3. (a) $E(Y) = E(2.9X - 3) = 2.9\,E(X) - 3 = (2.9)(28) - 3 = 78.2$

(b) $\mathrm{Var}(Y) = \mathrm{Var}(2.9X - 3) = \mathrm{Var}(2.9X) = (2.9)^2\,\mathrm{Var}(X)$

$$= (2.9)^2(4.1) = 34.481$$

4. $V = \pi r^2 h \quad \Rightarrow \quad V(r+\Delta r, h+\Delta h) \approx V(r,h) + \frac{\partial V}{\partial r}(r,h)\,\Delta r + \frac{\partial V}{\partial h}(r,h)\,\Delta h$

$$u_V = \sqrt{(2\pi r h)^2 u_r^2 + (\pi r^2)^2 u_h^2}$$

At $(r,h) = (5.3, 11.2)$, $\quad V = \pi(5.3)^2(11.2) = 988.37$

and

$$u_V = \sqrt{4\pi^2(5.3)^2(11.2)^2(0.4)^2 + \pi^2(5.3)^4(0.3)^2} = 151.52$$

$$\Rightarrow \boxed{V = 990 \pm 150 \text{ cm}^3}$$

5. (a) A 94% CI for μ is constructed from

$$\bar{x} \pm qt(0.97, df = 11)\cdot\frac{s}{\sqrt{n}}.$$

That is,

$$32.14 \pm (2.096)\frac{2.67}{\sqrt{12}} \quad \Rightarrow \quad (30.52, 33.76).$$

(b) Option (iv) offers a correct interpretation of this confidence interval.

6. (a) Since X, Y are independent and both normal, Y − X is normal as well.

$$E(Y - X) = E(Y) - E(Y) = 38 - 31 = 7.$$

$$\mathrm{Var}(Y - X) = \mathrm{Var}(Y) + \mathrm{Var}(X) \quad \text{(by independence)}$$

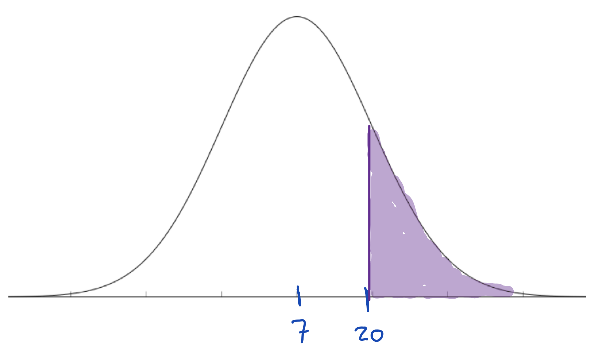
$$= 13^2 + 5^2 = 194$$

$$\Rightarrow Y - X \sim \mathrm{Norm}(7, \sqrt{194})$$

(b)

1 - pnorm(20, 7, 13.93)

since $\sqrt{194} \doteq 13.93$



How code for Problem 1 solutions might look

```
c(alpha1, lambda1, lambda2, alpha2, beta1)
```

```
## [1] 2.2800000 7.1600000 0.1061571 7.5100000 6.3400000
```

(a)

```
f = makeFun(dgamma(x, alpha1, lambda1) ~ x)
xF = antiD(x * f(x) ~ x)
xxF = antiD(x^2 * f(x) ~ x)
```

The expected value:

```
eX = xF(Inf) - xF(-Inf); eX
```

```
## [1] 0.3184358
```

The variance:

```
eXsq = xxF(Inf) - xxF(-Inf); eXsq
```

```
## [1] 0.1458756
```

```
aVar = eXsq - eX^2
```

mean	E(X^2)	variance
0.3184358	0.1458756	0.0444743

(b)

```
qexp(.7, lambda2)
```

```
## [1] 11.34142
```

(c)

```
manySums <- do(5000) * sum(~rbeta(50, alpha2, beta1))
mu = alpha2 / (alpha2 + beta1)
myVar = alpha2*beta1/((alpha2+beta1)^2*(alpha2+beta1+1))
```

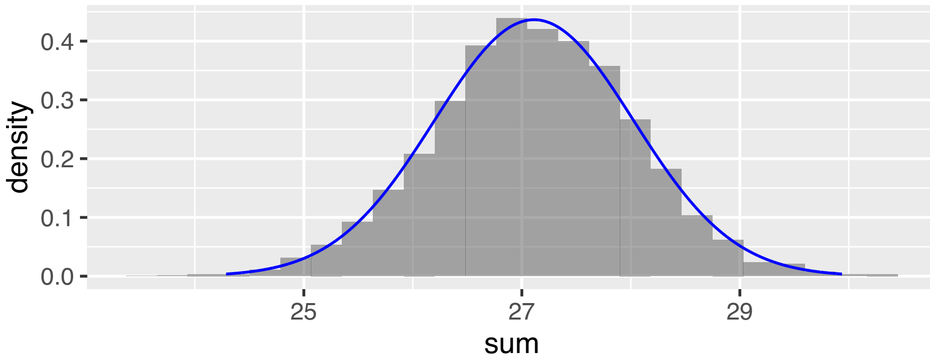
The population from which we are drawing an iid random sample of size 50 is $\text{Beta}(7.51, 6.34)$ As per Table 4.5, the mean and variance of this population are

$$\mu = 0.5422383 \qquad \text{and} \qquad \sigma = 0.129286.$$

Thus, the sum of an iid random sample of size 50, by the central limit theorem, as an approximate normal distribution,

$$S \sim \text{Norm}(27.1119134, 0.9141903)$$

```
gf_dhistogram(~sum, data=manySums) |>
  gf_dist("norm", params=c(50*mu, sqrt(50*myVar)), color="blue")
```



(d)

```
fitdistr(manySums$sum, "normal")
```

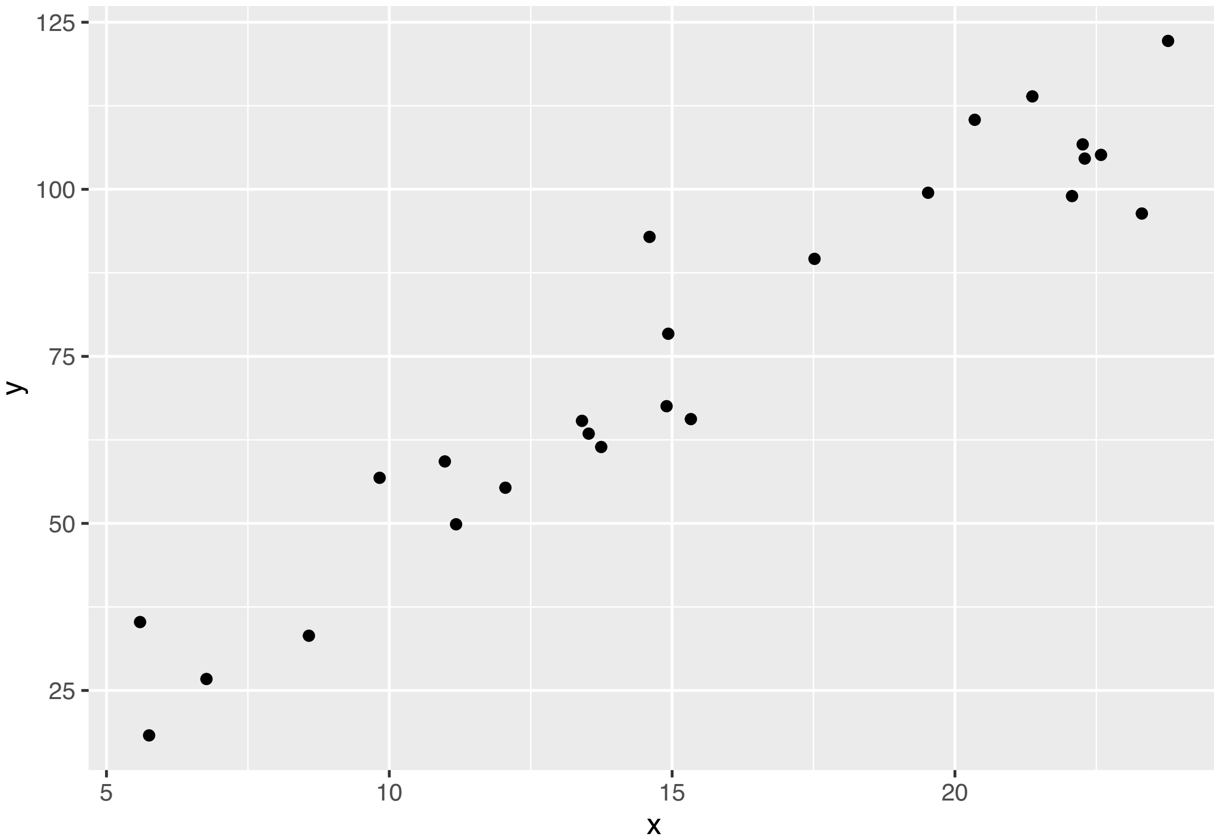
```
##        mean            sd
##   27.104725682    0.912193801
##  ( 0.012900368) ( 0.009121938)
```

How code for Problem 2 solutions might look

```
set.seed(1234567)
c0 = round(runif(1, -8, 12), 2)
c1 = round(runif(1, 2.1, 5.4), 2)
xs = runif(25, 5, 25)
ys = c0 + c1 * xs + rnorm(25, 0, 8)
mydat <- data.frame(x = xs, y = ys)
```

(a)

```
gf_point(y~x, data=mydat)
```



(b)

```
cor(y~x, data=mydat)
```

```
## [1] 0.9567243
```

(c)

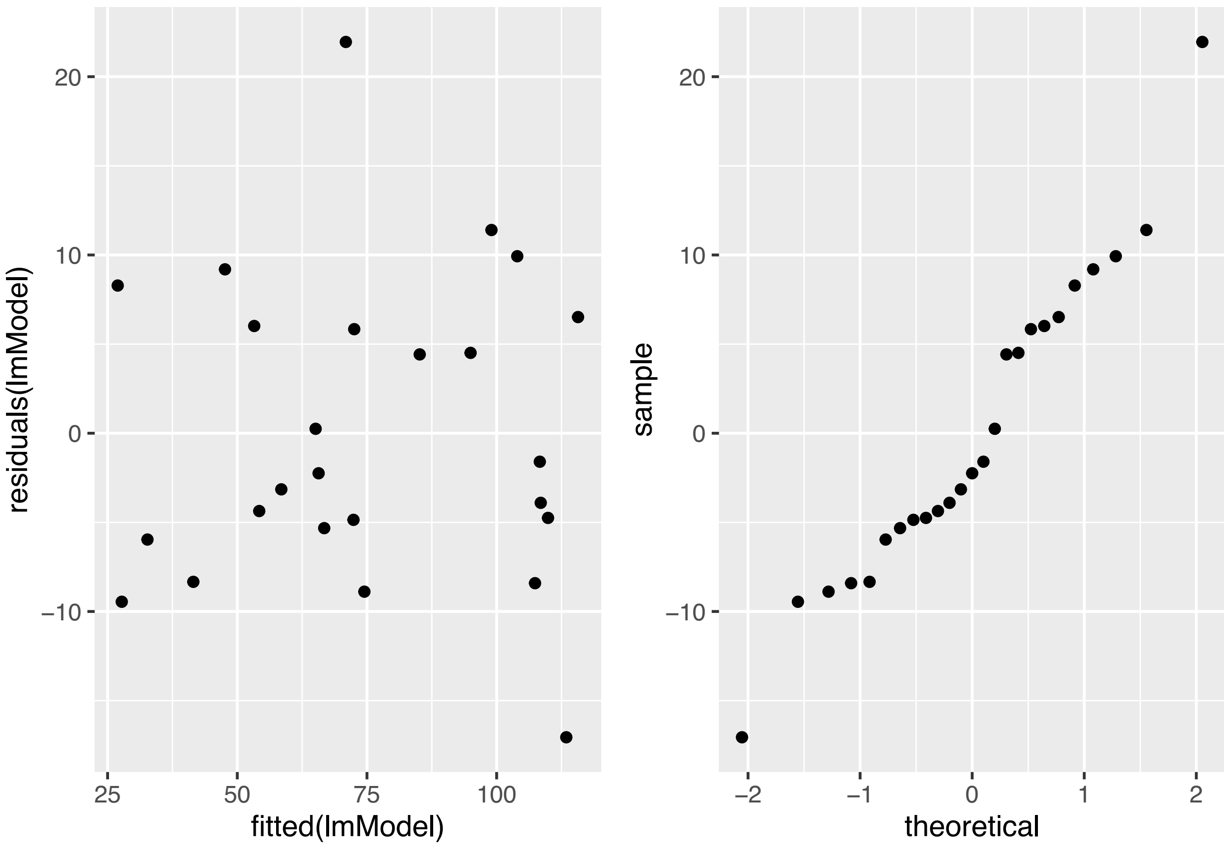
```
lmModel <- lm(y~x, data=mydat)
coef(lmModel)
```

```
## (Intercept)           x
##  -0.3611503   4.8826449
```

(d)

```
p1 <- gf_point(residuals(lmModel) ~ fitted(lmModel))
p2 <- gf_qq(~ residuals(lmModel))
```

```
grid.arrange(p1, p2, ncol=2)
```



(e)

```
confint(summary(lmModel), level=.9)
```

```
##                     5 %     95 %
## (Intercept) -9.096575 8.374275
## x            4.351920 5.413370
```

(f)

```
yPred <- makeFun(lmModel)
yPred(x=18, interval="prediction", level=0.92)
```

```
##        fit      lwr      upr
## 1 87.52646 71.04278 104.0101
```