

Math 417: Day 50

Suppose $X_1, X_2, \dots$ are i.i.d. real-valued random variables w/ mean 0 & variance σ^2 . Then $\frac{1}{n} \sum_{i=1}^n X_i$ has mean 0 & variance σ^2/n , so it is very likely to be near 0 when n is large (of course, this is what the weak law of large numbers says).

Of course, as we've seen, $\frac{1}{\sqrt{n}} \sum_{i=1}^n X_i$ has mean 0 & variance σ^2 ... the content of the Central Limit Theorem is that this goes to the Gaussian w/ mean 0 & variance σ^2 .

Central Limit Theorem: Let $(X_i)_{i=1}^n$ be a seq. of i.i.d., real-valued, L^2 random variables w/ mean μ & variance σ^2 .

As $n \rightarrow \infty$, the distribution of $\frac{1}{\sigma\sqrt{n}} \sum_{i=1}^n (X_i - \mu)$ converges vaguely to the standard normal distribution ν_0' .

Here the distribution $\nu_\mu^{\sigma^2}$ of the Gaussian w/ mean μ & variance σ^2 is given by

$$\nu_\mu^{\sigma^2}(E) = \int_E \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(t-\mu)^2}{2\sigma^2}} dt$$

& one can easily check that $\int_{\mathbb{R}} t d\nu_\mu^{\sigma^2}(t) = \mu$ & $\int_{\mathbb{R}} (t-\mu)^2 d\nu_\mu^{\sigma^2}(t) = \sigma^2$.

Now, in the CLT, we can replace X_i by $\frac{X_i - \mu}{\sigma}$, so we reduce to the case when $\mu=0$ & $\sigma^2=1$.

The strategy is to use Fourier analysis, so, for any real-valued r.v. X , we define the characteristic function $F_X: \mathbb{R} \rightarrow \mathbb{C}$ by

$$F_X(t) = E(e^{itX})$$

Prop: The Gaussian $\nu_\mu^{\sigma^2}$ has characteristic function $F(t) = e^{it\mu - \frac{\sigma^2 t^2}{2}}$.

Pf: $E(e^{itX}) = \int e^{it\zeta} \cdot \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(\zeta-\mu)^2}{2\sigma^2}} d\zeta = e^{it\mu - \frac{\sigma^2 t^2}{2}}$ □

If we Taylor expand e^{itX} & formally interchange expectation & sums, we expect something like $F_X(t) = \sum_{k=0}^{\infty} \frac{(it)^k}{k!} E(X^k)$ to be true. Of course we can't really do this in general, but something more or less like this is true:

Prop: If X is a real r.v. w/ finite k^{th} moment, then F_X is C^k w/

$$\frac{d^j}{dt^j} F_X(t) = i^j E(X^j e^{itX})$$

$\forall 0 \leq j \leq k$. In particular,

$$F_X(t) = \sum_{j=0}^k \frac{(it)^j}{j!} E(X^j) + o(|t|^k)$$

Pf: One can show that F_x is uniformly continuous. That means we can differentiate under the integral:

$$\begin{aligned}\frac{d^j}{dt^j} F_x(t) &= \frac{d^j}{dt^j} E(e^{itX}) = \frac{d^j}{dt^j} \int e^{it\xi} e^{-\frac{(\xi-\mu)^2}{2\sigma^2}} d\xi = \int \frac{d^j}{dt^j} (e^{it\xi}) dP_X(\xi) \\ &= \int (i\xi)^j e^{it\xi} dP_X(\xi) \\ &= i^j \int \xi^j e^{it\xi} dP_X(\xi) \\ &= i^j E(X^j e^{itX}).\end{aligned}$$

then the rest follows from the usual Taylor approximation theorem.

□