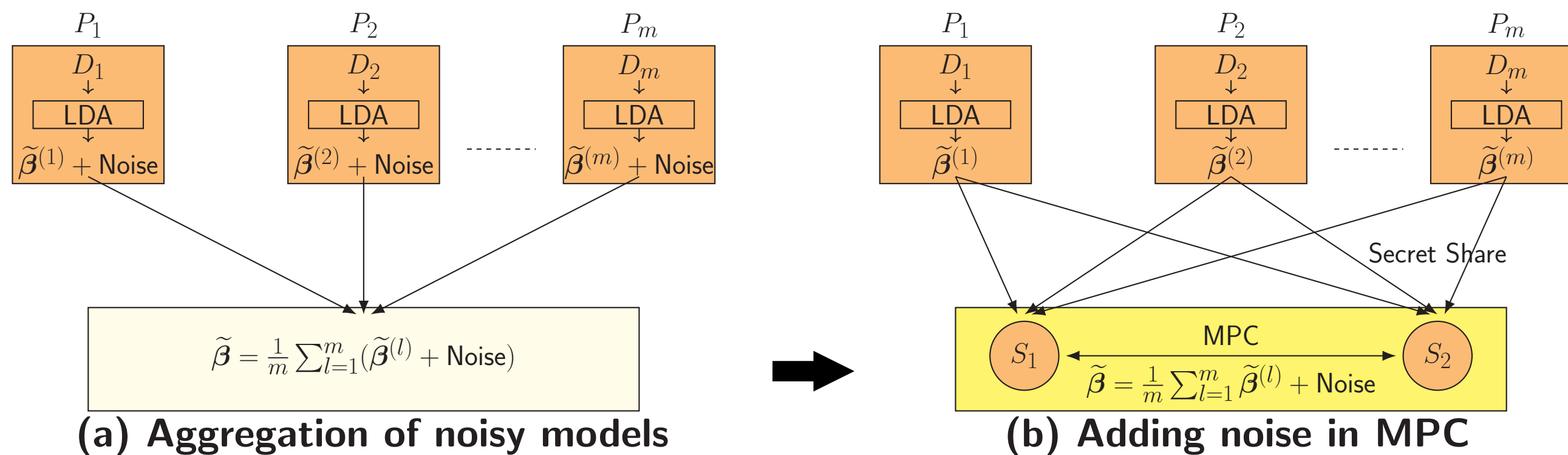


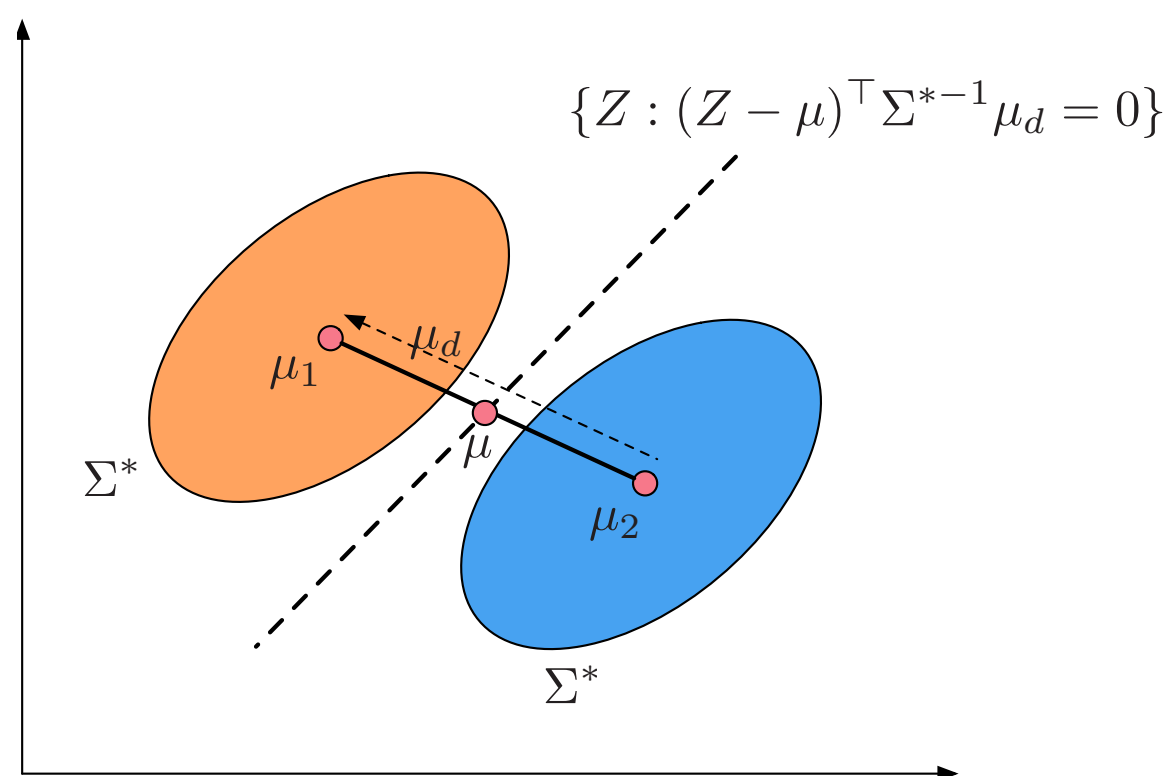
Secure Aggregation with Differential Privacy

We consider the problem of privately learning a sparse model across multiple sensitive datasets. Individual models are locally learned and privately aggregated using secure multi-party computation (MPC).



Adding privacy-preserving noise after aggregation, instead of before, leads to more accurate models.

Distributed Sparse Learning



We focus on distributively estimating

$$\beta^* := \Sigma^{*-1} \mu_d$$

Each party estimates biased discriminant function

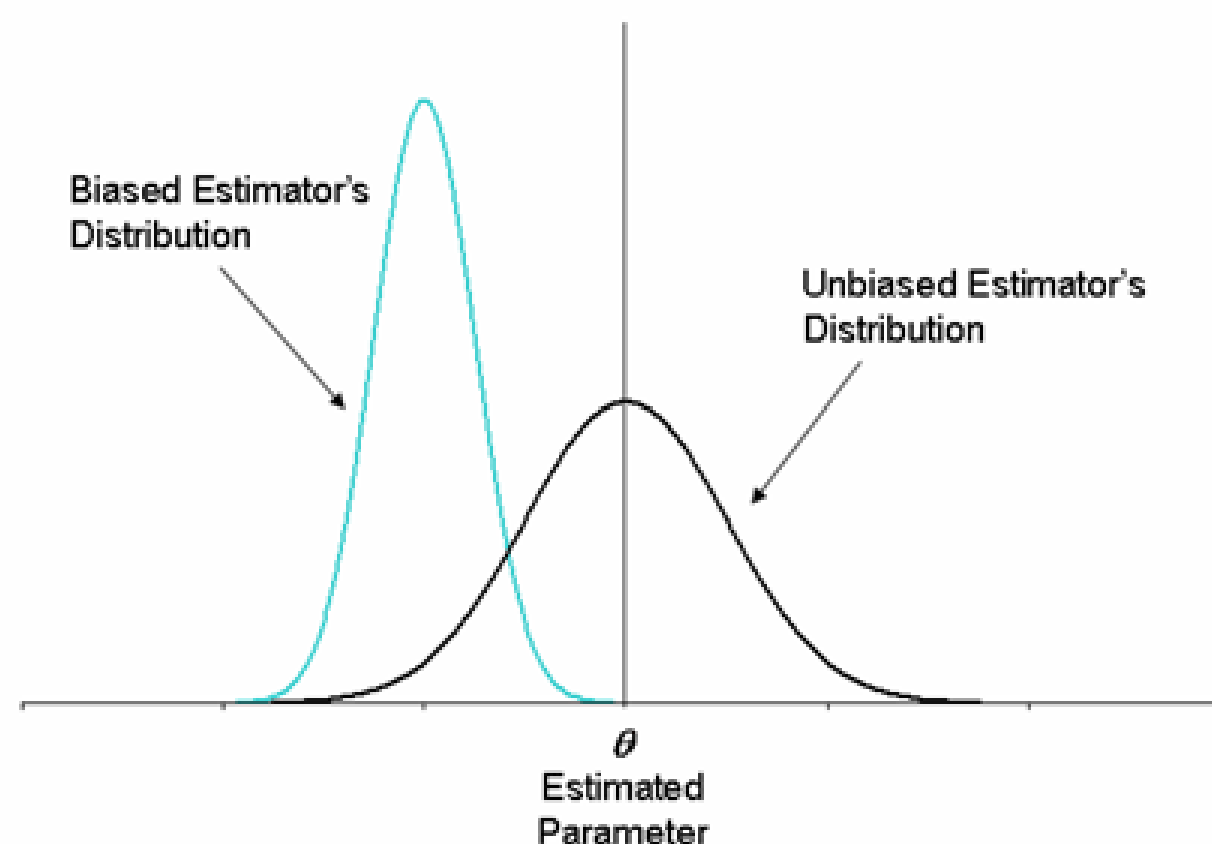
$$\hat{\beta}^{(l)} = \operatorname{argmin}_{\beta} \|\beta\|_1$$

$$\text{subject to } \|\hat{\Sigma}^{(l)} \beta - \hat{\mu}_d^{(l)}\|_\infty \leq \lambda$$

Debiasing Sparse Models

Each party estimates unbiased discriminant function

$$\tilde{\beta}^{(l)} = \hat{\beta}^{(l)} - \hat{\Theta}^{(l)\top} (\hat{\Sigma}^{(l)} \hat{\beta}^{(l)} - \hat{\mu}_d^{(l)})$$



Experiment Setting

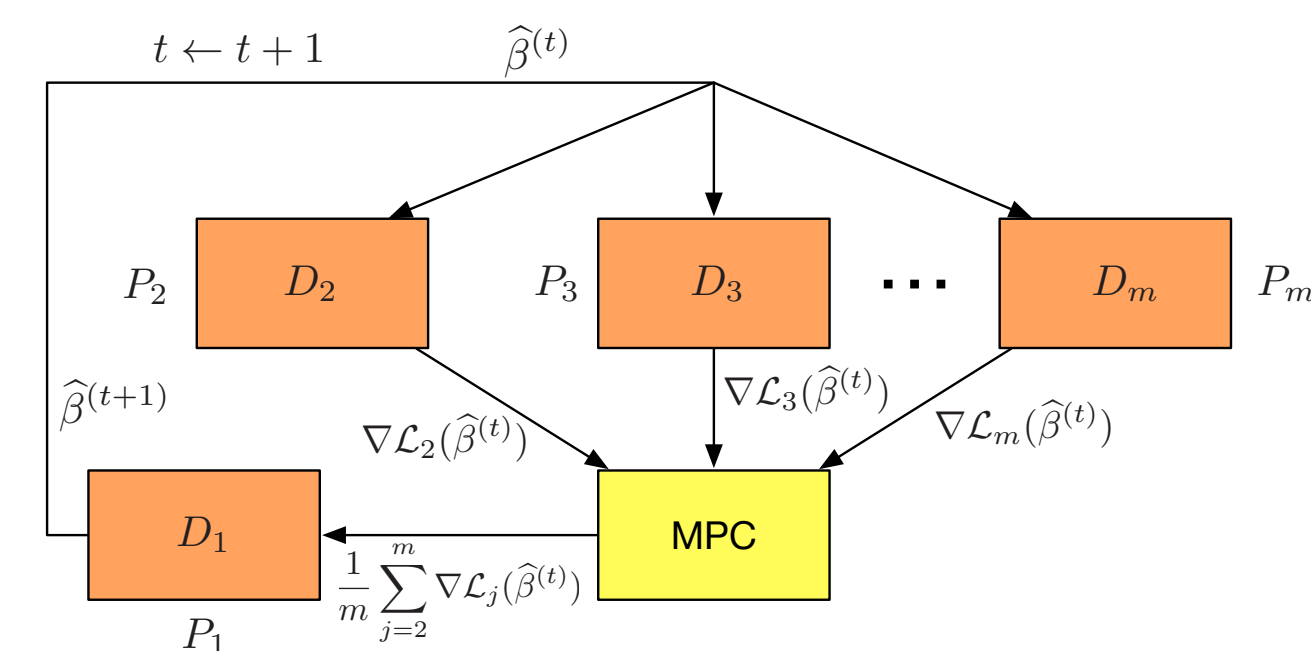
Synthetic Dataset: Number of parties varies from 20 to 100. The dimensionality of data is set as 200, with each party having 200 data instances generated from two Gaussian distributions.

Hospital Dataset: 920 patient records from 4 hospitals. Records contain personal information like age and gender, and clinical information such as laboratory test results. We aim at predicting whether a patient has heart disease.

Experiments

Dataset	m	Misclassification Rate		
		Centralized LDA	Naive Averaged	Our Approach
Synthetic	20	0.168 ± 0.002	0.240 ± 0.003	0.182 ± 0.003
Synthetic	60	0.166 ± 0.001	0.240 ± 0.002	0.179 ± 0.002
Synthetic	100	0.165 ± 0.001	0.240 ± 0.002	0.179 ± 0.001
Hospital	4	0.208 ± 0.012	0.329 ± 0.035	0.220 ± 0.017

Future Work: Iterative Learning



$\nabla \mathcal{L}_j(\cdot)$'s are gradient of loss functions.