# STAT 830 Landau Notation: big O and little o

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#### Purposes of These Notes

- Introduce Landau's formalism for "on the order of"
- Do O, o,  $O_P$  and  $o_P$
- Present some of the algebraic rules

### Notation for Size or 'Order' of sequences

#### Big "O"

**Definition**: If  $a_n$  and  $b_n$  are sequences of constants with  $a_n > 0$  then

$$b_n = O(a_n)$$

means there is a constant M such that for all n

$$|b_n| \leq Ma_n$$
.

**Definition**: If  $U_n$  is a sequence of random variables and  $a_n > 0$  a sequence of constants then we write

$$U_n = O_P(a_n)$$

if, for each  $\epsilon > 0$  there is an M (depending on  $\epsilon$  but not n) such that

$$P(|U_n| > M|a_n|) < \epsilon$$

## Notation for Size or 'Order' of sequences

#### Little "o"

If  $a_n$  and  $b_n$  are sequences of constants with  $a_n > 0$  then

**Definition**: We say  $b_n = o(a_n)$  if

$$\lim_{n\to\infty}\frac{b_n}{a_n}=0.$$

**Definition**: We say  $U_n = o_P(a_n)$  if  $U_n/a_n \to 0$  in probability: for each  $\epsilon > 0$ 

$$\lim_{n\to\infty}P(|U_n/a_n|>\epsilon)=0.$$

#### Algebra Rules

• Can manipulate these algebraically if we are careful.

$$O(a_n)O(b_n) = O(a_nb_n)$$
 $cO(a_n) = O(a_n)$ 
 $O(a_n)O_P(b_n) = O_P(a_nb_n)$ 
 $O_P(a_n)O_P(b_n) = O_P(a_nb_n)$ 
 $O(a_n) + O(b_n) = O(\max\{a_n, b_n\})$ 
 $O_P(a_n) + O_P(b_n) = O_P(\max\{a_n, b_n\})$ 

- All these rules hold with 'O' replaced by 'o'.
- In the rules both  $a_n > 0$  and  $b_n > 0$  and c is a constant not depending on n.

#### Big O with Little o

• The two go together sometimes:

$$O(a_n)o(b_n) = o(a_nb_n)$$
 $o(O(a_n)) = o(a_n)$ 
 $o(a_n)O_P(b_n) = o_P(a_nb_n)$ 
 $o(a_n)O_P(b_n) = o_P(a_nb_n)$ 
 $o(a_n) + O(b_n) = O(\max\{a_n, b_n\})$ 
 $o_P(a_n) + O_P(b_n) = O_P(\max\{a_n, b_n\})$ 

You can't cancel because each new occurence of O is different

$$O(a_n) - O(a_n) \neq 0.$$

• Only add and multiply and use positive rates.

# Some examples and proof ideas

• Suppose  $Y_n$  is a sequence of random variables with mean 0 and variance  $a_n^2$ . Then

$$Y_n = O_P(a_n)$$

because

$$P\left(\frac{|Y_n|}{a_n} > M\right) \le \frac{a_n^2}{a_n^2 M^2} = \frac{1}{M^2}$$

which is less than  $\epsilon$  if  $M > 1/\sqrt{\epsilon}$ .

So in an iid sampling problem

$$\frac{\sqrt{n}(\bar{X}_n-\mu)}{\sigma}=O_P(1).$$

# More examples and proof ideas

• In the same problem  $s_n$  converges to  $\sigma$  in probability so

$$s_n = \sigma + o_P(1)$$

Thus

$$\frac{\sigma}{s_n} = 1 + o_P(1)$$

So

$$\frac{\sqrt{n}(\bar{X}_n - \mu)}{s_n} = \frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma} \frac{\sigma}{s_n} \\ = (1 + o_P(1))O_P(1) = O_P(1) + o_P(1) = O_P(1)$$

#### More examples

 In a regular iid sampling problem each component of the score function is

$$O_P(\sqrt{n})$$

because the variance is n times the Fisher information in a single point

• The Hessian  $H(\theta)$  is  $O_P(n)$  and usually

$$H(\theta) = \mathcal{I}(\theta) + O_P(\sqrt{n})$$

and

$$H(\hat{\theta}) = \mathcal{I}(theta) + O_P(\sqrt{n}).$$

• The theory we proved said

$$\hat{\theta} = \theta_0 + O_P(1/\sqrt{n})$$

because

$$\hat{\theta} - \theta_0 = -H(\theta)^{-1}U(\theta) + o_P(1/\sqrt{n}).$$