

1.

$$E(a_1Y_1 + a_2Y_2) = a_1E(Y_1) + a_2E(Y_2) = a_1u_1 + a_2u_2$$

$$\text{Var}(a_1Y_1 + a_2Y_2) = E[(a_1Y_1 + a_2Y_2 - E(a_1Y_1 + a_2Y_2))^2]$$

$$= E[(a_1Y_1 - a_1u_1 + a_2Y_2 - a_2u_2)^2]$$

$$= E[(a_1Y_1 - a_1u_1)^2 + (a_2Y_2 - a_2u_2)^2 + 2a_1a_2(Y_1 - u_1)(Y_2 - u_2)]$$

$$= a_1^2 E[(Y_1 - u_1)^2] + a_2^2 E[(Y_2 - u_2)^2] + 2a_1a_2 \text{cov}(Y_1, Y_2)$$

$$= a_1^2 \sigma_1^2 + a_2^2 \sigma_2^2$$

$$E(a_1Y_1 - a_2Y_2) = a_1E(Y_1) - a_2E(Y_2) = a_1u_1 - a_2u_2$$

$$\text{Var}(a_1Y_1 - a_2Y_2) = E[(a_1Y_1 - a_2Y_2 - E(a_1Y_1 - a_2Y_2))^2]$$

$$= E[(a_1Y_1 - a_1u_1)^2 + (a_2Y_2 - a_2u_2)^2 - 2a_1a_2(Y_1 - u_1)(Y_2 - u_2)]$$

$$= a_1^2 E[(Y_1 - u_1)^2] + a_2^2 E[(Y_2 - u_2)^2] - 2a_1a_2 \text{cov}(Y_1, Y_2)$$

$$= a_1^2 \sigma_1^2 + a_2^2 \sigma_2^2$$

2.

$$a) P(X=0, Y=0) = P(Y=0|X=0) P(X=0) = 0.5 \cdot 0.4 = 0.2$$

$$P(X=0, Y=1) = P(Y=1|X=0) P(X=0) = 0.5 \cdot 0.6 = 0.3$$

$$P(X=1, Y=0) = P(Y=0|X=1) P(X=1) = 0.5 \cdot 0.6 = 0.3$$

$$P(X=1, Y=1) = P(Y=1|X=1) P(X=1) = 0.5 \cdot 0.4 = 0.2$$

	Y	
X	0	1
0	0.2	0.3
1	0.3	0.2

$$b) \text{ Since } Y|X=0 \sim \text{Bernoulli}(0.6)$$

$$Y|X=1 \sim \text{Bernoulli}(0.4)$$

$$E(Y) = E(E(Y|X)) = E(Y|X=0) P(X=0) + E(Y|X=1) P(X=1)$$

$$= 0.6 \times 0.5 + 0.4 \times 0.5$$

$$= 0.5$$

$$c) \text{ Var}(Y|X=0) = 0.6 \times (1-0.6) = 0.24$$

$$\text{Var}(Y|X=1) = 0.4 \times (1-0.4) = 0.24$$

$$\text{Since } P(Y=0) = \sum_x P(X=x, Y=0) = 0.5$$

$$P(Y=1) = \sum_x P(X=x, Y=1) = 0.5$$

$$\begin{aligned} \text{Var}(Y) &= E((Y-\mu)^2) \\ &= (0-0.5)^2 P(Y=0) + (1-0.5)^2 P(Y=1) \\ &= 0.5 \times 0.25 + 0.5 \times 0.25 \\ &= 0.25 \end{aligned}$$

Given $X=0$ or $X=1$, There is less uncertainty for Y , So $\text{Var}(Y|X=0)$ and $\text{Var}(Y|X=1)$ are less than $\text{Var}(Y)$

$$\begin{aligned} d) P(X=0|Y=1) &= \frac{P(Y=1|X=0)P(X=0)}{P(Y=1)} \\ &= \frac{0.6 \times 0.5}{0.5} \\ &= 0.6 \end{aligned}$$

3.

We interpret $p(E)$ as: willing to give $p(E)$ to someone, provided they give me \$1 if E occurs.

a) Since E sometimes occurs, in order not to lose money, I'm willing to give someone $p(E)$, which is ≤ 1 .
At the extreme case, E must occur, then $p(E) \leq 1$ can guarantee that I will not lose money.

b) E^c : willing to give $p(E^c)$ to someone, provided they give you \$1 if E does not occur.
Then, either E will occur or not occur.

∴ the other person will always give \$1 to me.

Since each time I am willing to give someone $p(E) + p(E^c)$ each time,
then $p(E) + p(E^c) \leq 1$

By another definition: $p(E) + p(E^c) \geq 1$ by same logic.

$$\therefore p(E) + p(E^c) = 1$$

4.

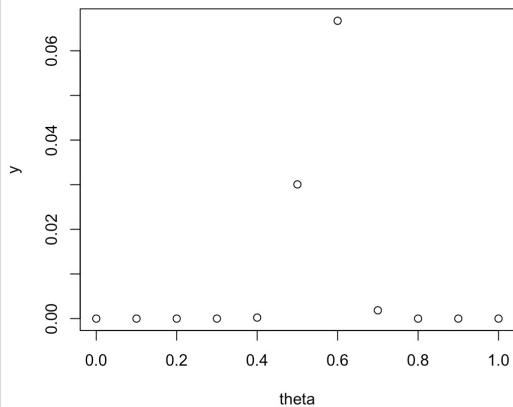
a) $Y_i|\theta \sim \text{iid Bernoulli}(\theta)$

$$\begin{aligned} \Pr(Y_1=y_1, \dots, Y_{100}=y_{100}|\theta) &= P(Y_1=y_1|\theta) P(Y_2=y_2|\theta) \cdots P(Y_{100}=y_{100}|\theta) \\ &= \theta^{y_1} (1-\theta)^{1-y_1} \cdots \theta^{y_{100}} (1-\theta)^{1-y_{100}} \\ &= \theta^{\sum y_i} (1-\theta)^{100 - \sum y_i} \end{aligned}$$

$$\Pr(\sum Y_i = y | \theta) = \binom{100}{y} \theta^y (1-\theta)^{100-y}$$

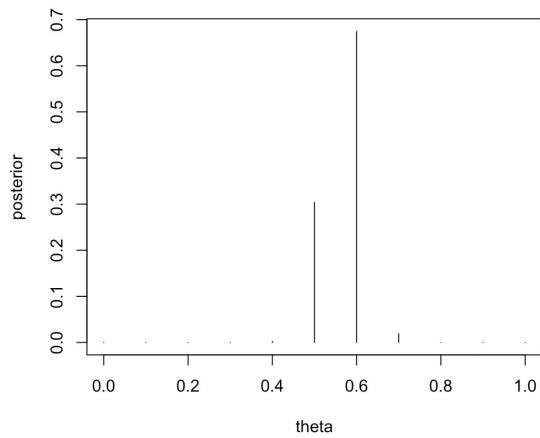
b) $\Pr(\sum Y_i = 57 | \theta) = \binom{100}{57} \theta^{57} (1-\theta)^{100-57}$

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> theta = seq(0,1,by=0.1)
> y = choose(100, 57) * theta^57 * (1-theta)^43
> plot(theta, y)
```



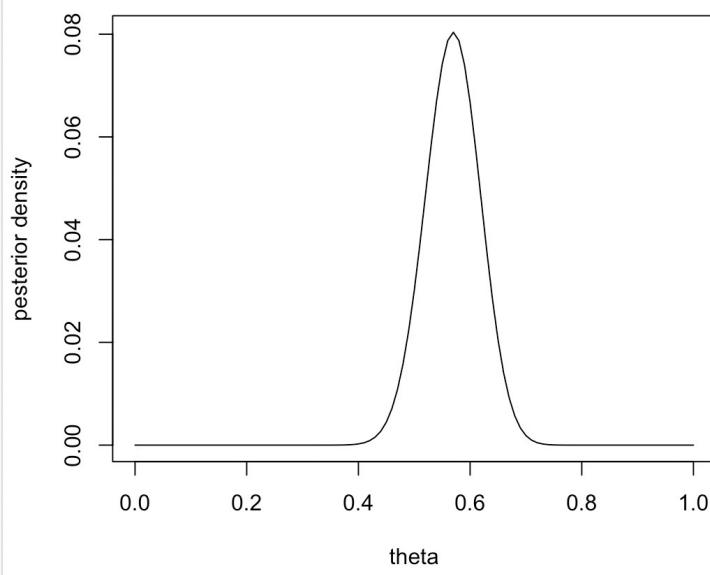
c) $P(\theta | \sum Y_i = 57) \propto P(\sum Y_i = 57 | \theta) P(\theta)$
 $\propto \theta^{57} (1-\theta)^{43}$

```
> theta = seq(0,1,by=0.1)
> prob = theta^57 * (1-theta)^43
> posterior = prob / sum(prob)
> plot(theta, posterior, type='h')
```

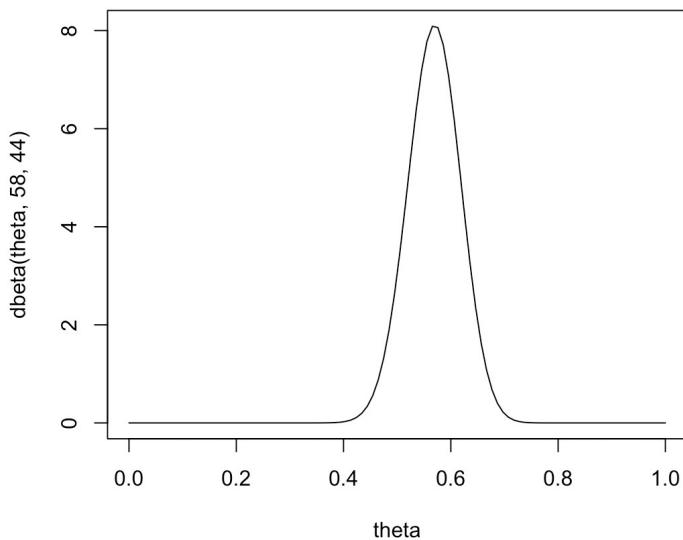


d) $P(\theta) \cdot \Pr(\sum Y_i = 57 | \theta) = \binom{100}{57} \theta^{57} (1-\theta)^{100-57}$

```
> eq = function(theta){choose(100, 57) * theta^57 * (1-theta)^43}
> curve(eq, from=0, to=1, xlab="theta", ylab="posterior density")
```



2) > theta = seq(0,1, length=100)
 > plot(theta, dbeta(theta, 58, 44), type='l')



Shapes of the four plots are same, but with different scale.

- (b) is a discrete plot of $p(\text{data} | \theta)$
- (c) is a discrete plot of the posterior $p(\theta | \text{data})$
- (d) is a posterior density with prior $U(0,1)$
- (e) is the posterior with prior $U(0,1)$

$$5. \quad a = \theta_0 n_0$$

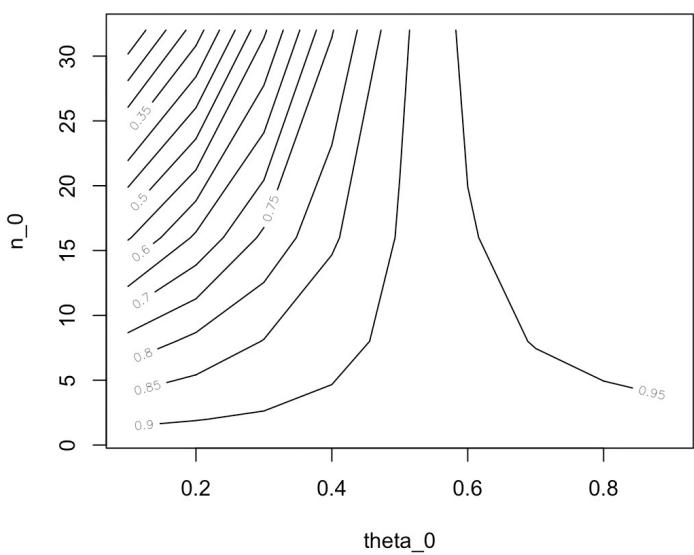
$$b = (1 - \theta_0) n_0$$

$$P(\theta | \sum Y_i = 57) = \frac{P(\sum Y_i = 57 | \theta) P(\theta)}{P(\sum Y_i = 57)}$$

$$\propto \theta^{57} (1-\theta)^{43} \theta^{a-1} (1-\theta)^{b-1}$$

$$= \theta^{57+a-1} (1-\theta)^{43+b-1}$$

$$\therefore P(\theta | \sum Y_i = 57) = \frac{\Gamma(100+a+b)}{\Gamma(57+a) \Gamma(43+b)} \theta^{57+a-1} (1-\theta)^{43+b-1} \sim \text{beta}(57+a, 43+b)$$



```

1 theta_0 <- seq(0.1, 0.9, by=0.1)
2 n_0 <- c(1, 2, 8, 16, 32)
3 a = outer(theta_0, n_0, FUN="*")
4 b = outer((1-theta_0), n_0, FUN="*")
5 probability = 1 - pbeta(0.5, 57+a, 43+b)
6 contour(theta_0, n_0, probability, nlevels = 20, xlab="theta_0", ylab="n_0")
  
```

θ_0 can be interpreted as prior expectation
 n_0 can be interpreted as prior sample size
 as θ_0 increases, $P(\theta > 0.5 | \sum Y_i = 57)$ increases.

as $n_0 \downarrow$, the outcome $\sum Y_i = 57$ tends to dominate the result, as $n_0 \uparrow$, the prior dominates the result.

When n is small, $P(\theta > 0.5 | \sum Y_i = 57)$ is large, so we tend to believe that $\theta > 0.5$.

6.

$$a) p(\theta) = 1 = \text{Beta}(1, 1)$$

$$p(y_1|\theta) = \binom{15}{y_1} \theta^{y_1} (1-\theta)^{15-y_1}$$

$$p(\theta|y_1) \propto p(\theta) p(y_1|\theta)$$

$$\propto \theta^{y_1} (1-\theta)^{15-y_1} = \theta^3 (1-\theta)^{13}$$

$$\therefore p(\theta|y_1) \sim \text{beta}(y_1+1, 16-y_1) = \text{beta}(3, 14)$$

$$E(\theta|y_1) = \frac{3}{17}$$

$$\text{Mode } (\theta|y_1) = \frac{2}{15}$$

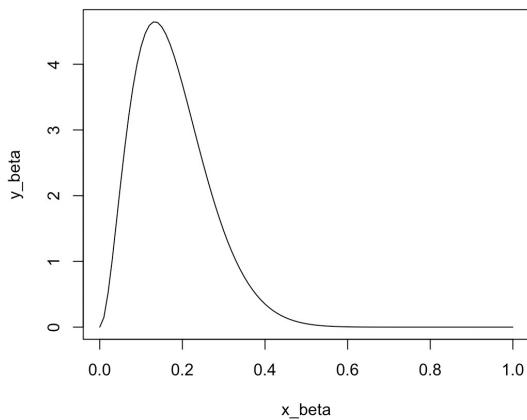
$$\text{Var } (\theta|y_1) = \frac{3 \times 14}{18 \times 17^2} = 0.09$$

```

1 x_beta <- seq(0, 1, by = 0.01)
2 y_beta <- dbeta(x_beta, shape1 = 3, shape2 = 14)
3 plot(x_beta, y_beta, type="l")

```

posterior distribution



$$b) i. \quad p(Y_2=y_2 | Y_1=2)$$

$$= \int_0^1 p(Y_2=y_2, \theta | Y_1=2) d\theta$$

$$= \int_0^1 p(Y_2=y_2 | \theta, Y_1=2) p(\theta | Y_1=2) d\theta$$

$$\therefore p(Y_2=y_2 | \theta, Y_1=2) = p(Y_2=y_2 | \theta)$$

$$\frac{p(Y_2=y_2, Y_1=2 | \theta)}{p(Y_1=2 | \theta)} = p(Y_2=y_2 | \theta)$$

$$\therefore p(Y_2=y_2, Y_1=2 | \theta) = p(Y_2=y_2 | \theta) p(Y_1=2 | \theta)$$

$\therefore Y_2=y_2$ and $Y_1=2$ are conditional independent given θ .

$$ii. \quad p(Y_2=y_2 | Y_1=2)$$

$$= \int_0^1 p(Y_2=y_2 | \theta) p(\theta | Y_1=2) d\theta$$

$$= \int_0^1 \left(\frac{278}{y_2} \right) \theta^{y_2} (1-\theta)^{278-y_2} \frac{16!}{13!} \theta^3 (1-\theta)^{13} d\theta$$

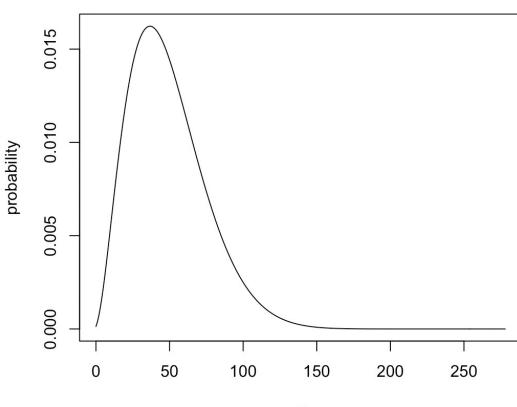
$$\text{iii. } \Pr(Y_2 = y_2 | Y_1 = 2)$$

$$= \binom{278}{y_2} \left(\frac{16!}{21!13!}\right) \int_0^1 \theta^{y_2+2} (1-\theta)^{291-y_2} d\theta$$

$$= \binom{278}{y_2} \frac{\Gamma(17)}{\Gamma(3)\Gamma(14)} \frac{\Gamma(y_2+3)\Gamma(292-y_2)}{\Gamma(295)}$$

c)

```
1 y = seq(0,278,by=1)
2 probability = choose(278, y)*16*choose(15, 2)/choose(294,y+2)/(292-y)
3 plot(y, probability, type="l")
```

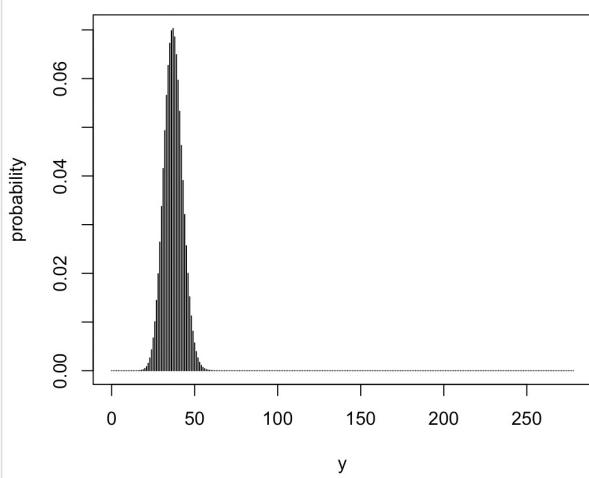


$$\begin{aligned} E(Y_2 | Y_1=2) &= 49.05882 &> \text{weighted.mean}(y, \text{probability}) \\ &[1] 49.05882 &> (\text{weighted.mean}((y-49.05882)^2, \text{probability}))^{0.5} \\ Sd(Y_2 | Y_1=2) &= 25.73196 &[1] 25.73196 \end{aligned}$$

$$\text{d) } \Pr(Y_2 = y_2 | \theta = \bar{\theta}) = \binom{278}{y_2} \bar{\theta}^{y_2} (1-\bar{\theta})^{278-y_2}$$

$$= \binom{278}{y_2} \left(\frac{2}{15}\right)^{y_2} \left(\frac{13}{15}\right)^{278-y_2}$$

```
1 y = seq(0,278,by=1)
2 probability = dbinom(y, 278, 2/15)
3 plot(y, probability, type="h")
```



$$E(Y_2 | \theta = \bar{\theta}) = 278 \cdot \frac{2}{15} = 37.0667$$

$$Sd(Y_2 | \theta = \bar{\theta}) = \sqrt{278 \cdot \frac{2}{15} \cdot \frac{13}{15}} = 5.667843$$

- (d) is the frequentists' view while (c) is bayesians' view.
 (d) has smaller standard deviation while (c) has larger standard deviation

I would use (c) because (d) fixes the value of $\theta = \hat{\theta}$, which is the MLE or mode.
But it's better not to fix $\theta = \hat{\theta}$, instead consider all θ using $P(Y_2 | Y_1) = \int_0^1 P(Y_2, \theta | Y_1)$.