

4/24/17

$$X_1, \dots, X_n | \theta, \sigma^2 \stackrel{\text{iid}}{\sim} N(\theta, \sigma^2)$$

$$P(\theta, \sigma^2) \propto \frac{1}{\sigma^2}$$

Both  $\theta, \sigma^2$  unknown.

$$\text{If } \sigma^2 \text{ known } (\theta^{??}) \quad P(\theta | x, \sigma^2) = N(\bar{x}, (\frac{\sigma}{\sqrt{n}})^2)$$

$$\text{If } \theta \text{ known } (\sigma^{??}) \quad P(\sigma^2 | x, \theta) = \text{Inv gamma}(\frac{n}{2}, \frac{n \hat{\sigma}_{MLE}^2}{2})$$

$$\text{If both unknown, } P(\theta, \sigma^2 | x) \propto P(x | \theta, \sigma^2) P(\theta, \sigma^2)$$

$$\begin{aligned} &= \left( \prod_{i=1}^n \frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{1}{2\sigma^2}(x_i - \theta)^2} \right) \left( \frac{1}{\sigma^2} \right) \\ &\propto (\sigma^2)^{-\frac{n}{2}-1} e^{-\frac{(n-1)s^2/2}{\sigma^2}} e^{-\frac{1}{2\sigma^2}(\bar{x} - \theta)^2} \\ &\propto \text{Norm Inv Gamma} \left( \mu = \bar{x}, \lambda = n, \alpha = \frac{n}{2}, \beta = \frac{(n-1)s^2}{2} \right) \end{aligned}$$

Sampling

("r" function on formula sheet) or "rnorm..."

$$X \sim \text{Bern}(0.5)?$$

Sampling means pull or draw a realization. Make data  
Flip a coin.

$$X \sim \text{Binomial}(10, 0.5)? \rightarrow \text{Flip 10 coins.}$$

$$X \sim \text{Binomial}(10, 0.238597642)? \quad \text{gets harder... how do you find a weighted coin?}$$

$$X \sim \text{Normal}(11.2, 3.7^2)? \quad \text{same thing...}$$

Recall:  $F(x) := P(X \leq x)$  CDF.For a cont. r.v.  $X$ , what is the distribution of  $Y := F(X)$ ?  
 $t''(X)$ not on exam  
just proof for  
next thing

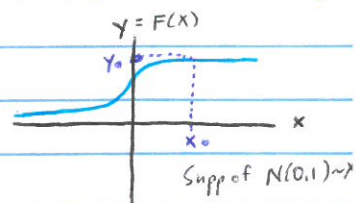
$$f_Y(y) = f_X(x) \left| \frac{dx}{dy} \right|$$

$$= f_X(x) \frac{1}{\left| \frac{dy}{dx} \right|}$$

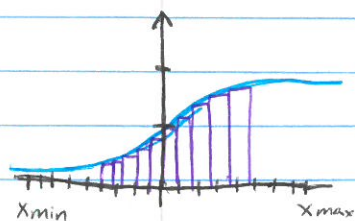
$$= f_X(x) \frac{1}{\left| \frac{d}{dx} [F(x)] \right|}$$

$$= f_X(x) \frac{1}{|f_X(x)|} \leftarrow \text{always (+) so } \neq \text{ need abs. value.}$$

$$= 1$$

So,  $\text{Supp}\{Y\} = [0, 1]$ ,  $f_Y(y) = 1$ ,  $\Rightarrow Y \sim \text{Uniform}(0, 1) \Rightarrow X = F^{-1}(y)$ To sample  $x$ , 1. Sample  $y_0$  from  $\text{Uniform}(0, 1)$ 2. Compute  $x_0 = F^{-1}(y_0)$ 3. Return  $x_0$ .

If  $F^{-1}$  is not available, pick  $X_{\min}, X_{\max}, \Delta X$ . Using these, create a "grid".  $G := \langle X_{\min}, X_{\min} + \Delta X, X_{\min} + 2\Delta X, X_{\min} + 3\Delta X, \dots, X_{\max} \rangle$



Compute  $F(x) \forall x \in G$

Approximate  $x_0 \approx \min_{y_0 \in G} F(x_0) \geq y$

- can lower  $\Delta x$ , stretch  $X_{\min}, X_{\max}$  but comp. has to do more work.

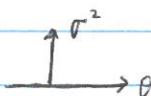
What if  $X$  is discrete?

• Can set  $G := \text{Supp}\{X\}$ . and do the same thing.

for 1-Dimensional

But NormInv Gamma is 2-Dimensional

$\theta, \sigma^2 | X \sim \text{NormInvGamma}(\dots)$



We know how to sample from  $f(x)$ , but how do we sample from  $f(x, y)$ ?

	$\sigma^2$	4	6	$\epsilon$	$f(x, y)$ joint probabilities
$X$	1	0.2	0.05	0.1	0.35
	3	0.1	0.05	0.1	0.25
	5	0.2	0.1	0.1	0.4
	$\Sigma \downarrow$	0.5	0.2	0.3	
		$\leftarrow \rightarrow$ $f(y)$			

$$\text{if } \frac{0.2 + 0.05 + 0.1}{0.35} = f(y | X=1)$$

Recall Bayes Rule:  $f(x, y) = f(y | x) f(x)$

Sampling from 2-Dimension: 1. ~~Draw~~ Draw  $x_0$  from  $f(x)$ .

2. Draw  $y_0$  from  $f(y | x = x_0)$

3. Return  $\langle x_0, y_0 \rangle$



$$P(\theta, \sigma^2 | X) = P(\theta | X, \sigma^2) P(\sigma^2 | X)$$

$$P(\theta | X, \sigma^2) = \text{Norma}(\bar{X}, (\frac{\sigma}{\sqrt{n}})^2)$$

solve for  $P(\sigma^2 | X)$

$$P(\sigma^2 | X) = \frac{P(\theta, \sigma^2 | X)}{P(\theta | X, \sigma^2)}$$

$$\propto \frac{(\sigma^2)^{-\frac{n}{2}-1} e^{-\frac{(n-1)s^2}{2\sigma^2}} e^{-\frac{1}{2\sigma^2}(\bar{X}-\theta)^2}}{\underbrace{\frac{1}{\sqrt{2\pi}\sigma}}_{(\sigma^2)^{-1/2}} e^{-\frac{1}{2\sigma^2}(\bar{X}-\theta)^2}}$$

$$\propto (\sigma^2)^{-\frac{n}{2}-\frac{1}{2}} e^{-\frac{(n-1)s^2}{2\sigma^2}}$$

$$\propto \underbrace{(\sigma^2)^{-\frac{n}{2}-\frac{1}{2}}}_{\text{need } -\alpha-1} e^{-\frac{(n-1)s^2}{2\sigma^2}}$$

$$(-\frac{n}{2} - \frac{1}{2} + 1) - 1$$

$$= -(\frac{n}{2} + \frac{1}{2} - 1) - 1$$

$$= -(\frac{n}{2} - \frac{1}{2}) - 1$$

$$= -(\frac{n-1}{2}) - 1$$

$$\propto (\sigma^2)^{-(\frac{n-1}{2})-1} e^{-\frac{(n-1)s^2}{2\sigma^2}} \quad \text{kernel of Inv Gamma} \quad \checkmark$$

$$\propto \text{Invgamma}(\frac{n-1}{2}, \frac{(n-1)s^2}{2})$$

- Sampling from Norm Inv Gamma:
1. Sample  $\sigma_0^2$  from  $\text{Invgamma}(\frac{n-1}{2}, \frac{(n-1)s^2}{2})$
  2. Sample  $\theta_0$  from  $N(\bar{X}, (\frac{\sigma_0}{\sqrt{n}})^2)$
  3. Return  $(\theta_0, \sigma_0^2)$

What is  $P(\sigma^2 | X)$ ? Is it  $P(\sigma^2 | X, \theta)$ ?

$$\hookrightarrow \text{No. } P(\sigma^2 | X) = \text{InvGamma}(\frac{n-1}{2}, \frac{(n-1)s^2}{2})$$

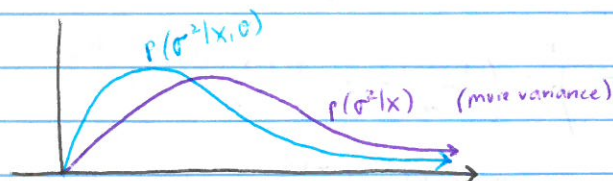
$$P(\sigma^2 | X, \theta) = \text{InvGamma}(\frac{n}{2}, \frac{n\hat{\sigma}_{MLE}^2}{2})$$

← # care about  $\theta$   
← main knowledge of  $\theta$

← check w/ notes

$$\text{Recall, } P(\sigma^2 | X) = \int_{\mathbb{R}} P(\theta, \sigma^2 | X) d\theta$$

"marginal distribution"



What is  $P(\theta | X)$ ?

$$\hookrightarrow P(\theta | X) = \int_{\text{supp. of } \sigma^2}^{\infty} P(\theta, \sigma^2 | X) d\sigma^2 \quad \text{HW...}$$

$\sigma^2$  is the "nuisance parameter": Don't care about the  $\sigma^2$  (variance).

but you have to use it to get what you want.

$X_1, \dots, X_n$

$$X_1, \dots, X_n | \theta, \sigma^2 \stackrel{iid}{\sim} N(\theta, \sigma^2)$$

$$\frac{\bar{X} - \theta}{\frac{\sigma}{\sqrt{n}}} \sim N(0, 1) \quad (\text{Math 241})$$

$$\frac{\bar{X} - \theta}{\frac{s}{\sqrt{n}}} \sim T_{n-1} \quad (\text{Math 242}) \quad \text{"Student's T distribution"} \quad (\text{Beer Stony})$$

$$V \sim T_n = \frac{\Gamma(\frac{n+1}{2})}{\sqrt{n\pi} \Gamma(\frac{n}{2})} \left(1 + \frac{V^2}{n}\right)^{-\frac{n+1}{2}}$$

Student's T distribution or "Standard T distr."

$$W = \sigma V + \mu = t(V)$$

$$V = t^{-1}\left(\frac{W - \mu}{\sigma}\right)$$

$$f_W(w) = f_V(t^{-1}(w)) \left| \frac{d}{dw} [t^{-1}(w)] \right|$$

$$= \frac{\Gamma(\frac{n+1}{2})}{\sqrt{n\pi} \sigma^2 \Gamma(\frac{n}{2})} \left(1 + \frac{1}{n} \left(\frac{w - \mu}{\sigma}\right)^2\right)^{-\frac{n+1}{2}}$$

$$= T_n(\mu, \sigma) \quad \text{Non-Standard T dist.}$$

$$P(\theta | x) = \frac{P(\theta, \sigma^2 | x)}{P(\sigma^2 | x)} = \frac{\left( \prod_{i=1}^n \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2\sigma^2}(x_i - \theta)^2} \right) \left( \frac{1}{\sigma^2} \right)}{\left( \frac{n\hat{\sigma}^2}{2} \right)^{n/2} (\sigma^2)^{-\frac{n}{2}-1} e^{-\frac{n\hat{\sigma}^2}{2\sigma^2}}}$$

$$\sim \ln \text{Gamma}\left(\frac{n}{2}, \frac{n\hat{\sigma}^2}{2}\right) \leftarrow$$

$$\sim \ln \text{Gamma}\left(\frac{n}{2}, \frac{\sum (x_i - \theta)^2}{2}\right)$$

Also

$$q \sim \text{invGamma}(\alpha, \beta) := \frac{\beta^\alpha}{\Gamma(\alpha)} e^{-\frac{\beta}{q}}$$

$$\propto \frac{e^{-\frac{1}{2\sigma^2} \sum (x_i - \theta)^2}}{\left(\frac{n\hat{\sigma}^2}{2}\right)^{n/2} e^{-\frac{1}{2\sigma^2} \sum (x_i - \theta)^2}}$$

$$= \left(\frac{n\hat{\sigma}^2}{2}\right)^{n/2} \quad \text{Recall: } n\hat{\sigma}^2_{MLE} = \dots = (n-1)s^2 + n(\bar{X} - \theta)^2$$

$$= \left(\frac{(n-1)s^2}{2} + \frac{n(\bar{X} - \theta)^2}{2}\right)^{-n/2}$$

$$\propto \left(\frac{1}{\frac{(n-1)s^2}{2}}\right)^{-n/2} \left(\frac{(n-1)s^2}{2} + \frac{n(\bar{X} - \theta)^2}{2}\right)^{-n/2}$$

$$\propto \left(1 + \frac{\frac{n(\bar{X} - \theta)^2}{2}}{\frac{(n-1)s^2}{2}}\right)^{-n/2} = \left(1 + \frac{1}{n-1} \left(\frac{\bar{X} - \theta}{\frac{s}{\sqrt{n}}}\right)^2\right)^{-n/2}$$

$$\propto T_{n-1}\left(\bar{X}, \frac{s}{\sqrt{n}}\right) = \int_0^\infty P(\theta, \sigma^2 | x) d\theta^2$$

Summary:  $P(\theta, \sigma^2 | x) \checkmark$   $P(\sigma^2 | x, \theta) \checkmark$   
 $P(\theta | x, \sigma^2) \checkmark$   $P(\theta | x) \checkmark$   
 $P(\sigma^2 | x) \checkmark$

$\theta$  is free variable

gt conf. int.  
 pt p-value.  
 rt draw out.