# Math 254A Lecture 9 Notes

#### Daniel Raban

April 16, 2021

# 1 Cramér's Theorem and Recovering Entropy as the Exponent

### 1.1 Cramér's theorem

We have a  $\sigma$ -finite measure space  $(M, \lambda)$ , and a measurable map  $\varphi : M \to X$ , where  $X = Y^*$  is a locally convex space with the weak<sup>\*</sup> topology. We found that

$$\lambda^{\times n}\left(\left\{p\in M^n: \frac{1}{n}\sum_{i=1}^n\varphi(p_i)\in U\right\}\right) = e^{n\cdot s(U)+o(n)},$$

where  $s(U) = \sup_{x \in U} s(x)$  for some point function s which is upper semicontinuous and concave. To study s, we have introduced Fenchel-Legendre duality:

$$s(x) = \inf_{y} s^{*}(y) - \langle y, x \rangle,$$

where

$$s^*(y) := \sup_x s(x) + \langle y, x \rangle$$

is sometimes known as the **convex conjugate** of s. Last time, we proved a formula: if  $s(x) < \infty$  for all n, then

$$s^*(y) = \log \int e^{\langle y, \varphi \rangle} d\lambda.$$

**Remark 1.1.** In the proof of this integral formula, to show  $(\leq)$ , we showed that  $s(x) + \langle y, x \rangle \leq \text{RHS}$  for all x, y. For this, given  $\varepsilon > 0$ , we found  $U \ni x$  such that

$$\lambda^{\times n}(\{\dots \in U\}) \le e^{\varepsilon n + o(n)} \left(\int e^{\langle y, \varphi \rangle} d\lambda\right)^n.$$

This part of the proof does not require that s is finite. In fact, it gives a way to prove  $s(U) < \infty$  and hence  $s(x) < \infty$ . So if there is some  $y \in Y$  such that  $\int e^{\langle y, \varphi \rangle} d\lambda < \infty$ , then  $s < \infty$  and  $s^*$  is as in the theorem. The mantra is that  $s < \infty$  everywhere iff  $s^* < \infty$  somewhere.

A special case is when  $(M, \lambda)$  is a probability space and  $X = \mathbb{R}^d$ . In this case, we get the following version of the theorem we proved before:

**Theorem 1.1** (Cramér, 1937). Let  $\xi_1, \xi_2, \ldots$  are *i.i.d.* random vectors in  $\mathbb{R}^d$ . Then

$$\mathbb{P}\left(\frac{1}{n}\sum_{i=1}^{n}\xi\in U\right) = \exp\left(n\cdot\sup_{x\in U}s(x) + o(n)\right),$$

where

$$s(x) = \inf_{y \in \mathbb{R}^d} \Lambda(y) - \langle y, x \rangle,$$

and

$$\Lambda(y) = \log M(y) = \log \mathbb{E}[e^{\langle y, \xi_1 \rangle}]$$

#### is the cumulant generating function.

In a number of texts, our s is denoted by -I (so the inf becomes a sup, etc.).

### 1.2 Connection to the Kullback-Leibler divergence in the case of empirical distributions

Let K be a compact metric space,  $\lambda$  be a finite Borel measure, X = M(K) be the space of measures on K (equal to  $C(K)^*$  by Riesz representation), and  $\varphi(p) = \delta_p$ . In this case,  $\frac{1}{n} \sum_{i=1}^{n} \varphi(p_i)$  is the empirical distribution of  $(p_1, \ldots, p_n)$ .

**Theorem 1.2.** In this setting,  $s(\mu) = -\infty$  unless  $\mu \in P(K)$  and  $\mu \ll \lambda$ , and in that case,

$$s(\mu) = -\int \frac{d\mu}{d\lambda} \log \frac{d\mu}{d\lambda} d\lambda.$$

We will denote the right hand side by  $\tilde{s}(\mu)$  until we have proven the theorem; that way, the proof is to show that  $s = \tilde{s}$ .

Remark 1.2. Note that

$$\widetilde{s}(\mu) = \int \eta \left(\frac{d\mu}{d\lambda}\right) d\eta, \qquad \eta(t) = \begin{cases} -t\log t & t > 0\\ 0 & t = 0. \end{cases}$$

If  $|\eta(\frac{d\mu}{d\lambda})| \in L^1(\lambda)$ , then  $\tilde{s}(\mu) > -\infty$ . Otherwise, we set  $s(\mu) := -\infty$ .

**Remark 1.3.** Here is an alternative formula that will be useful:

$$\widetilde{s}(\mu) = -\int \log \frac{d\mu}{d\lambda} \, d\mu.$$

This formula is useful, but it is a little harder to see the natural  $-\infty$  convention with this version.

Here are 2 special cases:

**Example 1.1.** Let K be finite with  $\lambda$  being counting measure. Then  $\frac{d\mu}{d\lambda}(a) = \mu(\{a\})$ , and so

$$\widetilde{s}(\mu) = -\sum_{a} \mu(\{a\}) \log \mu(\{a\}) = H(\mu)$$

is the Shannon entropy.

**Example 1.2.** If  $\lambda(K) = 1$ , then

$$-\widetilde{s}(\mu) = \begin{cases} \int \frac{d\mu}{d\lambda} \log \frac{d\mu}{d\lambda} \, d\lambda \\ +\infty & \text{in the cases described above} \end{cases}$$

is called the **Kullback-Leibler divergence**. The standard notation for this is  $D(\mu \| \lambda)$ .

**Lemma 1.1.** If  $\lambda(K) = 1$ , then  $D(\mu \| \lambda) \ge 0$ , with equality if  $\mu = \lambda$ .

Proof.

$$D(\mu \| \lambda) = \int \frac{d\mu}{d\lambda} \log \frac{d\mu}{d\lambda}$$
$$= \int -\eta \left(\frac{d\mu}{d\lambda}\right) d\lambda$$

 $-\eta$  is strictly concave, so using Jensen's inequality gives

$$-\eta \left( \int \frac{d\mu}{d\lambda} d\lambda \right)$$
$$= -\eta(1)$$
$$= 1 \log 1$$
$$= 0.$$

We get equality iff  $\frac{d\mu}{d\lambda}$  is constant for  $\lambda$ -a.e., that is, iff  $\mu = \lambda$ .

Let's prove the theorem:

*Proof.* We want to prove that  $s = \tilde{s}$ . Using the expression for s in terms of the Fenchel-Legendre transform and using the integral formula, we want to show that

$$\inf\left\{\log\int e^{f(p)}\,d\lambda(p)-\langle f,\mu\rangle:f\in C(K)\right\}=\widetilde{s}(\mu).$$

This is known as Gibbs' variational formula.

 $(\geq)$ : We want

$$\log \int e^f d\lambda - \langle f, \mu \rangle \ge -\int \frac{d\mu}{d\lambda} \log \frac{d\mu}{d\lambda} d\lambda.$$

The key object is

$$d\mu_f(p) = \frac{e^{f(p)}}{Z(f)} d\lambda(p), \qquad Z(f) = \int e^f d\lambda,$$

which is sometimes called the **Gibbs measure** of f with respect to  $\lambda$ . Observe that  $\lambda \ll \mu_f$  and  $\mu_f \ll \lambda$ , so if  $\mu \ll \lambda$ , then  $\mu \ll \mu_f$ , then  $\frac{d\mu}{d\lambda} = \frac{d\mu}{d\mu_f} \frac{d\mu_f}{d\lambda}$ , and so

$$\widetilde{s}(\mu) = -\int \log \frac{d\mu}{d\lambda} d\mu$$
  
=  $-\int \log \frac{d\mu}{d\mu_f} d\mu - \int \log \frac{d\mu_f}{d\lambda} d\mu$   
=  $-D(\mu \| \mu_f) - \int (f - \log Z) d\mu$   
=  $-D(\mu \| \mu_f) + \{\log Z - \langle f, \mu \rangle\}.$ 

Rearrange this to get

$$\log Z - \langle f, \mu \rangle = \widetilde{s}(\mu) + D(\mu \| \mu_f) \ge \widetilde{s}(\mu),$$

with equality iff  $\mu = \mu_f$ .

 $(\leq)$ : We already know this if  $\mu = \mu_f$  for some  $f \in C(K)$ . The summary of the rest of the proof is "such measures  $\mu_f$  are dense as f varies." In more detail:

- (a)  $\inf\{\log \int e^f d\lambda \langle f, \mu \rangle : f \in C(K)\}$  has the same value if we enlarge C(K) to B(K), the bounded Borel functions. This is because given  $\lambda$  and  $\mu$ , C(K) is dense in  $L^1(\lambda + \mu)$ , so for all  $g \in B(K)$  (all uniformly bounded), there is some  $(f_n)_n$  in C(K)with  $f_n \to g$  in  $L^1(\lambda)$  and  $L^1(\mu)$ . Then  $\langle f_n, \mu \rangle \to \langle g, \mu \rangle$ , and  $\int e^{f_n} d\lambda \to \int e^g d\lambda$ .
- (b) Now suppose  $\mu \ll \lambda$ . Then there is an A such that  $\lambda(A) = 0$  and  $\mu(A) > 0$ . Let  $g = c \mathbb{1}_A \in B(K)$ . This gives

$$\log \int e^g d\lambda - \langle g, \mu \rangle = 0 - c\mu(A) \to -\infty$$

as  $c \to +\infty$ . So  $\inf\{\cdots\} = -\infty$ , as required.

(c) Lastly, suppose  $d\mu = \rho d\lambda$ . If  $\rho = e^g$  with  $g \in B(K)$ , we are done by the previous calculation. Otherwise, choose  $(g_n)_n$  in B(K) such that

$$e^{g_n} \to \rho \begin{cases} \text{from below} & \text{if } \rho > 1 \\ \text{from above} & \text{if } \rho \le 1. \end{cases}$$

Now show that:

•  

$$\log \int_{\{\rho \le 1\}} e^{g_n} d\lambda \to \log \int \rho \, d\lambda = \log 1 = 0,$$
•  

$$\log \int_{\{\rho > 1\}} e^{g_n} d\lambda \to \log \int \rho \, d\lambda = \log 1 = 0,$$
•  
•  

$$\langle g_n, \mu \rangle \to \langle \log \rho, \mu \rangle = \tilde{s}(\mu).$$