

**Lecture in FYS4411,  
March 8, 2024**

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Standard Bootstrap assumes  
that the stochastic variables

$x_i$  are i.i.d.  $\begin{matrix} \nearrow \\ \text{independent} \end{matrix}$   $\begin{matrix} \searrow \\ \text{identically} \end{matrix}$  distributed,

The estimations are typically  
the mean value (sample  
mean)  
and the variance

$$E[\bar{x}] = \int_{x \in D} p(x) \times dx$$

PDF  
 $p(x)dx$

or  $\sum_{x \in D} x_i p(x_i)$

in our case we don't have  $p(x)$

sample mean

$$\mu = \frac{1}{n} \sum_{i=1}^n x_i \neq E[\bar{x}]$$

when  $n$   
is not  
infinitely large.

$$\int_{x \in D} p(x) dx = 1$$

$$\text{var}[x] = \int_{x \in D} p(x) (x - E[x])^2 dx$$

$$\sum_{i \in D} p(x_i) (x_i - E[x])^2$$

sample variance

$$s^2 = \frac{1}{n} \sum_{i \in D} (x_i - \mu)^2$$

$$(p(x_i) = \frac{1}{n})$$

# Bootstrap

original sample  $X = \{x_1, x_2, \dots, x_n\}$

We assume we can produce new samples  $X^*$  and produce new estimators for

$\mu$  and  $\sigma^2$

$\hat{\theta}_n^{*(1)}, \hat{\theta}_n^{*(2)}, \dots, \hat{\theta}_n^{*(B)}$

$$\hat{\theta}_n^{*(i)} = \frac{1}{n} \sum_{j=1}^n x_j^{*(i)}$$

# Example

$$X = \{1, 2, 3, 4, 5\}$$

$$\xrightarrow{*} X^* = \{2, 3, 3, 5, 1\}$$

Do  $B-1$  times -

shuffle  
randomly  
with  
replacement

$$\bar{\theta}_B^* = \frac{1}{B} \sum_{i=1}^B \theta_n^{*(i)}$$

$$\text{var} [\bar{\theta}_B^*] = \frac{1}{B-1} \sum_{i=1}^B (\theta_n^{*(i)} - \bar{\theta}_B^*)^2$$

Central limit theorem.

m-experiments, each of  
these have

$$\bar{X}_i = \frac{1}{m} \sum_{j=1}^m X_j^{(i)}$$

↑  
nd

Simplify notation

$$\bar{x}_i \Rightarrow \boxed{x_i}$$

same  
PDF

Total mean value

$$z = \frac{x_1 + x_2 + \dots + x_m}{m}$$

what is the distribution  
of  $z$ ?  $P(z) = ?$

$$P(z) = \int_{x_1 \in D} dx_1 \underline{P(x_1)} \int_{x_2 \in D} dx_2 \underline{P(x_2)}$$

$$\cdots \int_{x_m \in D} dx_m \underline{P(x_m)}$$

$$\times \delta\left(z - \frac{\underline{(x_1 + x_2 + \dots + x_m)}}{m}\right)$$

$$\begin{aligned}
 S(z - \frac{(x_1 + x_2 + \dots + x_m)}{m}) & \\
 = \frac{1}{2\pi} \int_{-\infty}^{\infty} dq \exp \left[ iq \left( z - \frac{x_1 + x_2 + \dots + x_m}{m} \right) \right] &
 \end{aligned}$$

in  $p(z)$  insert

$$1 = e^{i\mu q - i\bar{\mu} q}$$

$$\mu = \int_{x \in D} p(x) x dx$$

$$P(z) = \frac{1}{2\pi} \int_{-\infty}^{\infty} dq e^{iq(z-\mu)}$$

$$\times \left[ \int_{x \in D} dx P(x) \exp \left[ \frac{i q (\mu - x)}{m} \right] \right]^m$$

$$\int_{x \in D} P(x) dx = 1$$

$$\int_{x \in D} dx P(x) e^{iq(\mu-x)/m}$$

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$$= \int_{x \in D} p(x) dx \left[ 1 + \frac{i q (\mu - x)}{m} \right]$$

$$= \frac{q^2 (\mu - x)^2}{2 m^2} + \dots \quad ]$$

$$\left( \mu = \int_{x \in D} x p(x) dx \quad \int_{x \in D} p(x) dx = 1 \right)$$

$$= \left[ 1 + 0 - \frac{q^2 \nabla^2}{2 m^2} + \dots \right]$$

in the limit  $m \rightarrow \infty$

$$P(z) = \frac{1}{\sqrt{2\pi \sigma^2/m}} \exp\left[-\frac{(z-\mu)^2}{2\sigma^2/m}\right]$$

Gaussian with mean value  $\mu$  and variance

$$\sigma^2/m \Rightarrow \text{STD} = \sqrt{\sigma^2/m}$$

$$\sigma^2 = \int_{x \in D} P(x) (x-\mu)^2 dx$$