Math 3280   20-10-15

Review.

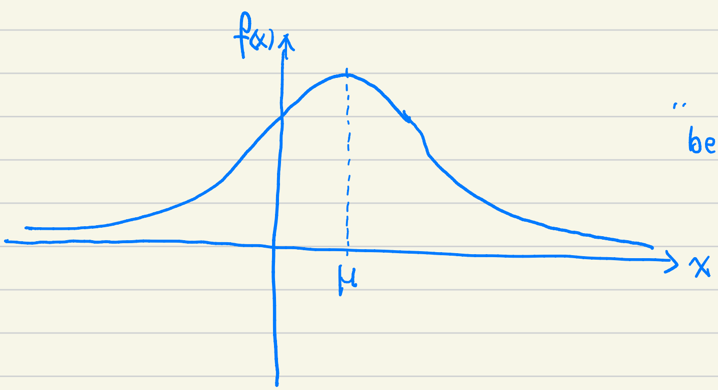
- uniform r.v. on $[a, b]$,

$$f(x) = \begin{cases} \frac{1}{b-a} & \text{if } x \in [a,b] \\ 0 & \text{otherwise} \end{cases}$$

§ 5.4 Normal r.v.

Def. Let $\mu \in \mathbb{R}$ and $\sigma > 0$. Say X is a normal r.v. with parameters μ and σ^2 if its pdf is given by

$$f(x) = \frac{1}{\sqrt{2\pi}\,\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \quad -\infty < x < \infty$$



"bell-shaped"

- The above f is indeed a pdf.

To see this,

$$\frac{1}{\sqrt{2\pi}\sigma}\int_{-\infty}^{\infty} e^{-\frac{(x-\mu)^2}{2\sigma^2}}\,dx \ \underline{\underline{\text{Letting } y=\frac{x-\mu}{\sigma}}} \ \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{\infty} e^{-\frac{y^2}{2}}\,dy$$

We need to show $\int_{-\infty}^{\infty} e^{-\frac{y^2}{2}}\,dy = \sqrt{2\pi}$. Notice

(*) $$\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} e^{-\frac{(x^2+y^2)}{2}}\,dx\,dy$$

$$\underline{\underline{\text{Letting } \begin{cases} r=\sqrt{x^2+y^2} \\ \theta=\arctan\frac{y}{x}\end{cases}}} \quad \int_0^{\infty}\int_0^{2\pi} e^{-\frac{r^2}{2}}\, r\,dr\,d\theta$$

$$= \int_0^{2\pi}\left(\int_0^{\infty} e^{-\frac{r^2}{2}}\, r\,dr\right) d\theta$$

$$= 2\pi \int_0^{\infty} e^{-\frac{r^2}{2}}\, r\,dr$$

$$= 2\pi \left(-e^{-\frac{r^2}{2}}\right)\Big|_0^{\infty}$$

$$= 2\pi.$$

Since (*) $= \left(\int_{-\infty}^{\infty} e^{-\frac{y^2}{2}}\,dy\right)^2$, we obtain the desired identity.

② Let X be a normal r.v with parameters μ and σ^2,

then

$$Z := \frac{X-\mu}{\sigma}$$

is a normal r.v with parameters 0 and 1.

We call Z a standard normal r.v.

Pf. Calculate the cumulative distribution of Z,

$$F_Z(a) = P\{Z \leq a\}$$

$$= P\left\{\frac{X-\mu}{\sigma} \leq a\right\}$$

$$= P\{X \leq a\sigma + \mu\}$$

$$= \int_{-\infty}^{a\sigma+\mu} \frac{1}{\sqrt{2\pi}\,\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$$

$$\underset{\text{Letting } y = \frac{x-\mu}{\sigma}}{=} \int_{-\infty}^{a} \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} dy$$

Taking derivative of $F_Z(a)$ gives

$$f_Z(a) = \frac{1}{\sqrt{2\pi}} e^{-\frac{a^2}{2}}.$$

$\square$

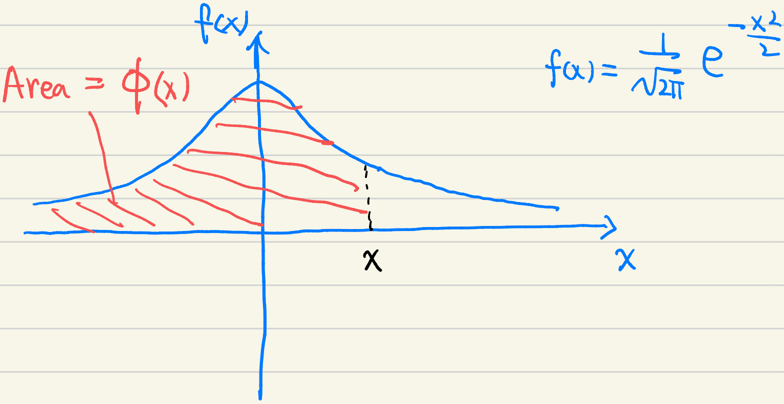
- Let

$$\phi(x) = P\{Z \leq x\}$$

be the CDF of Z.

Then

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-\frac{y^2}{2}} dy$$



Example: Calculate $E[Z]$ and $V(Z)$.

Solution:

$$E[Z] = \int_{-\infty}^{\infty} x \cdot f(x)\, dx$$

$$= \int_{-\infty}^{\infty} x \cdot \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}\, dx$$

$$= -\frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \Big|_{-\infty}^{\infty}$$

$$= 0$$

$$E[Z^2] = \int_{-\infty}^{\infty} x^2 \cdot \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}\, dx$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \cdot x \cdot \left(-e^{-\frac{x^2}{2}}\right)'\, dx$$

$$\overset{\text{int by parts}}{=} \frac{1}{\sqrt{2\pi}} \cdot x \cdot \left(-e^{-\frac{x^2}{2}}\right) \Big|_{-\infty}^{\infty} + \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \cdot (x)'\, dx$$

$$= 1$$

Hence

$$V(Z) = E[Z^2] - (E[Z])^2$$
$$= 1 - 0^2 = 1.$$

Lem 1. Let $Y = aX + b$, where $a, b \in \mathbb{R}$ and X is a cts r.v.

Then ① $E[Y] = aE[X] + b$

② $V(Y) = a^2 V(X)$.

Pf. Let f be the pdf of X.

Then

$$E[Y] = \int_{-\infty}^{\infty} (ax+b) f(x)\,dx$$
$$= a\int_{-\infty}^{\infty} x f(x)\,dx + b\int_{-\infty}^{\infty} f(x)\,dx$$
$$= aE[X] + b$$

$$E[Y^2] = \int_{-\infty}^{\infty} (ax+b)^2 f(x)\,dx$$
$$= \int_{-\infty}^{\infty} (a^2x^2 + 2abx + b^2) f(x)\,dx$$
$$= a^2\int_{-\infty}^{\infty} x^2 f(x)\,dx + 2ab\int_{-\infty}^{\infty} x f(x)\,dx$$
$$+ b^2 \int_{-\infty}^{\infty} f(x)\,dx$$
$$= a^2 E[X^2] + 2ab\,E[X] + b^2$$

Hence

$$V(Y) = E[Y^2] - (E[Y])^2$$
$$= a^2E[X^2] + 2ab\,E[X] + b^2$$
$$- (aE[X] + b)^2$$
$$= a^2\left(E[X^2] - (E[X])^2\right)$$
$$= a^2\,V(X).$$

$\boxtimes$

Prop 2: Let X be a normal r.v. with parameters μ and σ^2.

Then $E[X] = \mu$

$V(X) = \sigma^2$.

Pf. Let $Z = \frac{X-\mu}{\sigma}$. Then Z is a standard normal r.v. Hence $E[Z]=0$, $V(Z)=1$.

Now $X = \sigma Z + \mu$. By Lem 1,

$$E[X] = \sigma E[Z] + \mu = \sigma \cdot 0 + \mu = \mu.$$

$$V(X) = \sigma^2 V(Z) = \sigma^2 \cdot 1 = \sigma^2.$$ $\boxed{}$.

The most important property of normal r.v is that it can be used to approximate a binomial r.v with parameters (n, p) when n is large.

Thm 3. (DeMoivre-Laplace Thm)

Let $0 < p < 1$. Let X_n be a binomial r.v with parameters (n, p). Then for given $a, b \in \mathbb{R}$,

$$P\left\{ a < \frac{X_n - np}{\sqrt{np(1-p)}} < b \right\}$$

$$\longrightarrow P\{ a < Z < b \}$$

$$= \int_a^b \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx$$

$$= \phi(b) - \phi(a).$$

as $n \to \infty$.

- In other word, for large n,

$\frac{X_n - np}{\sqrt{np(1-p)}}$ has approximately the same distribution as Z.

Example 4. Let X be a binomial r.v with parameters $n = 40$ and $p = \frac{1}{2}$. Find $P\{X = 20\}$.

Solution: We first find the precise value of this prob.

$$P\{X = 20\} = \binom{40}{20} \cdot \left(\frac{1}{2}\right)^{40}$$

$$\approx .1254.$$

Next we estimate this prob. by using normal distribution.

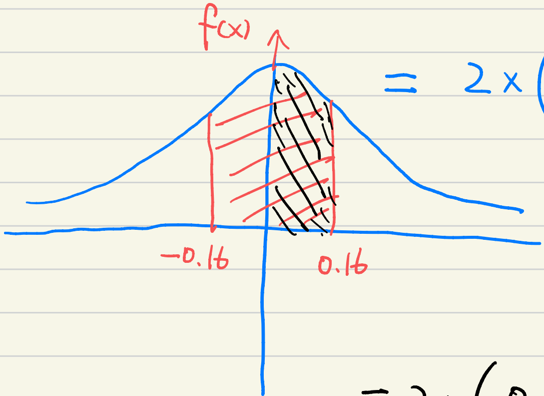
$$P\{X = 20\} = P\{19.5 \leq X \leq 20.5\}$$

(continuity correction)

$$= P\left\{\frac{-0.5}{\sqrt{10}} \leq \frac{X - 20}{\sqrt{10}} \leq \frac{0.5}{\sqrt{10}}\right\}$$

$$\approx P\left\{ \frac{-0.5}{\sqrt{10}} \le Z \le \frac{0.5}{\sqrt{10}} \right\}$$

$$\approx P\{-0.16 \le Z \le 0.16\}$$



$$= 2 \times \left(\Phi(0.16) - \tfrac{1}{2} \right)$$

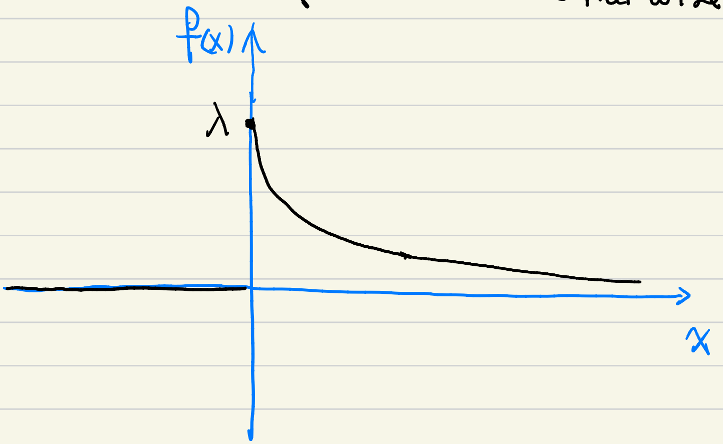
$$= 2 \times \left(0.5636 - \tfrac{1}{2} \right)$$

$$= .1274.$$

§ 5.5 Exponential r.v.

Def. Let $\lambda > 0$. Say X is an exponential r.v. with parameter λ if X has the following density

$$f(x) = \begin{cases} \lambda e^{-\lambda x} & \text{if} \quad x > 0 \\ 0 & \text{otherwise.} \end{cases}$$



Example: Find $E[X]$ and $V(X)$.

Solution: We first estimate

$$E[X^n] \quad \text{for} \quad n \geq 2$$

Notice that

$$E[X^n] = \int_{-\infty}^{\infty} x^n f(x)\, dx$$

$$= \int_{0}^{\infty} x^n \lambda e^{-\lambda x}\, dx$$

$$= \int_0^\infty x^n \cdot \left(-e^{-\lambda x}\right)' dx$$

$$\overset{\text{int by parts}}{=} \quad x^n \cdot \left(-e^{-\lambda x}\right)\Big|_0^\infty + \int_0^\infty e^{-\lambda x} \cdot \left(x^n\right)' dx$$

$$= 0 + \int_0^\infty n\, x^{n-1} e^{-\lambda x} dx$$

$$= 0 + \frac{n}{\lambda} \int_0^\infty x^{n-1} \cdot \lambda e^{-\lambda x} dx$$

$$= \frac{n}{\lambda} E[X^{n-1}].$$

That is,

$$(*) \quad E[X^n] = \frac{n}{\lambda} E[X^{n-1}], \quad n \geq 2.$$

Now

$$E[X] = \int_0^\infty \lambda x e^{-\lambda x} dx$$

$$= \int_0^\infty x \left(-e^{-\lambda x}\right)' dx$$

$$= x\left(-e^{-\lambda x}\right)\Big|_0^\infty + \int_0^\infty e^{-\lambda x} dx$$

$$= \frac{1}{\lambda} \int_0^\infty \lambda e^{-\lambda x} dx = \frac{1}{\lambda}$$

Usig (*), $E[X^2] = \frac{2}{\lambda} \cdot E[X]$

$$= \frac{2}{\lambda} \cdot \frac{1}{\lambda}$$

$$= \frac{2}{\lambda^2}$$

Hence

$$V(X) = E[X^2] - \left(E[X]\right)^2$$

$$= \frac{2}{\lambda^2} - \frac{1}{\lambda^2} = \frac{1}{\lambda^2}.$$

Table 5.1 Area $\Phi(x)$ Under the Standard Normal Curve to the Left of X.

X	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
.0	.5000	.5040	.5080	.5120	.5160	.5199	.5239	.5279	.5319	.5359
.1	.5398	.5438	.5478	.5517	.5557	.5596	.5636	.5675	.5714	.5753
.2	.5793	.5832	.5871	.5910	.5948	.5987	.6026	.6064	.6103	.6141
.3	.6179	.6217	.6255	.6293	.6331	.6368	.6406	.6443	.6480	.6517
.4	.6554	.6591	.6628	.6664	.6700	.6736	.6772	.6808	.6844	.6879
.5	.6915	.6950	.6985	.7019	.7054	.7088	.7123	.7157	.7190	.7224
.6	.7257	.7291	.7324	.7357	.7389	.7422	.7454	.7486	.7517	.7549
.7	.7580	.7611	.7642	.7673	.7704	.7734	.7764	.7794	.7823	.7852
.8	.7881	.7910	.7939	.7967	.7995	.8023	.8051	.8078	.8106	.8133
.9	.8159	.8186	.8212	.8238	.8264	.8289	.8315	.8340	.8365	.8389
1.0	.8413	.8438	.8461	.8485	.8508	.8531	.8554	.8577	.8599	.8621
1.1	.8643	.8665	.8686	.8708	.8729	.8749	.8770	.8790	.8810	.8830
1.2	.8849	.8869	.8888	.8907	.8925	.8944	.8962	.8980	.8997	.9015
1.3	.9032	.9049	.9066	.9082	.9099	.9115	.9131	.9147	.9162	.9177
1.4	.9192	.9207	.9222	.9236	.9251	.9265	.9279	.9292	.9306	.9319
1.5	.9332	.9345	.9357	.9370	.9382	.9394	.9406	.9418	.9429	.9441
1.6	.9452	.9463	.9474	.9484	.9495	.9505	.9515	.9525	.9535	.9545
1.7	.9554	.9564	.9573	.9582	.9591	.9599	.9608	.9616	.9625	.9633
1.8	.9641	.9649	.9656	.9664	.9671	.9678	.9686	.9693	.9699	.9706
1.9	.9713	.9719	.9726	.9732	.9738	.9744	.9750	.9756	.9761	.9767
2.0	.9772	.9778	.9783	.9788	.9793	.9798	.9803	.9808	.9812	.9817
2.1	.9821	.9826	.9830	.9834	.9838	.9842	.9846	.9850	.9854	.9857
2.2	.9861	.9864	.9868	.9871	.9875	.9878	.9881	.9884	.9887	.9890
2.3	.9893	.9896	.9898	.9901	.9904	.9906	.9909	.9911	.9913	.9916
2.4	.9918	.9920	.9922	.9925	.9927	.9929	.9931	.9932	.9934	.9936
2.5	.9938	.9940	.9941	.9943	.9945	.9946	.9948	.9949	.9951	.9952
2.6	.9953	.9955	.9956	.9957	.9959	.9960	.9961	.9962	.9963	.9964
2.7	.9965	.9966	.9967	.9968	.9969	.9970	.9971	.9972	.9973	.9974
2.8	.9974	.9975	.9976	.9977	.9977	.9978	.9979	.9979	.9980	.9981
2.9	.9981	.9982	.9982	.9983	.9984	.9984	.9985	.9985	.9986	.9986
3.0	.9987	.9987	.9987	.9988	.9988	.9989	.9989	.9989	.9990	.9990
3.1	.9990	.9991	.9991	.9991	.9992	.9992	.9992	.9992	.9993	.9993
3.2	.9993	.9993	.9994	.9994	.9994	.9994	.9994	.9995	.9995	.9995
3.3	.9995	.9995	.9995	.9996	.9996	.9996	.9996	.9996	.9996	.9997
3.4	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9998

$\phi(0.16)$

The values of $\Phi(x)$ for nonnegative x are given in Table 5.1. For negative values of x, $\Phi(x)$ can be obtained from the relationship

$$\Phi(-x) = 1 - \Phi(x) \qquad -\infty < x < \infty \tag{4.1}$$

The proof of Equation (4.1), which follows from the symmetry of the standard normal density, is left as an exercise. This equation states that if Z is a standard normal random variable, then

$$P\{Z \le -x\} = P\{Z > x\} \qquad -\infty < x < \infty$$