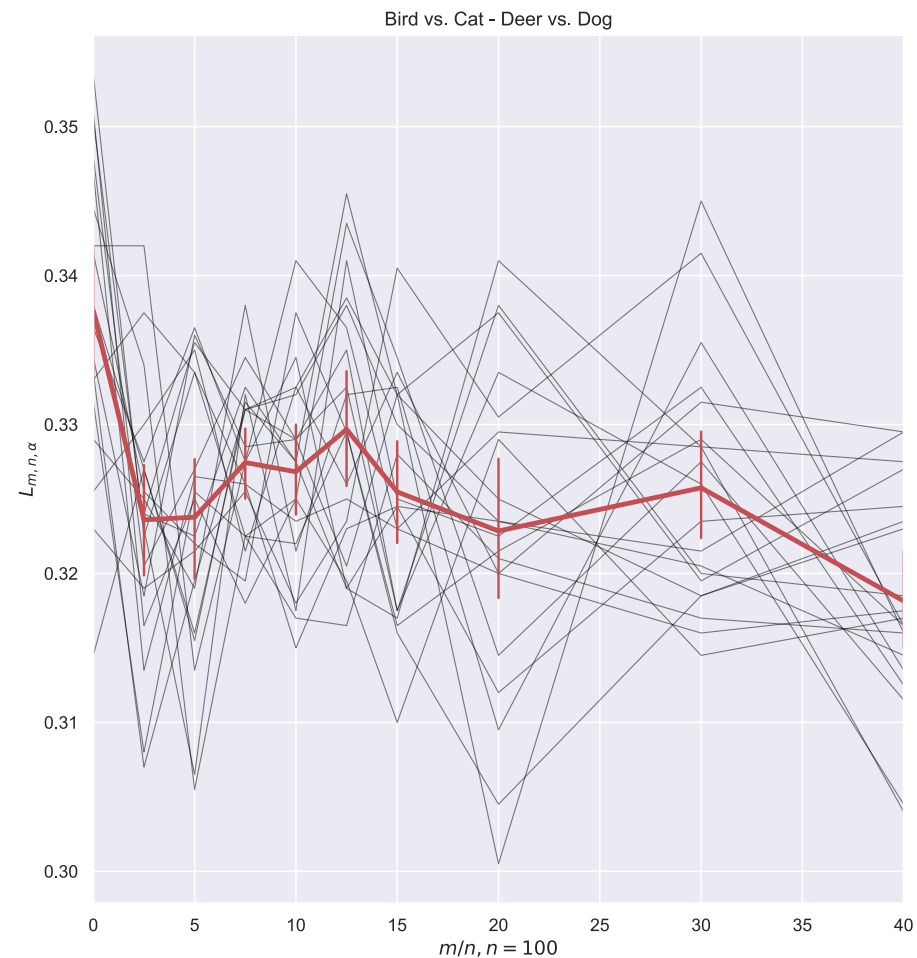
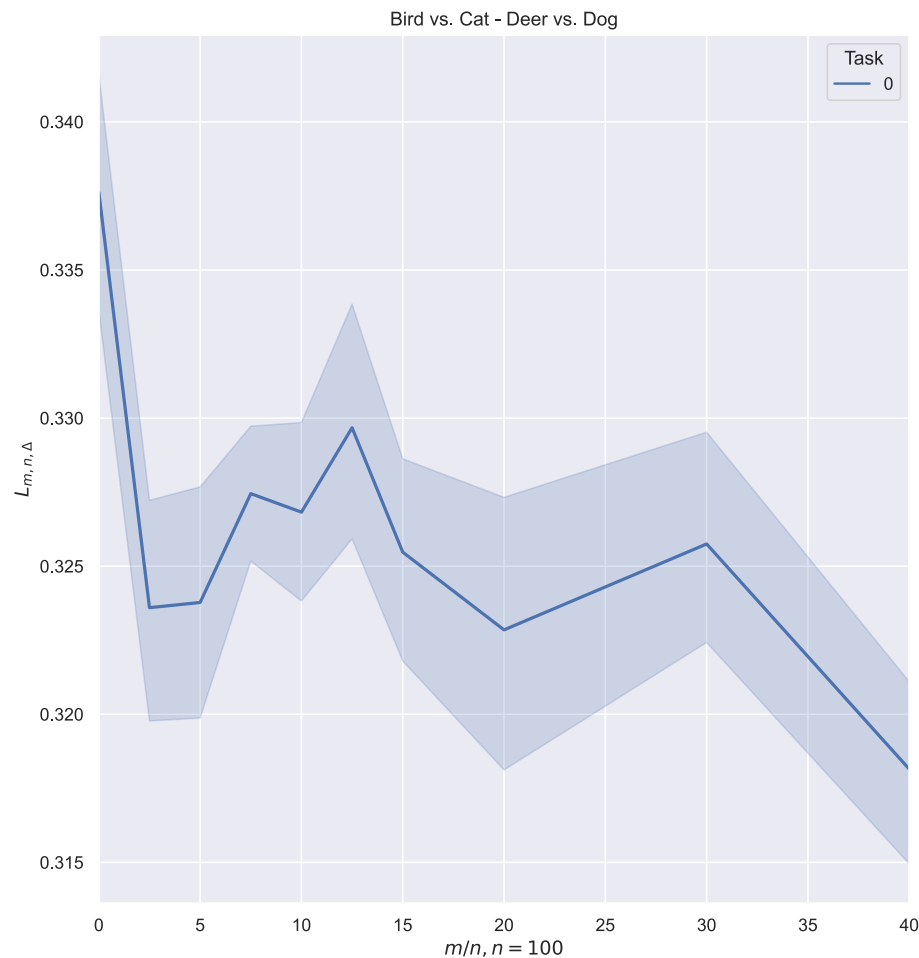
## Task 2: Bird vs. Cat & Task 3: Deer vs. Dog (Single-Head Network)

- Number of replicates: 20, Network: SmallConv, each model was trained for 100 epochs



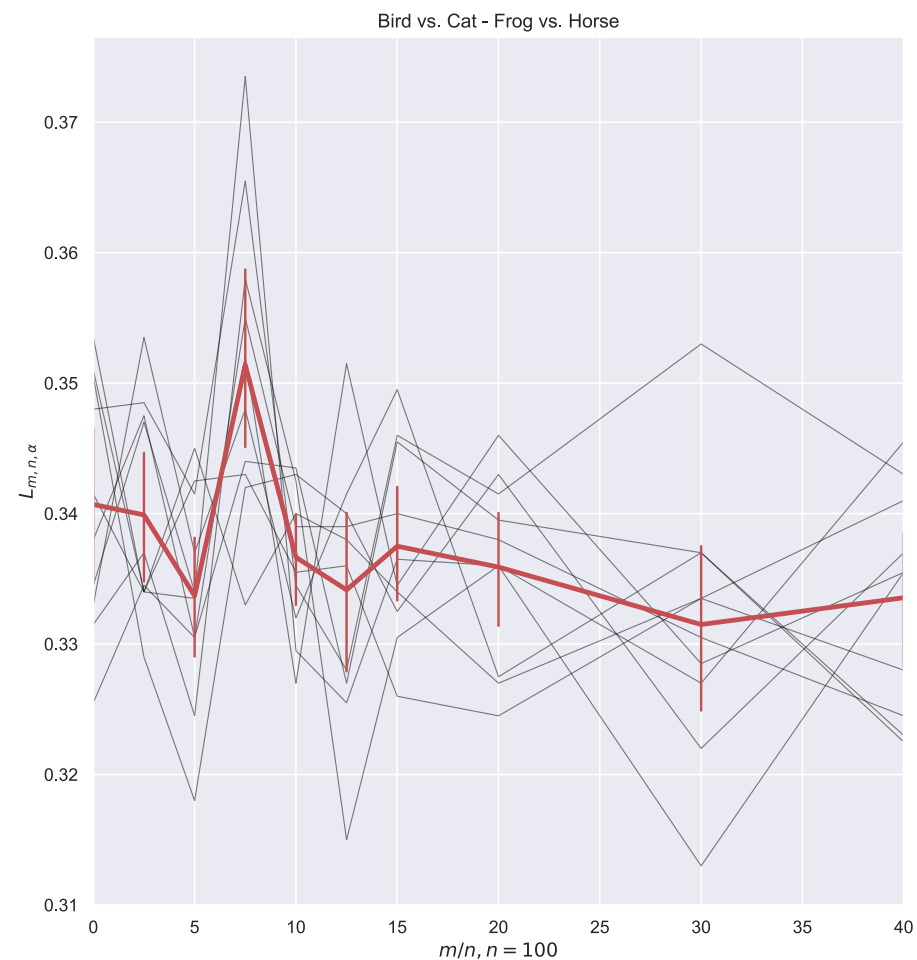
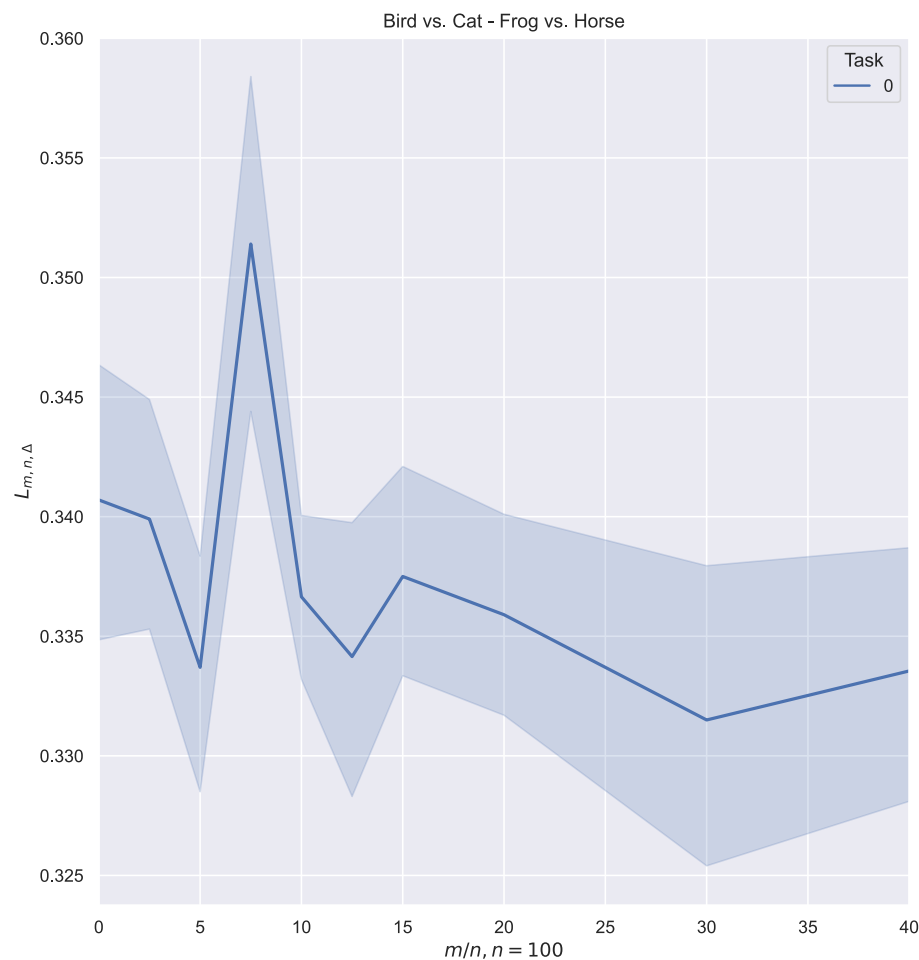
## Task 2: Bird vs. Cat & Task 3: Deer vs. Dog (Multi-Head Network)

- Number of replicates: 20, Network: SmallConv



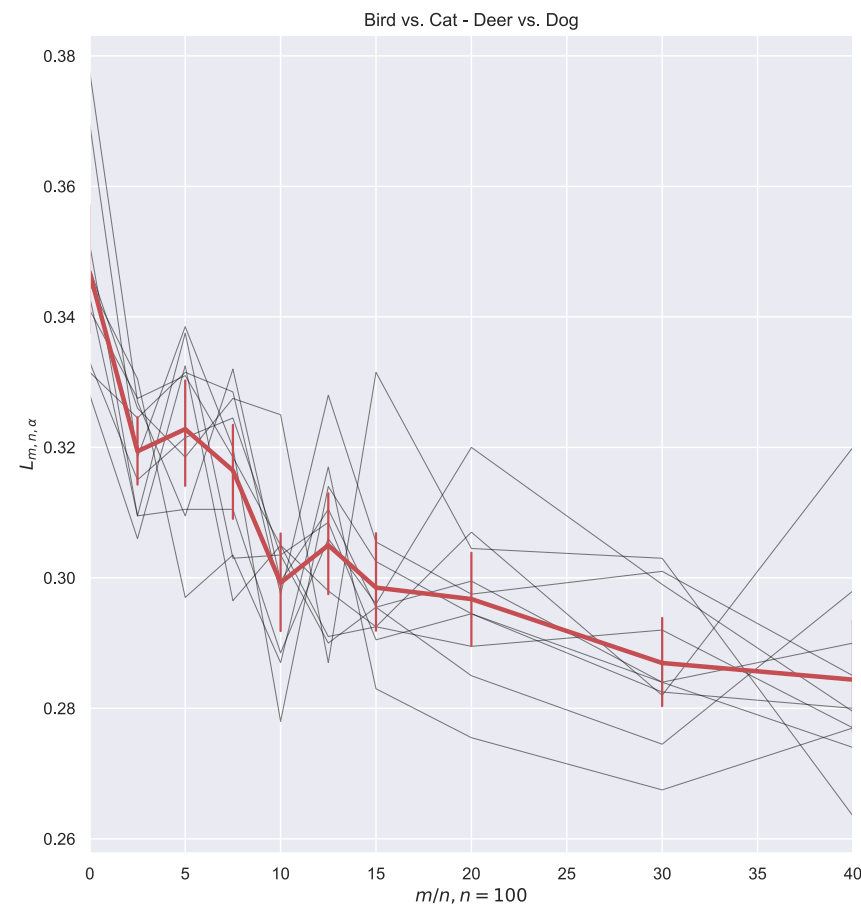
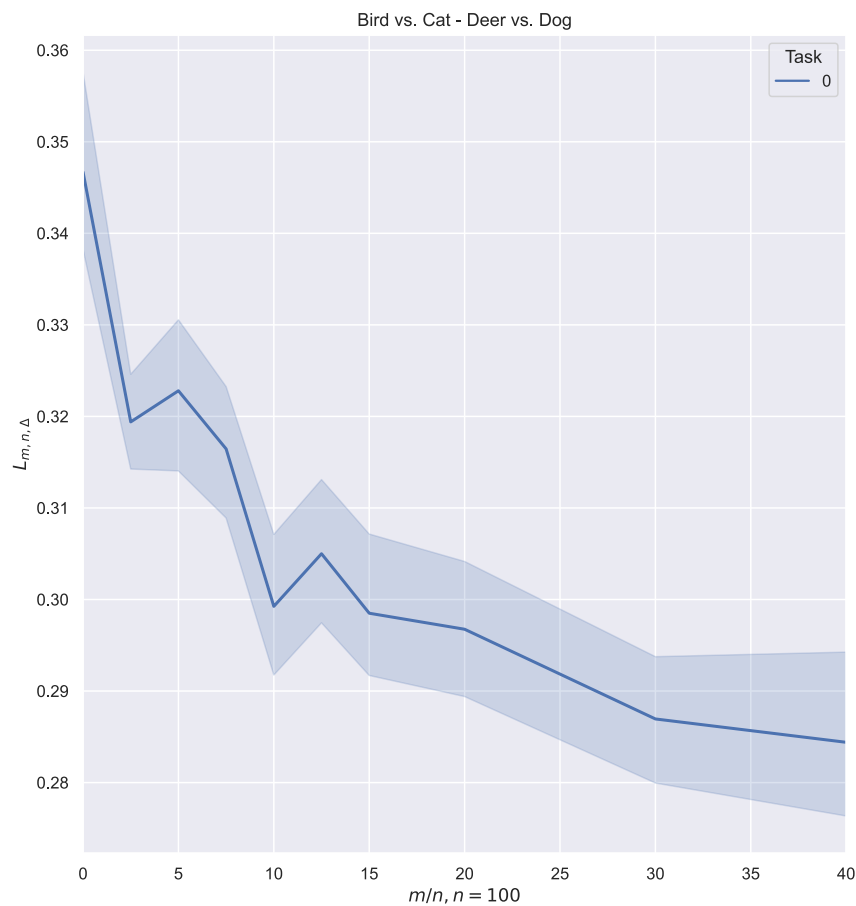
## Task 2: Bird vs. Cat & Task 4: Frog vs. Horse (Multi-Head Network)

- Number of replicates: 20, Network: SmallConv



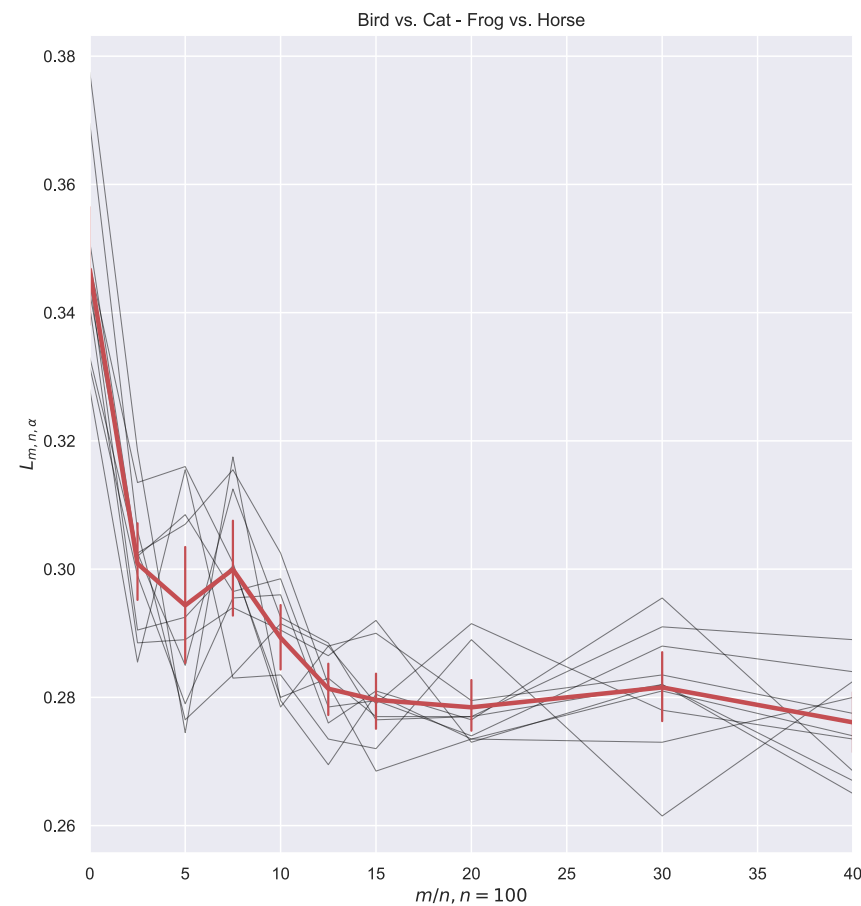
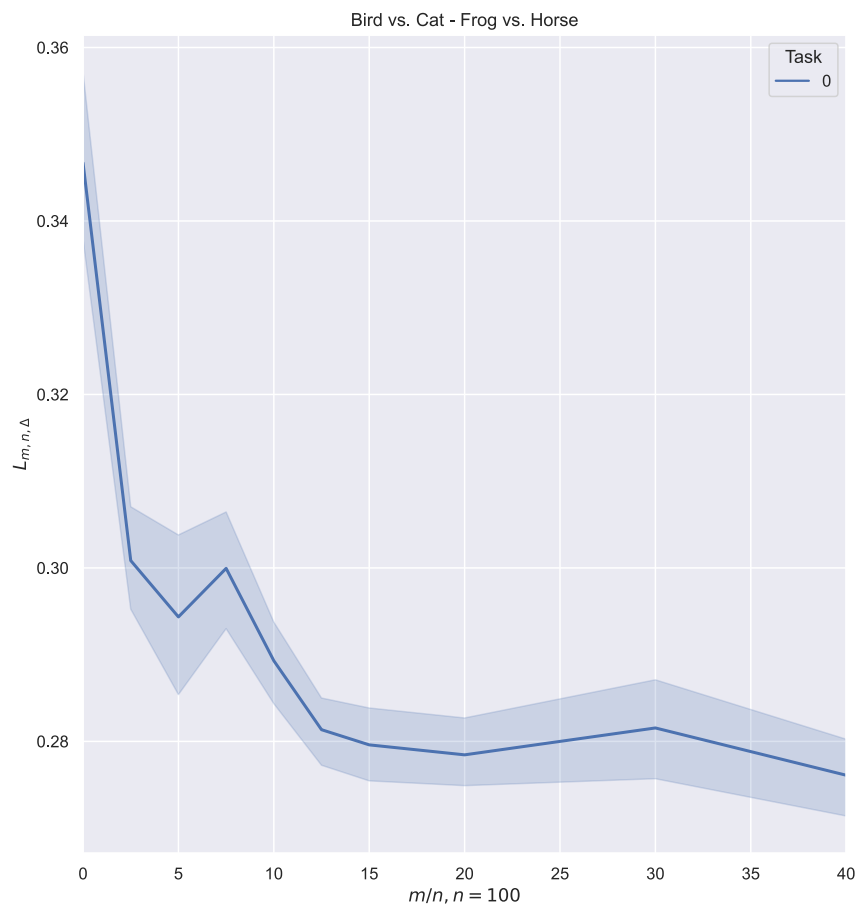
## Task 2: Bird vs. Cat & Task 3: Deer vs. Dog (Multi-Head Network)

- Number of replicates: 10, Network: Wide Res-Net



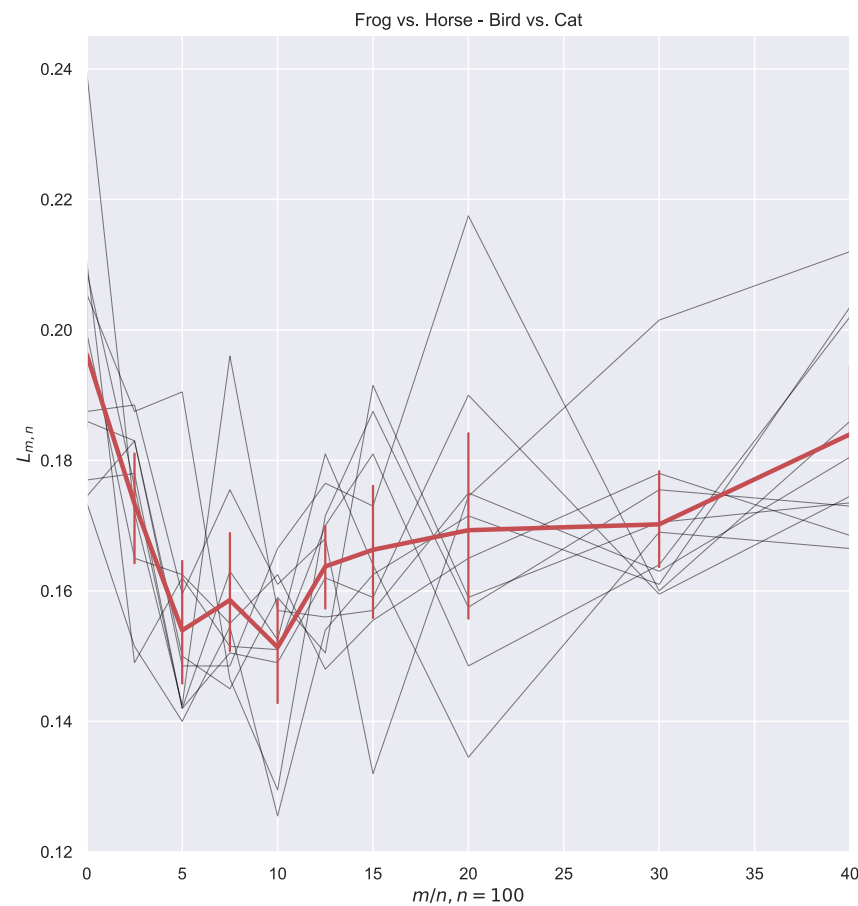
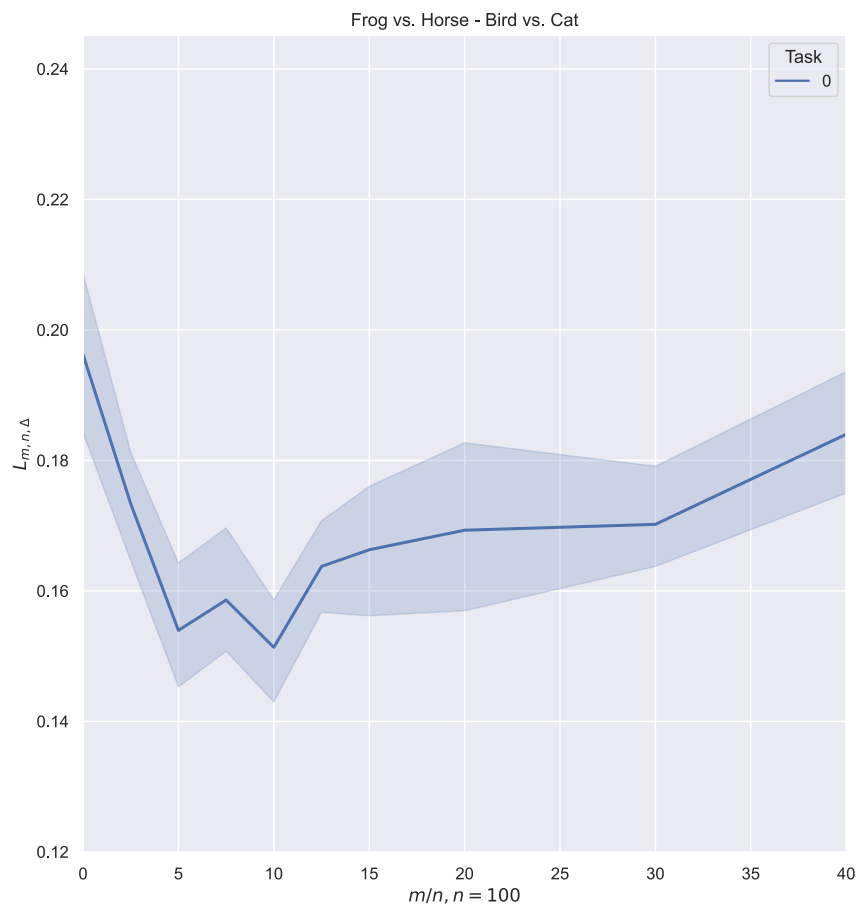
## Task 2: Bird vs. Cat & Task 4: Frog vs. Horse (Multi-Head Network)

- Number of replicates: 10, Network: Wide Res-Net



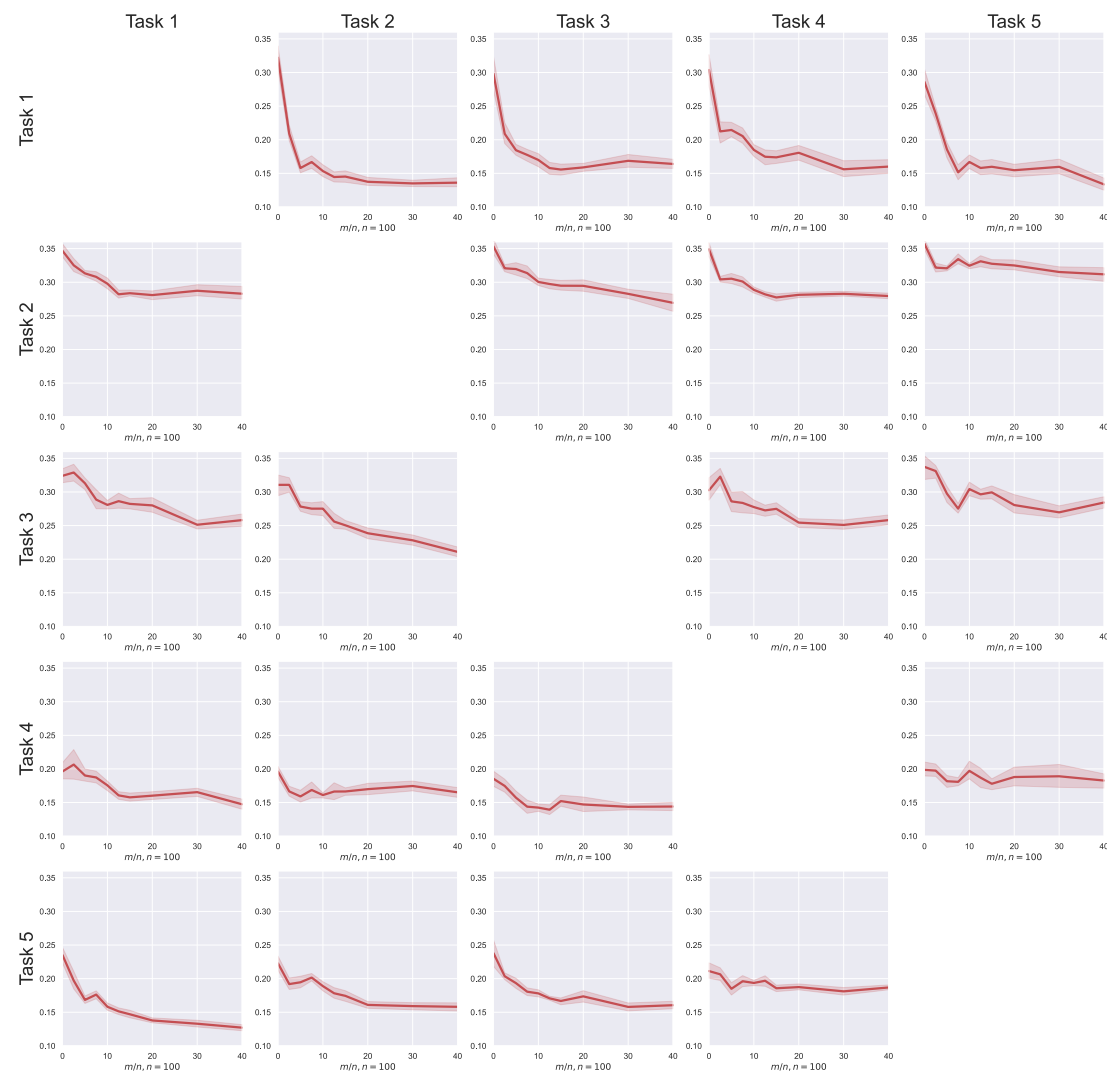
# Task 4: Frog vs. Horse & Task 2: Bird vs. Cat (Multi-Head Network)

- Number of replicates: 10, Network: Wide Res-Net

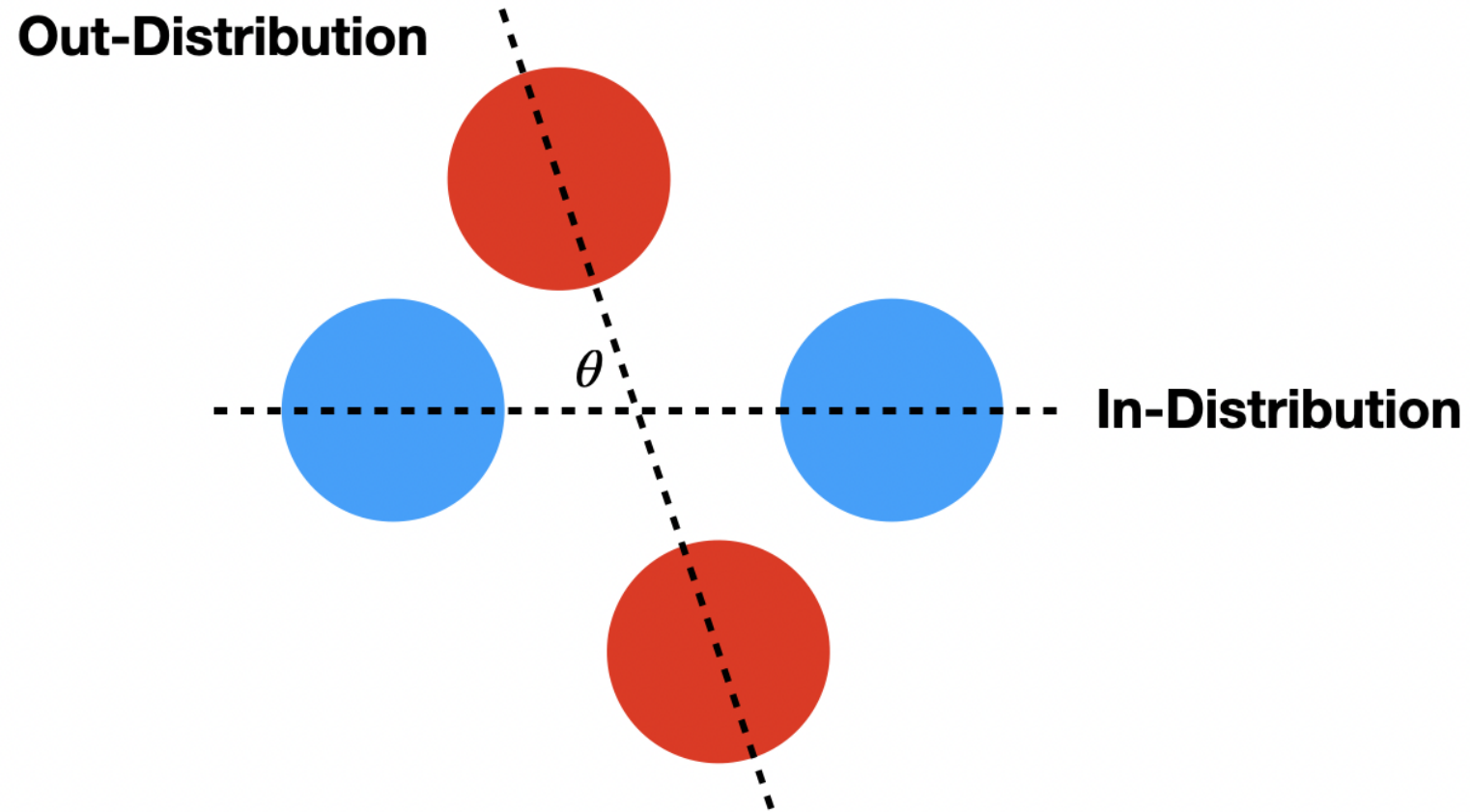




# CIFAR-10 Tasks (Multi-Head Network)



# Bivariate LDA Problem



## Bivariate LDA Problem

- $X|Y = -1 \sim \mathcal{N}(-\mu_0, \Sigma)$  and  $X|Y = +1 \sim \mathcal{N}(\mu_0, \Sigma)$  constitute the in-distribution where  $\mu_0 = [\mu, 0]^\top$
- $X|Y = -1 \sim \mathcal{N}(-\mu_\theta, \Sigma)$  and  $X|Y = +1 \sim \mathcal{N}(\mu_\theta, \Sigma)$  constitute the out-of-distribution where  $\mu_\theta = [\mu \cos \theta, -\mu \sin \theta]^\top$
- Then, the estimated class means  $\hat{\mu}_{-1}$  and  $\hat{\mu}_{+1}$  are given by,

$$\hat{\mu}_{-1} \sim \mathcal{N}\left(\left[\frac{-\mu(n + m \cos \theta)}{n + m}, \frac{\mu m \sin \theta}{n + m}\right]^\top, \frac{1}{n + m} \Sigma\right)$$
$$\hat{\mu}_{+1} = -\hat{\mu}_{-1} \sim \mathcal{N}\left(\left[\frac{\mu(n + m \cos \theta)}{n + m}, -\frac{\mu m \sin \theta}{n + m}\right]^\top, \frac{1}{n + m} \Sigma\right)$$

## Bivariate LDA Problem

- The LDA's classification rule is given by,

$$g(x) = \text{sign}(w \cdot x > c)$$

where,

$$w = \Sigma^{-1}(\hat{\mu}_{+1} - \hat{\mu}_{-1}) = 2\Sigma^{-1}\hat{\mu}_{+1}$$

$$c = \frac{1}{2}(\hat{\mu}_{+1} + \hat{\mu}_{-1}) = 0$$

- Therefore,

$$g(x) = \text{sign}(\hat{\mu}_{+1} \cdot x > 0)$$

## Bivariate LDA Problem

- If  $\mu = 1$  and  $\Sigma = I$ ,

$$\hat{\mu}_{+1} \sim \mathcal{N}\left(\left[\frac{(n + m \cos \theta)}{n + m}, -\frac{m \sin \theta}{n + m}\right]^\top, \frac{1}{n + m} I\right)$$

$$x|y = -1 \sim f_{-1} = \mathcal{N}([-1, 0]^\top, \Sigma))$$

$$x|y = +1 \sim f_{+1} = \mathcal{N}([1, 0]^\top, \Sigma))$$

- Hence, the error  $L(\hat{\mu}_{+1})$  is given by,

$$L(\hat{\mu}_{+1}) = \mathbb{P}_{x \sim f_{-1}}[\hat{\mu}_{+1} \cdot x > 0] + \mathbb{P}_{x \sim f_{+1}}[\hat{\mu}_{+1} \cdot x < 0]$$

- Therefore,

$$\mathbb{E}[L_{m,n,\theta}] = \mathbb{E}_{\hat{\mu}_{+1}}[L(\hat{\mu}_{+1})]$$