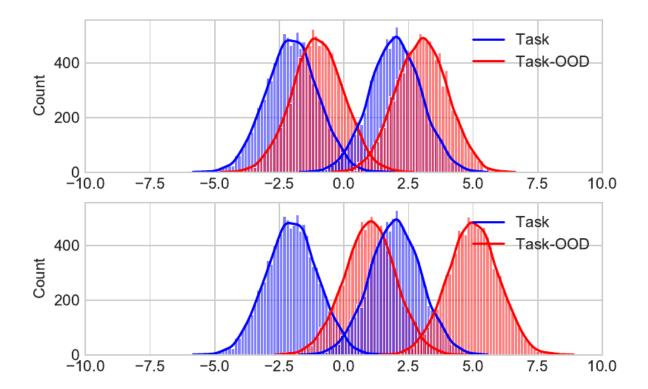
#### **Gaussian Task**

We consider a family of tasks

$$P(x,y) = \delta(y=1)X_1 + \delta(y=-1)X_{-1}$$

where  $X_1$  and  $X_2$  are Gaussians with means  $\pm \mu$ 



# **Error of Hypothesis**

Consider random variable  $ar{h}$ . If  $ar{h}=h$ , then

$$e_t(h)=rac{1}{2}\left(\left(1-\Phi(h+\mu)+\Phi(h-\mu)
ight).$$

If we assume  $ar{h} \sim \mathcal{N}(ar{\mu}, ar{\sigma})$ 

$$\mathbb{E}[e_t(ar{h})] = rac{ar{\sigma}}{2} - rac{ar{\sigma}}{2}\Phi\left(rac{ar{\mu} + \mu}{\sqrt{1 + ar{\sigma}^2}}
ight) + rac{ar{\sigma}}{2}\Phi\left(rac{ar{\mu} - \mu}{\sqrt{1 + ar{\sigma}^2}}
ight)$$

# LDA - Single-head model

Consider the samples to be weighted as

$$S = \alpha S_t + (1 - alpha)S_{ood}$$

For LDA

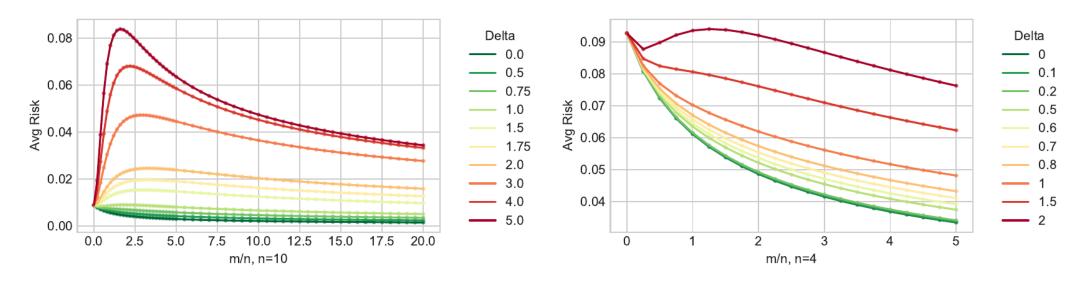
$$ar{\mu} = rac{(1-lpha)m\Delta}{lpha n + (1-lpha)m}$$

and

$$ar{\sigma}^2 = rac{(1-lpha)^2 m + lpha^2 n}{(lpha n + (1-lpha)m)^2}$$

### LDA with lpha=0.5

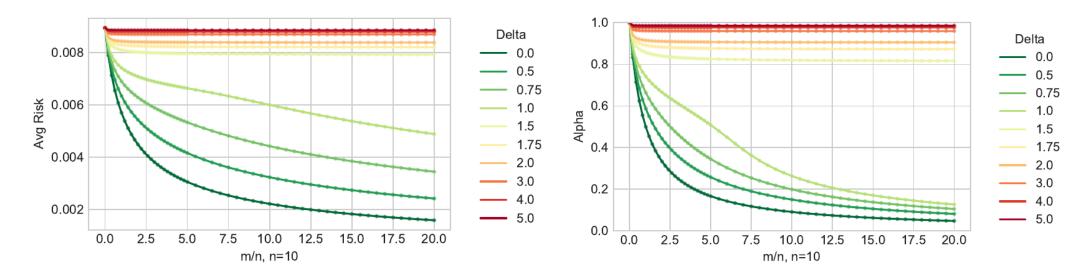
When both datasets are naively combined (lpha=0.5)



the loss increases/decreases depending on  $\Delta$ .

## LDA with optimized lpha

However if we optimize  $\alpha$ , the loss is always better



## Note on optimizing $\alpha$

lpha is only usable if we can seperate out samples in  $S_{ood}$  and  $S_t$ . Otherwise, we are forced to use lpha=0.5.