

# STATS300B – Lecture 8

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Suppose we have a model  $\mathcal{P} = \{P_\theta : \theta \in \Omega\}$  and  $\Omega \subseteq \mathbb{R}^d$ . Define  $l_\theta(x) = \log(p_\theta(x))$  where  $p_\theta$  is the density of  $P_\theta$ . The *Fisher information of  $\theta$*  is defined to be the matrix,

$$I(\theta) = \mathbb{E}[\nabla l_\theta(X) \nabla l_\theta(X)^T] = \text{Var}_\theta(\nabla l_\theta(X)).$$

If integration and differentiation can be exchanged, then

$$I(\theta) = -\mathbb{E}[\nabla^2 l_\theta(X)].$$

Under appropriate assumptions about the regularity of the map  $\theta \mapsto l_\theta$ , then for all  $\theta$  in the interior of  $\Omega$ ,

$$\sqrt{n}(\hat{\theta}_n - \theta) \xrightarrow{d} \mathbf{N}_k(0, I(\theta)^{-1}),$$

where  $\hat{\theta}_n$  is the MLE from a sample  $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} P_\theta$ . We can combine this result with the delta method. If  $g : \Omega \rightarrow \mathbb{R}$  is differentiable at  $\theta$ , then

$$\sqrt{n}(g(\hat{\theta}_n) - g(\theta)) \xrightarrow{d} N(0, \nabla g(\theta)^T I(\theta)^{-1} \nabla g(\theta)).$$

And there is also a multivariate version, if  $g : \Omega \rightarrow \mathbb{R}^p$ , then

$$\sqrt{n}(g(\hat{\theta}_n) - g(\theta)) \xrightarrow{d} \mathbf{N}_p(0, (Dg(\theta))^T I(\theta)^{-1} (Dg(\theta))).$$