

Stat 343, Thu 22-Oct-2020 -- Thu 22-Oct-2020
Probability and Statistics
Fall 2020

Thursday, October 22nd 2020

Wk 8, Th

Topic:: Joint normal distributions

Read:: FAST 3.8

at start: explore normal quantile plots for several distribution types

```
gf_qq(~rexp(1000,2))
```

```
gf_qq(~rbeta(1000,8,2))
```

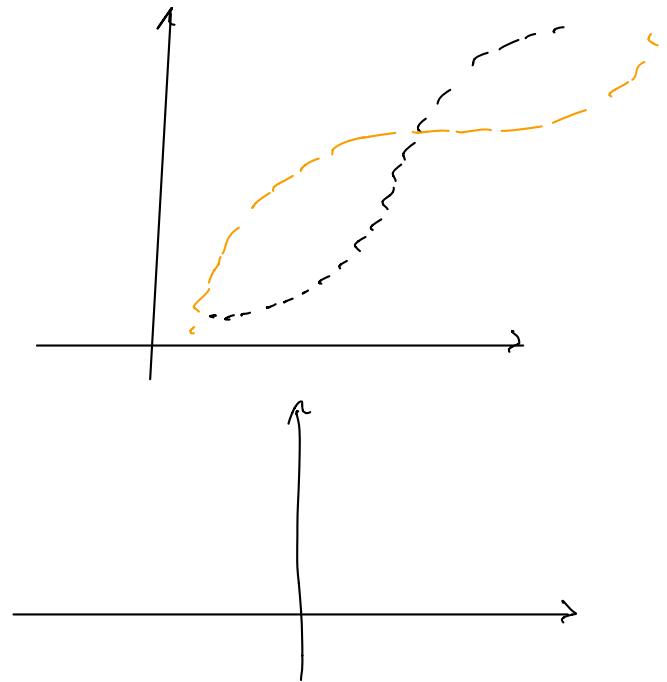
```
gf_qq(~rt(1000,2))
```

Working with vectors, matrices in R

- mosaic commands:

```
dot(u, v)
```

```
vlength(u)
```



iid = independent \equiv identically distributed

Sums of iid random variables

Lemma 1: Suppose X_1, \dots, X_n are i.i.d. and that each $E(X_i) = \mu$, each $\text{Var}(X_i) = \sigma^2$. Let $S = X_1 + X_2 + \dots + X_n$, and $\bar{X} = \frac{1}{n}S$. Then

$$\begin{aligned} \text{(i)} \quad E(S) &= n\mu \text{ and } \text{Var}(S) = n\sigma^2 \\ \text{(ii)} \quad E(\bar{X}) &= \mu \text{ and } \text{Var}(\bar{X}) = \frac{\sigma^2}{n} \\ \text{Var}\left(\frac{1}{n}S\right) &= \frac{1}{n^2} \text{Var}(S) = \frac{1}{n^2} \cdot n\sigma^2 \\ E(X_1 + X_2 + \dots + X_n) &= \sum E(X_i) = n\mu \\ \text{Var}(X_1 + \dots + X_n) &= \sum \text{Var}(X_i) = n\sigma^2 \end{aligned}$$

Lemma 2: Suppose $\mathbf{X} \stackrel{\text{i.i.d.}}{\sim} \text{Norm}(\mu, \sigma)$, and define S, \bar{X} as in the previous lemma. Then

$$\begin{aligned} \text{(i)} \quad \underline{S} &\sim \text{Norm}(n\mu, \sigma\sqrt{n}), \text{ and} \\ \text{(ii)} \quad \underline{\bar{X}} &\sim \text{Norm}(\mu, \sigma/\sqrt{n}). \end{aligned}$$

Extra: sum/average are normal once again.

Prove this, using Theorems 3.8.10 (p. 189) and 3.3.6 (p. 155).

Question: What if the components X_i of \mathbf{X} have different means μ_i and standard deviations σ_i ?

Moment generating functions for joint distributions

Definition 1: Let \mathbf{X} be the random vector with jointly distributed component r.v.s X_1, X_2, \dots, X_n . We define the **expected value** of \mathbf{X} to be the vector whose components are the expected values of the individual X_i s. That is,

$$E(\mathbf{X}) := \langle E(X_1), E(X_2), \dots, E(X_n) \rangle.$$

$$E(\vec{X})$$

Definition 2: For random vector \mathbf{X} whose components are jointly distributed r.v.s, define the **moment generating function** (mgf) for \mathbf{X} to be

$$M_{\mathbf{X}}(\mathbf{t}) = E(e^{\mathbf{t} \cdot \mathbf{X}}) = E(e^{t_1 X_1 + t_2 X_2 + \dots + t_n X_n}).$$

vector

$$M_{\langle X_1, X_2, \dots, X_n \rangle}(\langle t_1, t_2, \dots, t_n \rangle)$$

Example 1:

Suppose $\vec{X} \stackrel{\text{i.i.d.}}{\sim} \text{Norm}(\mu, \sigma)$. $\vec{X} = \langle X_1, X_2 \rangle$ w/ both $X_i \sim \text{Norm}(\mu, \sigma)$

(a) Compute $M_{\vec{X}}(\vec{t})$.

$$\begin{aligned} M_{\vec{X}}(\vec{t}) &:= E\left(e^{\vec{t} \cdot \vec{X}}\right) = E\left(e^{\langle t_1, t_2 \rangle \cdot \langle X_1, X_2 \rangle}\right) \\ &= E\left(e^{t_1 X_1 + t_2 X_2}\right) = E\left(\underbrace{e^{t_1 X_1}}_{\text{ind. vars since } X_1, X_2 \text{ are}} \cdot \underbrace{e^{t_2 X_2}}_{\text{ind. vars since } X_1, X_2 \text{ are}}\right) = \underline{E(e^{t_1 X_1})} \cdot \underline{E(e^{t_2 X_2})} \\ &= M_{X_1}(t_1) M_{X_2}(t_2) = e^{\mu t_1 + \sigma^2 t_1^2 / 2} e^{\mu t_2 + \sigma^2 t_2^2 / 2} \end{aligned}$$

(b) Recover $M_{X_1}(t)$ from the answer to (a).

$$= e^{\mu(t, t_2) + \sigma^2(t_1^2 + t_2^2)/2}$$

Get individual components' mgf — that of X_1 , by setting $t_1 = t, t_2 = 0$:

$$M_{\vec{X}}(\vec{t}) = e^{\mu(t, t_2) + \sigma^2(t_1^2 + t_2^2)/2}$$

$$M_{X_1}(t) = e^{\mu(t+0) + \sigma^2(t^2+0)/2} = e^{\mu t + \sigma^2 t^2 / 2} \quad \blacksquare$$

New Example 2
~~Example 2:~~

Suppose $M_X(t) = e^{\vec{\mu} \cdot \vec{t} + \frac{1}{2} \vec{t} \cdot \Sigma \vec{t}}$, where $\vec{\mu} = \langle 3, -1 \rangle$, $\Sigma = \begin{bmatrix} 1 & 1.5 \\ 1.5 & 4 \end{bmatrix}$. $\vec{X} = \langle X_1, X_2 \rangle$

(a) Find the moment generating functions for the components of X .

$$\vec{\mu} \cdot \vec{t} + \frac{1}{2} \vec{t} \cdot (\Sigma \vec{t}) = \langle 3, -1 \rangle \cdot \langle t_1, t_2 \rangle + \frac{1}{2} \langle t_1, t_2 \rangle \cdot \begin{bmatrix} 1 & 1.5 \\ 1.5 & 4 \end{bmatrix} \begin{bmatrix} t_1 \\ t_2 \end{bmatrix}$$

$$= \frac{1}{2} (t_1^2 + 3t_1 t_2 + 4t_2^2) + 3t_1 - t_2$$

$$M_{\vec{X}}(\vec{t}) = e^{\frac{1}{2} t_1^2 + 3/2 t_1 t_2 + 2t_2^2 + 3t_1 - t_2}$$

$X_1 \sim \text{Norm}(3, 1)$
 $X_2 \sim \text{Norm}(-1, 2)$

$M_{X_1}(t) = M_{\vec{X}}(\langle t, 0 \rangle) = e^{3t + \frac{1}{2} t^2}$ ← mgf for $\text{Norm}(3, 1)$
 $e^{-t + \frac{4}{2} t^2}$

(b) Compute partial derivatives up to 2nd order. $M_{\text{normal}} = e^{\mu t + \sigma^2 t^2 / 2}$

$$\frac{\partial}{\partial t_1} \left(e^{\frac{1}{2} t_1^2 + \frac{3}{2} t_1 t_2 + 2t_2^2 + 3t_1 - t_2} \right) = e^{\frac{1}{2} t_1^2 + \frac{3}{2} t_1 t_2 + 2t_2^2 + 3t_1 - t_2} \cdot (t_1 + \frac{3}{2} t_2 + 3)$$

$$= \frac{\partial M_{\vec{X}}(t_1, t_2)}{\partial t_1}$$

Insert $(0,0)$ for (t_1, t_2)

$$\frac{\partial M_X(0,0)}{\partial t_1} = 3 = E(X_1)$$

$$E(X_2) = \frac{\partial M_X(0,0)}{\partial t_2} = \dots = -1$$

$$E(X_1^2) = \frac{\partial}{\partial t_1} \left(\frac{\partial}{\partial t_1} M_X(0,0) \right)$$

$$E(X_1 X_2) = \frac{\partial}{\partial t_1} \left(\frac{\partial}{\partial t_2} M_X \right) \Big|_{(0,0)}$$

$$\text{Cov}(X_1, X_2) = E(X_1 X_2) - E(X_1)E(X_2)$$

$$\text{Var}(X_1) = E(X_1^2) - [E(X_1)]^2 = 5 - (-1)^2 = 4$$

$$\vec{t} \cdot \Sigma \vec{t}$$

$$\begin{aligned}
\langle t_1, t_2 \rangle \cdot \begin{bmatrix} 1 & 1.5 \\ 1.5 & 4 \end{bmatrix} \begin{bmatrix} t_1 \\ t_2 \end{bmatrix} &= \langle t_1, t_2 \rangle \cdot \left(t_1 \begin{bmatrix} 1 \\ 1.5 \end{bmatrix} + t_2 \begin{bmatrix} 1.5 \\ 4 \end{bmatrix} \right) \\
&= \langle t_1, t_2 \rangle \cdot \begin{bmatrix} t_1 + 1.5t_2 \\ 1.5t_1 + 4t_2 \end{bmatrix} = t_1(t_1 + 1.5t_2) + t_2(1.5t_1 + 4t_2) \\
&= t_1^2 + 3t_1t_2 + 4t_2^2
\end{aligned}$$

$$\vec{\mu} \cdot \vec{t} + \frac{1}{2} \vec{t} \cdot \Sigma \vec{t} = 3t_1 - t_2 + \frac{1}{2}t_1^2 + \frac{3}{2}t_1t_2 + 2t_2^2$$

$$\begin{aligned}
\Rightarrow M_{\vec{X}}(\vec{t}) &= e^{\vec{\mu} \cdot \vec{t} + \frac{1}{2} \vec{t} \cdot \Sigma \vec{t}} \\
&= e^{\frac{1}{2}t_1^2 + \frac{3}{2}t_1t_2 + 2t_2^2 + 3t_1 - t_2}
\end{aligned}$$

$$\text{For } X_1, \quad M_{X_1}(t) = M_{\vec{X}}(\langle t, 0 \rangle) = e^{3t + t^2/2} \Rightarrow X_1 \sim \text{Norm}(3, 1)$$

$$\begin{aligned}
\text{and } X_2, \quad M_{X_2}(t) &= M_{\vec{X}}(\langle 0, t \rangle) = e^{-t + 2t^2} = e^{-t + 4t^2/2} \\
&\Rightarrow X_2 \sim \text{Norm}(-1, 2).
\end{aligned}$$

\Rightarrow the variables X_1, X_2 are non-independent jointly distributed normal r.v.s.

$$\begin{aligned}
\frac{\partial}{\partial t_1} M_{\vec{X}}(\vec{t}) &= \frac{\partial}{\partial t_1} \left(e^{\frac{1}{2}t_1^2 + \frac{3}{2}t_1t_2 + 2t_2^2 + 3t_1 - t_2} \right) \\
&= \left(t_1 + \frac{3}{2}t_2 + 3 \right) e^{\frac{1}{2}t_1^2 + \frac{3}{2}t_1t_2 + 2t_2^2 + 3t_1 - t_2} \\
\Rightarrow \frac{\partial}{\partial t_1} M_{\vec{X}}(\vec{t}) \Big|_{\vec{t} = \langle 0, 0 \rangle} &= 3 \cdot 1 = 3
\end{aligned}$$

$$\begin{aligned}
\frac{\partial^2}{\partial t_1^2} M_{\vec{X}}(\vec{t}) &= \frac{\partial}{\partial t_1} \left[\left(t_1 + \frac{3}{2}t_2 + 3 \right) e^{\frac{1}{2}t_1^2 + \frac{3}{2}t_1t_2 + 2t_2^2 + 3t_1 - t_2} \right] \\
&= e^{\frac{1}{2}t_1^2 + \frac{3}{2}t_1t_2 + 2t_2^2 + 3t_1 - t_2} \cdot \left[1 + \left(t_1 + \frac{3}{2}t_2 + 3 \right)^2 \right] \\
\Rightarrow \frac{\partial^2}{\partial t_1^2} M_{\vec{X}}(\vec{t}) \Big|_{\vec{t} = \langle 0, 0 \rangle} &= 10
\end{aligned}$$

$$\begin{aligned}
\frac{\partial^2}{\partial t_1 \partial t_2} M_X(\vec{t}) &= \frac{\partial}{\partial t_2} \left[\left(t_1 + \frac{3}{2} t_2 + 3 \right) e^{\frac{1}{2} t_1^2 + \frac{3}{2} t_1 t_2 + 2 t_2^2 + 3 t_1 - t_2} \right] \\
&= e^{\frac{1}{2} t_1^2 + \frac{3}{2} t_1 t_2 + 2 t_2^2 + 3 t_1 - t_2} \left[\frac{3}{2} + \left(t_1 + \frac{3}{2} t_2 + 3 \right) \left(\frac{3}{2} t_1 + 4 t_2 - 1 \right) \right] \\
\Rightarrow \frac{\partial^2}{\partial t_1 \partial t_2} M_X(\vec{t}) \Big|_{\vec{t} = \langle 0, 0 \rangle} &= \left(\frac{3}{2} - 3 \right) = -\frac{3}{2}.
\end{aligned}$$

$$\begin{aligned}
\frac{\partial}{\partial t_2} M_X(\vec{t}) &= \frac{\partial}{\partial t_2} \left(e^{\frac{1}{2} t_1^2 + \frac{3}{2} t_1 t_2 + 2 t_2^2 + 3 t_1 - t_2} \right) \\
&= \left(\frac{3}{2} t_1 + 4 t_2 - 1 \right) e^{\frac{1}{2} t_1^2 + \frac{3}{2} t_1 t_2 + 2 t_2^2 + 3 t_1 - t_2} \\
\Rightarrow \frac{\partial}{\partial t_2} M_X(\vec{t}) \Big|_{\vec{t} = \langle 0, 0 \rangle} &= -1
\end{aligned}$$

$$\begin{aligned}
\frac{\partial^2}{\partial t_1 \partial t_2} M_X(\vec{t}) &= \frac{\partial^2}{\partial t_1 \partial t_2} M_X(\vec{t}) \quad (\text{result from MATH 271}) \\
\Rightarrow \frac{\partial^2}{\partial t_1 \partial t_2} M_X(\vec{t}) \Big|_{\vec{t} = \langle 0, 0 \rangle} &= -\frac{3}{2} \quad \text{again}
\end{aligned}$$

$$\begin{aligned}
\frac{\partial^2}{\partial t_2^2} M_X(\vec{t}) &= \frac{\partial}{\partial t_2} \left[\left(\frac{3}{2} t_1 + 4 t_2 - 1 \right) e^{\frac{1}{2} t_1^2 + \frac{3}{2} t_1 t_2 + 2 t_2^2 + 3 t_1 - t_2} \right] \\
&= e^{\frac{1}{2} t_1^2 + \frac{3}{2} t_1 t_2 + 2 t_2^2 + 3 t_1 - t_2} \cdot \left[4 + \left(\frac{3}{2} t_1 + 4 t_2 - 1 \right)^2 \right] \\
\Rightarrow \frac{\partial^2}{\partial t_2^2} M_X(\vec{t}) \Big|_{\vec{t} = \langle 0, 0 \rangle} &= 5
\end{aligned}$$