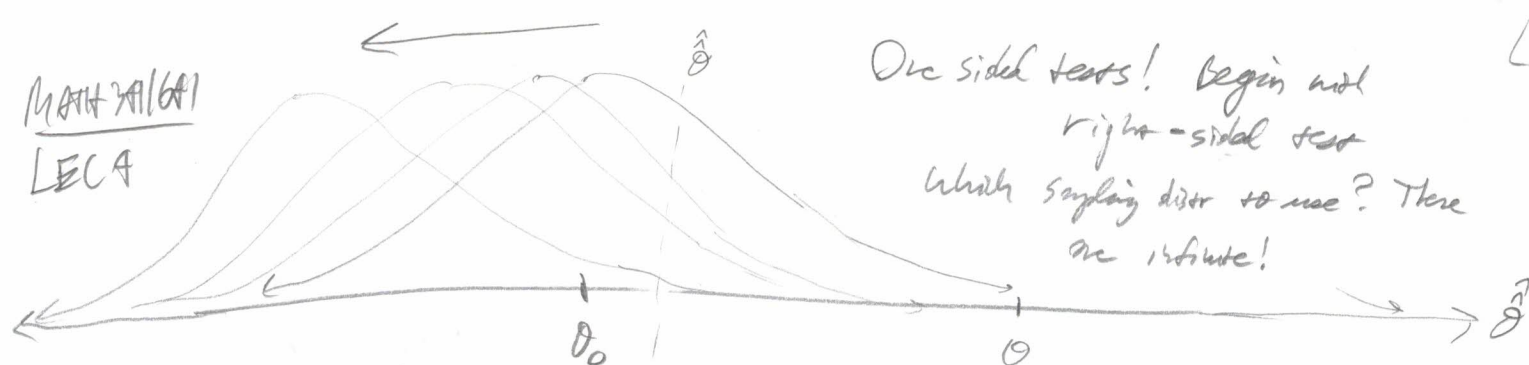


One sided tests! begin with  
right-sided test  
Which sampling dist to use? There  
are infinite!



$$H_0: \theta \leq \theta_0 \Rightarrow \mathcal{H}_0 = (-\infty, \theta_0]$$

$$H_1: \theta > \theta_0 \Rightarrow \mathcal{H}_1 = (\theta_0, \infty)$$

Reject  $H_0$  if  $p\text{-val} < \alpha \Rightarrow$   
there is significant evidence against  $H_0$ .

Depending on the Null Distr used, we can always reject  $H_0$ !  
There is something wrong somewhere. C&B p397-398.

For a one-sided test, we define  $p\text{-val}$  a bit more exactly:

$$p\text{-val} = \max_{\theta \in \mathcal{H}_0} \left\{ \arg\max_{\alpha} \left\{ \alpha : \hat{\theta} \in \text{RET}_{\alpha, \theta_0} \right\} \right\}$$

the rejection region changes  
with the value of  $\theta_0$   
we want to make sure to  
be as conservative as possible

Effectively then...

$$H_0: \theta = \theta_0$$

$$H_1: \theta > \theta_0$$

Back to Ted's question... why Reject  $H_0$  and Accept  $H_1$ ?

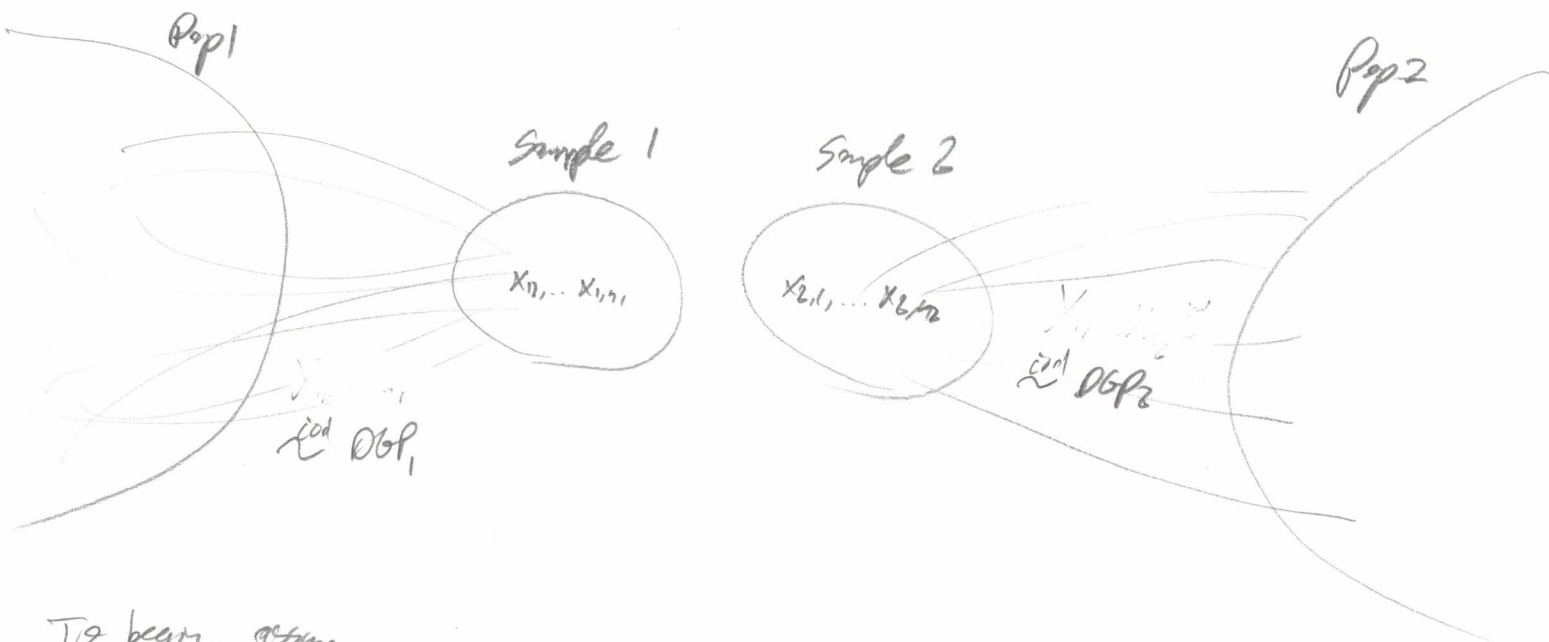
This is how scientific theories work. Every theory is an exact mathematical statement about reality. E.g.  $F = G \frac{m_1 m_2}{r^2}$

which has one way to be right and infinite ways to be wrong.

We never "accept" our theories (i.e. calling them absolutely true), we only retain them as "the best we got right now". If evidence surfaces that they're wrong, we reject them. This is akin to accepting that it's wrong. E.g.  $H_0: \theta = \theta_0$ ,  $H_1: \theta \neq \theta_0$ . Accepting  $H_1$  is not the same as accepting a new, ~~exact~~ theory.

New setting: two infinitely sized populations (or DGP's)

3



To begin, assume

$$x_{1,1}, \dots, x_{1,n_1} \stackrel{\text{i.i.d.}}{\sim} N(\theta_1, \sigma_1^2) \text{ ind. of } x_{2,1}, \dots, x_{2,n_2} \stackrel{\text{i.i.d.}}{\sim} N(\theta_2, \sigma_2^2)$$

Just like before, we assume  $\sigma_1^2$  and  $\sigma_2^2$  are known.

There are three common tests:

$$H_a: \theta_1 \neq \theta_2 \Leftrightarrow H_0: \theta_1 = \theta_2 \quad (H_a: \theta_1 - \theta_2 \neq 0 \Leftrightarrow H_0: \theta_1 - \theta_2 = 0) \quad \text{Two-sided, two-sample test}$$

$$H_a: \theta_1 < \theta_2 \Leftrightarrow H_0: \theta_1 \geq \theta_2 \quad (H_a: \theta_1 - \theta_2 < 0 \Leftrightarrow H_0: \theta_1 - \theta_2 \geq 0) \quad \text{Left-sided, two-sample test}$$

$$H_a: \theta_1 > \theta_2 \Leftrightarrow H_0: \theta_1 \leq \theta_2 \quad (H_a: \theta_1 - \theta_2 > 0 \Leftrightarrow H_0: \theta_1 - \theta_2 \leq 0) \quad \text{Right-sided, two-sample test}$$

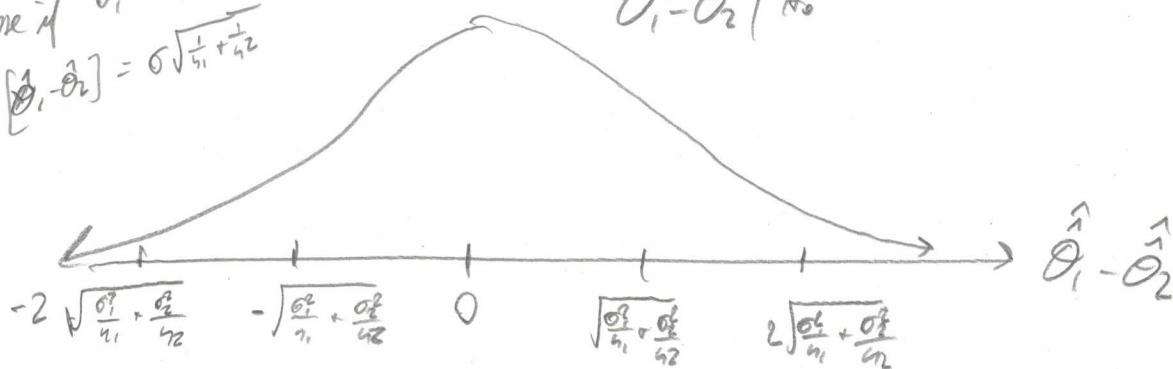
How to run the test? Find a test statistic that captures departure from  $H_0$ .  $\hat{\theta}_1 - \hat{\theta}_2 = \bar{x}_1 - \bar{x}_2$  or  $\frac{\bar{x}_1}{\sigma_1} - \frac{\bar{x}_2}{\sigma_2}$ . Now we need its sampling distr under the null. For all 1-sided and 2-sided, the sampling distr uses  $\theta_1 - \theta_2 = 0$

$$\hat{\theta}_1 - \hat{\theta}_2 | H_0 \sim N\left(0, \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}\right)$$

amazing: we don't need to know anything about the values  $\theta_1, \theta_2$ .  
Very convenient!!

Note if  $\sigma_1^2 = \sigma_2^2 = \sigma^2$   
 $SE[\hat{\theta}_1 - \hat{\theta}_2] = \sigma \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}$

$$\hat{\theta}_1 - \hat{\theta}_2 | H_0$$



RET 5%

in 300-level STEM classes in QC!

Let's test if <sup>mean</sup> male height  $\neq$  mean female height

Assume:  $\sigma_{MALE}^2 = 4''^2$ ,  $\sigma_{FEMALE}^2 = 3.5''^2$

Let pop 1 be male, pop 2 be female

$$\hat{\theta}_1 = 68.85'' \quad n_1 = 13$$

$$\hat{\theta}_2 = 65.33'' \quad n_2 = 6$$

$$\Rightarrow H_A: \theta_1 - \theta_2 \neq 0$$

$$\hat{\theta}_1 - \hat{\theta}_2 =$$

$$SE[\hat{\theta}_1 - \hat{\theta}_2] = \sqrt{\frac{4^2}{13} + \frac{3.5^2}{6}} = 1.81$$

How does p-value work? Assume a true  $\Delta = \theta_1 - \theta_2$ . Assume the pop's share

$$\hat{\theta}_1 - \hat{\theta}_2 | H_0 \sim N(0, SE[\hat{\theta}_1 - \hat{\theta}_2])$$

$$\hat{\theta}_1 - \hat{\theta}_2 \sim N(\Delta, SE[\hat{\theta}_1 - \hat{\theta}_2])$$



We will return to Hypothesis tests later!



If there are  $k$  parameters, there exist a system of  $k$  equations:

$$\begin{aligned} \mu_1 &= \alpha_1(\theta_1, \dots, \theta_k) & \theta_1 &= \beta_1(\mu_1, \dots, \mu_k) \\ \mu_2 &= \alpha_2(\theta_1, \dots, \theta_k) & \theta_2 &= \beta_2(\mu_1, \dots, \mu_k) \\ &\vdots & & \\ \mu_k &= \alpha_k(\theta_1, \dots, \theta_k) & \theta_k &= \beta_k(\mu_1, \dots, \mu_k) \end{aligned} \iff$$

The Method of Moments (MM) estimator is then just finding the  $\beta_j$ th function and estimating its inputs with sample moments:

$$\hat{\theta}_j^{mm} = \beta_j(\hat{\mu}_1, \hat{\mu}_2, \dots, \hat{\mu}_k)$$

Goes back to Karl Pearson in 1890's.

MM usually works but rarely produces "great" estimators.

If  $k=1$ ,  $\theta = E[X] = \mu_1 \Rightarrow \theta = \beta(\mu_1) = \mu_1$

$$\Rightarrow \hat{\theta}^{mm} = \hat{\mu}_1 = \bar{X}$$

If  $k=2$ ,  $\theta_1 = E[X] = \mu_1$ ,  $\theta_2 = \text{Var}[X] = E[X^2] - E[X]^2 = \mu_2 - \mu_1^2$

$$\Rightarrow \hat{\theta}_1 = \hat{\mu}_1 = \bar{X}$$

$$\hat{\theta}_2 = \hat{\mu}_2 - \hat{\mu}_1^2 = \frac{1}{n} \sum_{i=1}^n X_i^2 - \left( \frac{1}{n} \sum_{i=1}^n X_i \right)^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2$$

Note:  $\sum (X_i - \bar{X})^2 = \sum (X_i^2 - 2X_i\bar{X} + \bar{X}^2)$   
 $= \sum X_i^2 - 2n\bar{X}^2 + n\bar{X}^2$   
 $= \sum X_i^2 - n\bar{X}^2$   
 $\Rightarrow \frac{1}{n} \sum (X_i - \bar{X})^2 = \frac{1}{n} \sum X_i^2 - \bar{X}^2 = \mu_2 - \mu_1^2$



$X_1, \dots, X_n \stackrel{iid}{\sim} \text{Bin}(\hat{\theta}_1, \hat{\theta}_2)$  Both unknown!! Param space  $\subseteq$   
 $\theta_1 \in \mathbb{N}, \theta_2 \in (0,1)$

Does this model correspond to anything remotely real?

Imagine  $X_i$  are the # of crimes reported each night in a city district.

Let  $\theta_1$  be the total # of crimes each night (unknown),

Let  $\theta_2$  be the prob. a crime gets called in.

Both  $\theta_1, \theta_2$  are interesting to estimate!

Use MM to get estimates:

$$\mu_1 = E[X] = \theta_1 \theta_2 = \alpha_1(\theta_1, \theta_2)$$

$$\begin{aligned} \mu_2 = E[X^2] &= \text{Var}[X] + E[X]^2 = \theta_1 \theta_2 (1 - \theta_2) + \theta_1^2 \theta_2^2 = \alpha_2(\theta_1, \theta_2) \\ &= \theta_1 \theta_2 - \theta_1 \theta_2^2 + \theta_1^2 \theta_2^2 \end{aligned}$$

$$\Rightarrow \theta_1 = \frac{\mu_1}{\theta_2}$$

Now we need  $\beta_1, \beta_2$  functions!

$$\Rightarrow \mu_2 = \frac{\mu_1}{\theta_2} \theta_2 - \frac{\mu_1}{\theta_2} \theta_2^2 + \frac{\mu_1^2}{\theta_2^2} \theta_2^2 = \mu_1 - \mu_1 \theta_2 + \mu_1^2 \theta_2$$

$$\Rightarrow \mu_2 - \mu_1 - \mu_1^2 \theta_2 = -\mu_1 \theta_2 \Rightarrow \theta_2 = \frac{\mu_1^2 + \mu_1 - \mu_2}{\mu_1} = \frac{\mu_1 - (\mu_2 - \mu_1^2)}{\mu_1} = \beta_2(\mu_1, \mu_2)$$

$$\Rightarrow \mu_1 = \theta_1 \frac{\mu_1 - (\mu_2 - \mu_1^2)}{\mu_1} \Rightarrow \theta_1 = \frac{\mu_1^2}{\mu_1 - (\mu_2 - \mu_1^2)} = \beta_1(\mu_1, \mu_2)$$

$$\Rightarrow \hat{\theta}_1^{MM} = \frac{\hat{\mu}_1 - (\hat{\mu}_2 - \hat{\mu}_1^2)}{\hat{\mu}_1} = \frac{\bar{X} - \hat{\sigma}^2}{\bar{X}}$$

$$\hat{\theta}_2^{MM} = \frac{\hat{\mu}_1^2}{\hat{\mu}_1 - (\hat{\mu}_2 - \hat{\mu}_1^2)} = \frac{\bar{X}}{\bar{X} - \hat{\sigma}^2}$$

Let data be  $\vec{x} = \langle 3, 7, 5, 5, 6 \rangle \Rightarrow \bar{x} = 5.2, \hat{\sigma}^2 = 2.69$

$$\hat{\theta}_1^{MM} = 1.56, \hat{\theta}_2^{MM} = 0.99 \quad \text{makes sense}$$

But what if...  $\vec{x} = (3, 7, 5, 11, 6) \Rightarrow \bar{x} = 6.4, \hat{\sigma}^2 = 10.56$

$\Rightarrow \hat{\theta}_{MM}^1 = -9.8, \hat{\theta}_{MM}^2 = -0.65$  Both estimates not in param space!

This is what I mean by "hardly very good"!

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$X_1, \dots, X_n \stackrel{iid}{\sim} N(0, \theta)$ . Find  $\hat{\theta}_{MM}$

$$\mu_1 = E[X] = \frac{\theta - 0}{2} = \frac{\theta}{2} \Rightarrow \theta = 2\mu_1 \Rightarrow \hat{\theta}_{MM} = 2\hat{\mu}_1 = 2\bar{X}$$

Let  $x = (1, 2, 3, 10) \Rightarrow \bar{x} = 4 \Rightarrow \hat{\theta}_{MM} = 2 \cdot 4 = 8$  Stupid! We obviously  
obtain  $\text{all } x_i < \hat{\theta}$ !

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Is there a better way to find estimators??