# $\mathbf{Review}$

				, . 1						
confidence interval			$\hat{p} \pm z^* \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$	$(\hat{p}_1 - \hat{p}_2) \pm$	$z^*\sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}}$	$\bar{x} \pm t_{df}^* \frac{s}{\sqrt{n}}$			$(\bar{x}_1  -  \bar{x}_2)  \pm$	$t_{df}^* \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}$
standard error			$\sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$	$\sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}}  (\hat{p}_1)$		$\frac{s}{\sqrt{n}}$	•		$\sqrt{rac{s_1^2}{n_1} + rac{s_2^2}{n_2}}$	
expected value of variance of the sam-	pling distribution		$\frac{p(1-p)}{n}$	$\frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2}$		$\frac{\sigma^2}{n}$			$\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}$	
expected value of	the sampling distri- pling distribution	bution	d	$p_1 - p_2$		$\eta$			$\mu_1 - \mu_2$	
parameter of inter-	est		d	$p_1 - p_2$		η			$\mu_1 - \mu_2$	
point	esti-	mate	$\hat{p}$	$\hat{p}_1 - \hat{p}_2$		$\bar{x}$			$\bar{x}_1 - \bar{x}_2$	
Question			single proportion	difference of two $\hat{p}_1 - \hat{p}_2$ $p_1 - p_2$	proportion		pendent samples,	paired data)	difference of two $\bar{x}_1 - \bar{x}_2$ $\mu_1 - \mu_2$	means

Hypothesis Testing

standard score (z or t) =  $\frac{\text{point estimate-null value}}{StandardError}$ 

# 2 Simple Linear Regression

You may recall from your high school algebra class (and your calculus class) the equation of a line as

y = mx + b where m represents the slope of the line and b represents the y-intercept.

In statistics we try to explain the relationship between two continuous variables using a linear regression model (if certain conditions are met).

The equation for a simple linear regression model is as follows:

$$y = \beta_0 + \beta_1 x + \epsilon$$

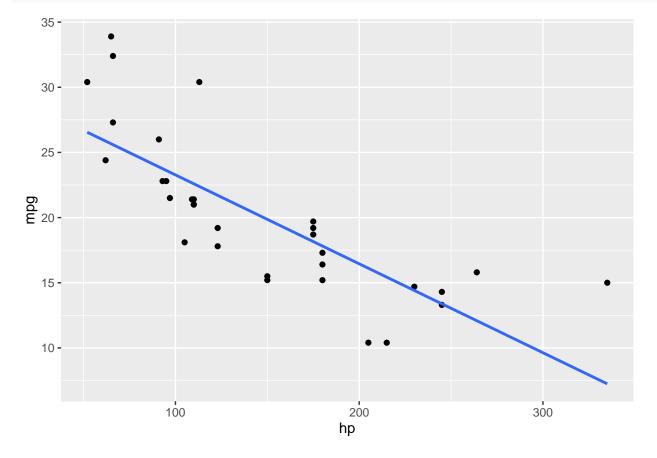
description	point estimate	parameter of inter-	Hypotheses	
		est		
intercept	OpenIntro: $b_0$	$\beta_0$	$H_0: \beta_0 = 0$	
	Other resources: $\hat{\beta}_0$			
slope	OpenIntro: $b_1$	$\beta_1$	$H_0: \beta_1 = 0$	
	Other resources: $\hat{\beta}_1$			

$$y = \beta_0 + \beta_1 x + \epsilon$$

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x$$

Error/residual:  $e = y - \hat{y}$ 

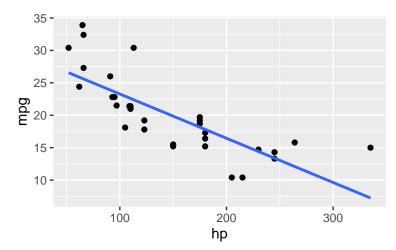
```
mtcars %>%
    ggplot(aes(x = hp, y = mpg)) +
    geom_point() +
    geom_smooth(method = 'lm', se = FALSE)
```



```
lm(mpg ~ hp, data = mtcars) %>%
 summary()
##
## Call:
## lm(formula = mpg ~ hp, data = mtcars)
##
## Residuals:
##
       Min
               1Q Median
                                3Q
                                       Max
## -5.7121 -2.1122 -0.8854 1.5819 8.2360
##
## Coefficients:
##
               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 30.09886
                          1.63392 18.421 < 2e-16 ***
                           0.01012 -6.742 1.79e-07 ***
## hp
               -0.06823
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## Residual standard error: 3.863 on 30 degrees of freedom
## Multiple R-squared: 0.6024, Adjusted R-squared: 0.5892
## F-statistic: 45.46 on 1 and 30 DF, p-value: 1.788e-07
Understanding the R output
```

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### Residuals



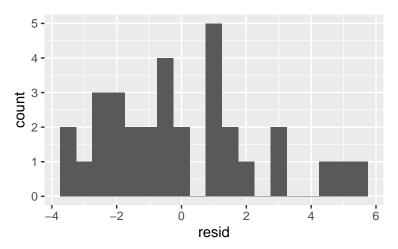
```
mtcars %>%
  select(mpg, hp) %>%
  slice(1)
##
     mpg hp
## 1 21 110
mtcars %>%
  select(mpg, hp) %>%
  slice(18)
      mpg hp
```

## 1 32.4 66

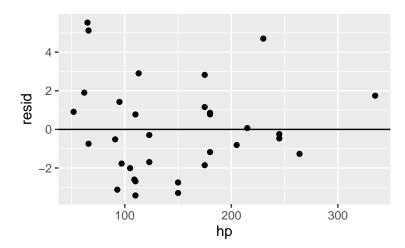
# 2.1 Estimation

### Conditions

- 1. Linearity: The relationship between  ${\bf x}$  and  ${\bf y}$  has to be linear.
- 2. Independent Observations
- 3. Normality of Residuals



## 4. Constant Varibility



#### 3 Multiple Linear Regression

```
Equation for multiple linear regression is
```

```
y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \dots + \beta_k x_k + \epsilon
```

```
where k is the number of predictors.
mtcars %>%
  select(mpg, hp, am, wt) %>%
  glimpse()
## Observations: 32
## Variables: 4
## $ mpg <dbl> 21.0, 21.0, 22.8, 21.4, 18.7, 18.1, 14.3, 24.4, 22.8, 19.2...
## $ hp <dbl> 110, 110, 93, 110, 175, 105, 245, 62, 95, 123, 123, 180, 1...
## $ wt <dbl> 2.620, 2.875, 2.320, 3.215, 3.440, 3.460, 3.570, 3.190, 3....
lm(mpg ~ hp + am + wt, data = mtcars) %>%
 summary()
##
## Call:
## lm(formula = mpg ~ hp + am + wt, data = mtcars)
##
## Residuals:
##
      Min
               1Q Median
                              ЗQ
                                    Max
## -3.4221 -1.7924 -0.3788 1.2249 5.5317
##
## Coefficients:
##
               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 34.002875
                         2.642659 12.867 2.82e-13 ***
                         0.009605 -3.902 0.000546 ***
## hp
              -0.037479
## am
               2.083710
                         1.376420
                                   1.514 0.141268
## wt
              -2.878575
                         0.904971 -3.181 0.003574 **
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.538 on 28 degrees of freedom
## Multiple R-squared: 0.8399, Adjusted R-squared: 0.8227
## F-statistic: 48.96 on 3 and 28 DF, p-value: 2.908e-11
```