

# STATS300A - Lecture 16

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## 1 Recap

Our current goal is to find uniformly most powerful unbiased (UMPU) tests for testing  $H_0 : \theta \in \Omega_0$  against  $H_1 : \theta \in \Omega_1$ . Recall that a test function  $\phi$  is unbiased at level  $\alpha$  if

$$\mathbb{E}_{\theta_0} \phi \leq \alpha \text{ for all } \theta_0 \in \Omega_0,$$

and

$$\mathbb{E}_{\theta_1} \phi \geq \alpha \text{ for all } \theta_1 \in \Omega_1.$$

We also say a test  $\phi$  was  $\alpha$ -similar if for all  $\theta \in W$  where  $W = \overline{\Omega}_0 \cap \overline{\Omega}_1$ . We previously proved the following theorem which relates unbiased and  $\alpha$ -similar tests.

**Theorem 1** (TSH 4.11). *If  $\theta \mapsto \mathbb{E}_{\theta} \phi$  is continuous for all tests  $\phi$  and  $\phi$  is uniformly most powerful among level  $\alpha$   $\alpha$ -similar tests, then  $\phi$  is UMPU at level  $\alpha$ .*

Today we will find optimal unbiased tests in multiparameter exponential families. Specifically we will derive optimal one sided tests in the presence of nuisance parameters.

## 2 Multiparameter exponential families

Suppose we have a model  $\{P_{\theta, \lambda}\}$  where  $(\theta, \lambda) \in \mathbb{R}^{k+1}$  is unknown and  $P_{\theta, \lambda}$  has density

$$p_{\theta, \lambda}(x) = h(x) \exp \left\{ \theta U(x) + \sum_{i=1}^k \lambda_i T_i(x) - A(\theta, \lambda) \right\}.$$

We wish to test  $H_0 : \theta \leq \theta_0$  against  $H_1 : \theta > \theta_0$ . For a fixed  $\theta$ , the family  $\{p_{\theta, \lambda}\}$  is an exponential family with sufficient statistics  $T = (T_1, \dots, T_k)$  and so

$$P_{\theta, \lambda}(X|T) = P_{\theta}(X|T).$$

In particular we have  $P_{\theta, \lambda}(U(X)|T(X)) = P_{\theta}(U(X)|T(X))$  and so  $U(X)|T(X)$  has no  $\lambda$  dependence.

**Remark 1.** This observation is important. We have shown that conditioning eliminates the nuisance parameters. Thus we can fix  $(\theta_0, \lambda_0) \in \Omega_1$  and  $(\theta_1, \lambda_1)$  and construct a test based on  $P_{\theta_0}(X|T)$  against  $P_{\theta_1}(X|T)$  which has no  $\lambda$  dependence. Even better, conditioning on  $T$  gives us a one-dimensional exponential family.

**Lemma 1.** For each  $t$ ,  $U(X)|T = t$  forms a one-dimensional exponential family in  $\theta$ .

*Proof.* We will only consider the discrete case. For all  $u$  and  $t$  let

$$A_{u,t} = \{x \in \mathcal{X} : U(x) = u, T(x) = t\} \quad \text{and} \quad A_t = \{x \in \mathcal{X} : T(x) = t\}.$$

$$\begin{aligned} P_{\theta,\lambda}(U(X) = u|T(X) = t) &= \frac{P_{\theta,\lambda}(U(X) = u, T(X) = t)}{P_{\theta,\lambda}(T(X) = t)} \\ &= \frac{\sum_{x \in A_{u,t}} p_{\theta,\lambda}(x)}{\sum_{x \in A_t} p_{\theta,\lambda}(x)} \\ &= \frac{\sum_{x \in A_{u,t}} \exp\left\{\theta u + \sum_{i=1}^k \lambda_i t_i\right\} h(x)}{\sum_{x \in A_t} \exp\left\{\theta U(x) + \sum_{i=1}^k \lambda_i t_i\right\} h(x)} \\ &= \underbrace{\exp\{\theta u\}}_{\text{exponential tilt}} \times \underbrace{\sum_{x \in A_{u,t}} h(x)}_{g(t,u)=\text{base measure}} \times \underbrace{\frac{1}{\sum_{x \in A_t} \exp\{\theta U(x)\} h(x)}}_{c(t,\theta)=\text{normalizing constant}}. \end{aligned}$$

So  $U(X)|T(X) = t$  is a one-dimensional exponential family with sufficient statistic  $U$ .  $\square$

Thus we can apply our previously developed theory to the conditional distribution  $U|T$ . Our general recipe for one sided testing  $\theta \leq \theta_0$  against  $\theta > \theta_0$  is

- (1) Fix an alternative  $\theta = \theta_1 > \theta_0$  and  $\lambda_1 \in \mathbb{R}^k$ .
- (2) Condition on  $T$  so that  $X|T$  does not depend on  $\lambda$  and  $U|T$  follows a one dimensional exponential family.
- (3) Construct the MP test for the conditional distribution. That is

$$\phi_t(u) = \begin{cases} 1 & \text{if } u > k(t), \\ \rho(t) & \text{if } u = k(t), \\ 0 & \text{if } u < k(t). \end{cases}$$

where  $k(t)$  and  $\rho(t)$  are determined by the conditional level constraint

$$\mathbb{E}_{\theta_0}[\phi_t|T = t] = \alpha. \tag{1}$$

We will next argue that under some assumptions that test  $\phi^*(u, t) = \phi_t(u)$  is the UMPU test for  $H_0$  against  $H_1$ . Note that for every test  $\phi$

$$\mathbb{E}_{\theta,\lambda}\phi = \mathbb{E}_{\theta,\lambda}[\mathbb{E}_{\theta,\lambda}[\phi|T]] = \mathbb{E}_{\theta,\lambda}[\mathbb{E}_{\theta}[\phi|T]].$$

In particular if  $\theta \leq \theta_0$ , then

$$\mathbb{E}_{\theta,\lambda}\phi^* = \mathbb{E}_{\theta,\lambda}[\mathbb{E}_{\theta}[\phi|T]] \leq \mathbb{E}_{\theta,\lambda}[\alpha] = \alpha,$$

and we have equality if  $\theta = \theta_0$ . Thus  $\phi^*$  is level  $\alpha$  and  $\alpha$ -similar.

By Neyman-Pearson, there is no test that satisfies the constraint (1) and has strictly large power than  $\phi^*$  for some fixed  $t$  and  $\theta_1 > \theta$ . Thus  $\phi^*$  is the most powerful test in the class of tests satisfying (1) for any fixed  $\theta_1 > \theta$ . Since  $\phi^*$  does not depend on  $\theta_1$ , the test  $\phi^*$  is in fact the UMP test among tests satisfying the constrain (1).

Recall that we are trying to show that  $\phi^*$  is the UMPU test.