### **Theoretical Statistics. Lecture 19. Peter Bartlett**

- 1. Functional delta method. [vdV20]
- 2. Differentiability in normed spaces: Hadamard derivatives. [vdV20]
- 3. Quantile estimates. [vdV21]

# **Recall: Delta method**

**Theorem:** If  $\phi : \mathbb{R}^k \to \mathbb{R}^m$  is differentiable at  $\theta$ , and  $\sqrt{n}(T_n - \theta) \rightsquigarrow T$ , then

$$
\sqrt{n}(\phi(T_n) - \phi(\theta)) \rightsquigarrow \phi'_{\theta}(T)
$$

$$
\sqrt{n}(\phi(T_n) - \phi(\theta)) - \phi'_{\theta}(\sqrt{n}(T_n - \theta)) \stackrel{P}{\to} 0.
$$

Here,  $\phi'_{\theta}$  is the derivative (linear map) satisfying

$$
\phi(\theta + h) - \phi(\theta) = \phi'_{\theta}(h) + o(||h||)
$$

for  $h \to 0$ .

- What about more complex cases? For instance, what if we are interested in a property of the probability distribution  $\phi(P)$ , and we use an estimator  $\phi(P_n)$ ?
- As <sup>a</sup> first example, we'll ge<sup>t</sup> some intuition by considering <sup>a</sup> "Taylor series" expansion about the value  $\phi(P)$ . But what does it mean for the Taylor series expansion of  $\phi$  to exist?
- To make this rigorous, we need to consider  $\phi$  as a map between normed linear spaces, and we need it to be appropriately differentiable.
- The right notion is *Hadamard differentiability*.

Given  $X_1, \ldots, X_n$  from a distribution P, and a parameter of interest  $\phi(P)$ , suppose that we estimate  $\phi(P)$  by  $\phi(P_n)$ , where  $P_n$  is the empirical distribution. What is the asymptotic behavior of  $\phi(P_n)$ ?

Define the derivative  $\phi_P^{(k)}(H)$  of the map  $t \mapsto \phi(P + tH)$  at  $t = 0$ , where H is a perturbation direction. Then if the derivatives exist we have a Taylor series expansion:

$$
\phi(P+tH) - \phi(P) = t\phi'_P(H) + \frac{1}{2}t^2\phi_P^{(2)}(H) + \dots + \frac{1}{m!}t^m\phi_P^{(m)}(H) + o(t^m).
$$

Substituting  $t = 1/\sqrt{n}$  and  $H = \mathbb{G}_n (=\sqrt{n}(P_n - P)X),$ 

$$
tH = \frac{1}{\sqrt{n}} \mathbb{G}_n = P_n - P,
$$

gives the *von Mises expansion*,

$$
\phi(P_n) - \phi(P) = \frac{1}{\sqrt{n}} \phi'_P(\mathbb{G}_n) + \frac{1}{2n} \phi_P^{(2)}(\mathbb{G}_n) + \cdots + \frac{1}{m!n^{m/2}} \phi_P^{(m)}(\mathbb{G}_n) + o(n^{-m/2}).
$$

(This is not rigorous: it requires <sup>a</sup> stronger notion of differentiability, because the perturbation direction is now random:  $H = \mathbb{G}_n$ .)

If  $\phi'_{P}$  is a linear map, we have

$$
\phi(P_n) - \phi(P) = \frac{1}{\sqrt{n}} \phi'_P(\mathbb{G}_n) + o(n^{-1/2})
$$
  
= 
$$
\frac{1}{n} \sum_{i=1}^n \phi'_P(\delta_{X_i} - P) + o(n^{-1/2}),
$$

where  $\delta_{X_i}$  is the discrete distribution concentrated on  $X_i$ .

So if  $\phi'_{i}$  $P_P(\delta_X - P)$  is mean zero and finite variance, we have that  $\sqrt{n}(\phi(P_n) - \phi(P))$  is asymptotically normal.

### **Aside: influence functions**

The function  $x \mapsto \phi'_P (\delta_x - P)$  is the *influence function* of  $\phi$ :

$$
\phi'_P(\delta_x - P) = \frac{d}{dt}\phi(P + t(\delta_x - P))\Big|_{t=0}
$$
  
= 
$$
\frac{d}{dt}\phi((1-t)P + t\delta_x)\Big|_{t=0}.
$$

This measures the impact of changing P by mixing in a tiny amount of  $\delta_{X_i}$ . It is important in robust statistics.

Suppose we wish to estimate the pth quantile of P, where  $p \in (0, 1)$ . We'll write it as  $\phi(F)$  for the cumulative distribution function F of P. If F is continuous at the appropriate point, we can define

$$
\phi(F) = F^{-1}(p).
$$

We need to calculate

$$
\phi'_{F}(s_{x} - F) = \frac{d}{dt}\phi((1 - t)F + ts_{x})\Big|_{t=0},
$$

where  $s_x$  is the cdf of  $\delta_x$ , i.e., the step function  $a \mapsto 1[a \ge x]$ .

Write  $F_t = (1 - t)F + ts_x$ , then differentiate both sides of the equation  $p = F_t(\phi(F_t))$  at  $t = 0$  (ignoring the non-differentiability at  $\phi(F_t) = x$ ):

$$
0 = \frac{d}{dt} F_t(\phi(F_t)) \Big|_{t=0}
$$
  
=  $\frac{d}{dt} (1-t) F(\phi(F_t)) + t s_x(\phi(F_t)) \Big|_{t=0}$   
=  $-F(\phi(F_t)) + (1-t) f(\phi(F_t)) \phi'_{F_t}(s_x - F) + s_x(\phi(F_t)) \Big|_{t=0}$   
=  $-F(\phi(F)) + f(\phi(F)) \phi'_{F}(s_x - F) + s_x(\phi(F)),$ 

where  $f$  is the density of  $P$ .

Rearranging, we have

$$
\phi'_F(s_x - F) = \frac{F(\phi(F)) - s_x(\phi(F))}{f(\phi(F))}
$$
  
= 
$$
\frac{p - s_x(F^{-1}(p))}{f(F^{-1}(p))}
$$
  
= 
$$
\begin{cases} \frac{p-1}{f(F^{-1}(p))} & \text{if } x \leq F^{-1}(p), \\ \frac{p}{f(F^{-1}(p))} & \text{if } x > F^{-1}(p). \end{cases}
$$

So

$$
\mathbf{E}\phi'_F(s_X - F) = \frac{p(p-1) + (1-p)p}{f(F^{-1}(p))} = 0
$$
  
var  $\phi'_F(s_X - F) = \frac{p(1-p)^2 + (1-p)p^2}{f(F^{-1}(p))^2}$   

$$
= \frac{p(1-p)}{f(F^{-1}(p))^2}.
$$

And we have

$$
\sqrt{n}(\phi(F_n) - \phi(F)) \rightsquigarrow N\left(0, \frac{p(1-p)}{(f(F^{-1}(p)))^2}\right).
$$

How do we make this rigorous? *Functional delta method.*

**Theorem:** Suppose  $\phi: D \to E$ , where D and E are normed linear spaces. Suppose the statistic  $T_n$ :  $\Omega_n \to D$  satisfies  $\sqrt{n}(T_n - \theta) \rightsquigarrow T$  for a random element T in  $D_0 \subset D$ .

If  $\phi$  is *Hadamard differentiable at*  $\theta$  *tangentially to*  $D_0$  then

$$
\sqrt{n}(\phi(T_n) - \phi(\theta)) \rightsquigarrow \phi'_{\theta}(T).
$$

If we can extend  $\phi' : D_0 \to E$  to a continuous map  $\phi' : D \to E$ , then

$$
\sqrt{n}(\phi(T_n) - \phi(\theta)) = \phi'_{\theta}(\sqrt{n}(T_n - \theta)) + o_P(1).
$$

For the von Mises expansion, we considered

$$
\phi'_P(H) = \left. \frac{d}{dt} \phi(P + tH) \right|_{t=0}
$$

for some perturbation direction  $H$ . This is the Gateaux derivative.

**Definition:**  $\phi: D \to E$  is *Gateaux differentiable* at  $\theta \in D$  if  $\forall h\in D,\,\exists \phi'_\theta$  $\theta'_\theta(h) \in E$ , s.t. as  $t \to 0$ ,  $\overline{\mathbf{u}}$  $\parallel$  $\parallel$  $\parallel$  $\phi(\theta+th)-\phi(\theta)$ t  $-\phi'_{\ell}$  $_{\theta }^{\prime }(h)$  $\overline{\mathbf{u}}$  $\parallel$  $\parallel$  $\parallel$  $\rightarrow 0.$ 

 $\phi'_{\theta}$  might not be (i) linear, or (ii) continuous (even if it's linear, it might not be continuous if  $D, E$  are infinite dimensional).

**Definition:**  $\phi: D \to E$  is *Hadamard differentiable* at  $\theta \in D$  if

 $\exists \phi'_\ell$  $\mathcal{L}_{\theta}: D \to E$  (linear, continuous),  $\forall h \in D$ , if  $t \to 0$ ,  $\| h_t \|$  $- h \| \rightarrow 0$ , then  $\overline{\mathbf{u}}$   $\phi(\theta+th_t)-\phi(\theta)$ t  $-\phi'_{\ell}$  $_{\theta }^{\prime }(h)$  $\overline{\mathbf{u}}$  $\parallel$  $\parallel$  $\parallel$  $\rightarrow 0.$ 

Gateaux requires the difference quotients to converge to some  $\phi'_\ell$  $\mathcal{C}_{\theta}(h)$  for each direction  $h$ ; Hadamard requires a single  $\phi^\prime_\theta$  that works for every direction  $h$ . It is equivalent to the convergence in the definition of Gateaux differentiability being uniform over  $h$  in a compact subset of  $D.$ 

**Definition:**  $\phi: D \to E$  is *Fréchet differentiable* at  $\theta \in D$  if

 $\exists \phi'_\ell$  $\theta'_{\theta}: D \to E$  (linear, continuous),  $\forall h \in D$ , if  $||h|| \to 0$ , then

$$
\left\|\frac{\phi(\theta+h)-\phi(\theta)-\phi'_{\theta}(h)}{\|h\|}\right\| \to 0.
$$

Hadamard requires the difference quotients to converge to zero for each direction, possibly with different rates for different directions; Fréchet requires the same rate for each direction. They are equivalent for  $D = \mathbb{R}^d$ .

We'll consider Hadamard differentiability, but allow the weaker notion of tangential differentiability: the limiting directions  $h$  can be constrained.

**Definition:**  $\phi: D \to E$  is *Hadamard differentiable* at  $\theta \in D$  *tangentially to*  $D_0 \subseteq D$  if

$$
\exists \phi'_{\theta} : D_0 \to E \text{ (linear, continuous)}, \forall h \in D_0,
$$
  
if  $t \to 0$ ,  $||h_t - h|| \to 0$ , then  

$$
\left\| \frac{\phi(\theta + th_t) - \phi(\theta)}{t} - \phi'_{\theta}(h) \right\| \to 0.
$$

**Theorem:** Suppose  $\phi: D \to E$ , where D and E are normed linear spaces. Suppose the statistic  $T_n$ :  $\Omega_n \to D$  satisfies  $\sqrt{n}(T_n - \theta) \rightsquigarrow T$  for a random element T in  $D_0 \subset D$ .

If  $\phi$  is *Hadamard differentiable at*  $\theta$  *tangentially to*  $D_0$  then

 $\sqrt{n}(\phi(T_n) - \phi(\theta)) \rightsquigarrow \phi'_\theta$  $_{\theta }^{\prime }(T).$ 

If we can extend  $\phi' : D_0 \to E$  to a continuous map  $\phi' : D \to E$ , then

$$
\sqrt{n}(\phi(T_n) - \phi(\theta)) = \phi'_{\theta}(\sqrt{n}(T_n - \theta)) + o_P(1).
$$

Proof:

Based on continuous mapping theorem. Consider the maps

$$
f_n(h) = \sqrt{n} \left( \phi \left( \theta + \frac{1}{\sqrt{n}} h \right) - \phi(\theta) \right).
$$

Hadamard differentiability implies that for any sequence  $h_n \to h \in D_0$ , we have  $f_n(h_n) \to \phi'_\theta$  $\phi_n^{\prime}(h)$ . So  $f_n(\sqrt{n}(T_n - \theta)) \rightsquigarrow \phi_n^{\prime}$  $_{\theta }^{\prime }(T).$ 

(Second statement follows from continuous mapping theorem for the function  $h \mapsto (\phi(h), \phi'_h)$  $'_\theta(h)).$ 

The chain rule lets us determine Hadamard derivatives of <sup>a</sup> composition of maps.

**Theorem:**  $\phi: D \to E$ ,  $\psi: E \to F$ , where D, E and F are normed linear spaces. If

1.  $\phi$  is Hadamard differentiable at  $\theta$  tangentially to  $D_0$ , and

2.  $\psi$  is Hadamard differentiable at  $\phi(\theta)$  tangentially to  $\phi'_\theta$  $'_\theta(D_0),$ 

then  $\psi \circ \phi : D \to F$  is Hadamard differentiable at  $\theta$  tangentially to  $D_0$ , with derivative  $\psi'$  $\phi'_{\theta}(\theta) \circ \phi'_{\theta}$  $\theta$  .



**Definition:** The *quantile function* of F is  $F^{-1}$  :  $(0,1) \rightarrow \mathbb{R}$ ,

 $F^{-1}(p) = \inf\{x : F(x) \geq p\}.$ 

[PICTURE]

For  $p \in (0,1)$  and  $x \in \mathbb{R}$ ,

$$
F^{-1}(p) \le x \iff p \le F(x),
$$

which implies the *quantile transformation*: for  $U$  uniform on  $(0, 1)$ ,

 $F^{-1}(U) \sim F$ .

Also,  $F(F^{-1}(p)) \geq p$ , with equality unless F has a discontinuity at  $F^{-1}(p)$ . This implies the *probability integral transformation*: for  $X \sim F$ ,  $F(X)$  is uniform on [0,1] iff F is continuous on R, because  $F(X) = F(F^{-1}(U)) = U$  in that case.

Finally,

 $F^{-1}(F(x)) \leq x,$ 

with equality unless F is flat to the left of x. Thus,  $F^{-1}$  is an inverse (i.e.,  $F^{-1}(F(x)) = x$  and  $F(F^{-1}(p)) = p$  for all x and p) iff F is continuous and strictly increasing.

### **Empirical quantile function**

For <sup>a</sup> sample with distribution function F, define the *empirical quantile function* as the quantile function  $F_n^{-1}$  of the empirical distribution function  $F_n$ .

$$
F_n^{-1}(p) = \inf\{x : F_n(x) \ge p\} = X_{n(i)},
$$

where  $i$  is chosen such that

$$
\frac{i-1}{n} < p \le \frac{i}{n},
$$

and  $X_{n(1)}, \ldots, X_{n(n)}$  are the order statistics of the sample, that is,  $X_{n(1)} \leq \cdots \leq X_{n(n)}$  and

$$
\big(X_{n(1)},\ldots,X_{n(n)}\big)
$$

is a permutation of the sample  $(X_1, \ldots, X_n)$ .