

Power Calculation

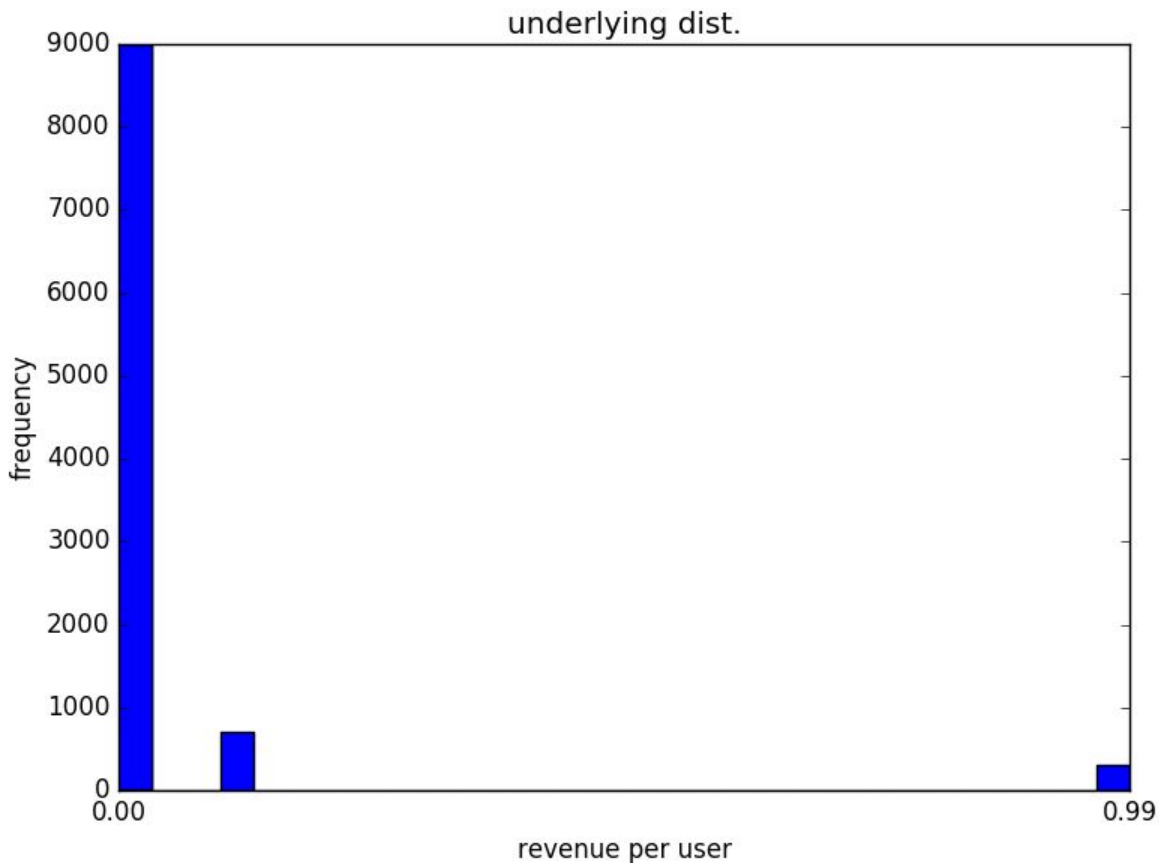
Natalie Hunt



1. Review:
 - a. Central Limit Theorem
 - b. Hypothesis Testing
2. Type I vs Type II errors
3. What is “Power”?
4. Calculating Power / Sample Size
5. A/B Testing w/ Power

Underlying Distribution:

Random variable: <i>X = revenue per visitor</i>	P(X):
$X = \$0.00$ (no revenue)	90%
$X = \$0.10$ (ad-click)	7%
$X = \$0.99$ (app purchase)	3%

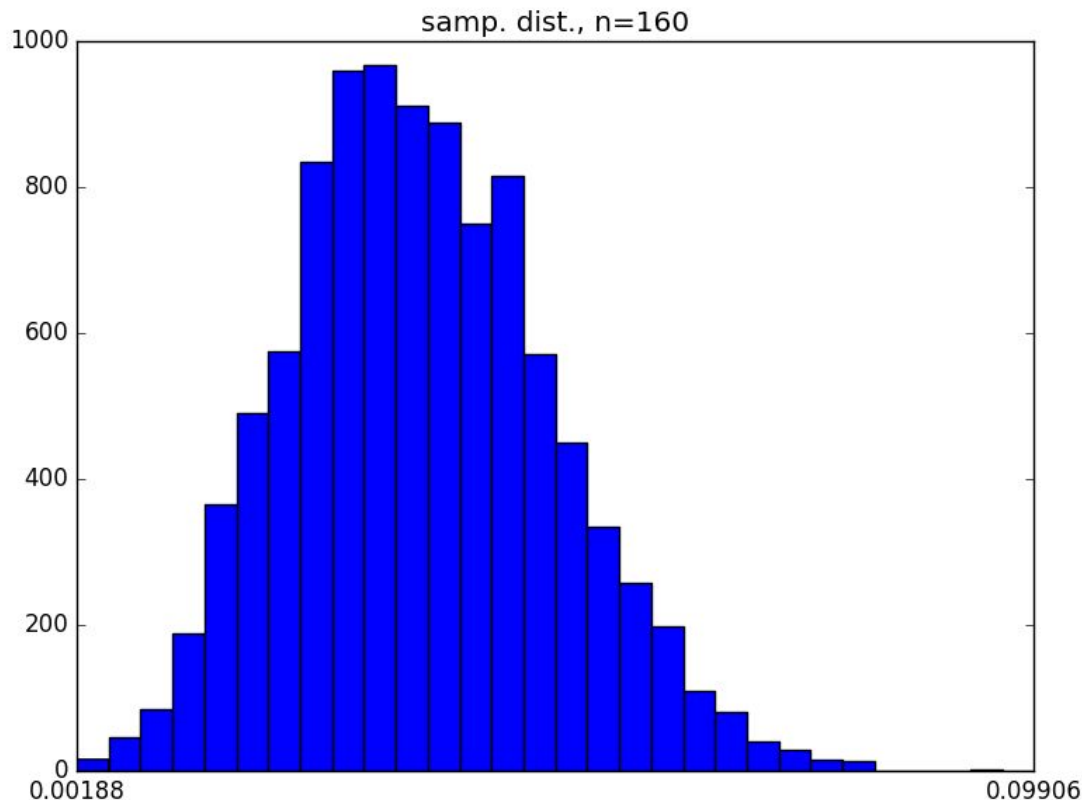


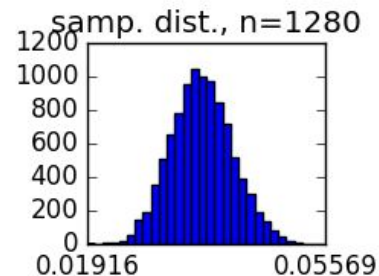
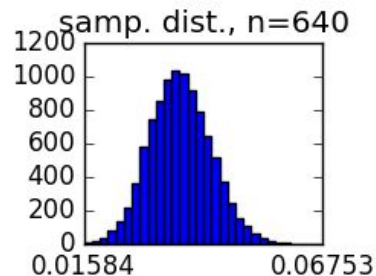
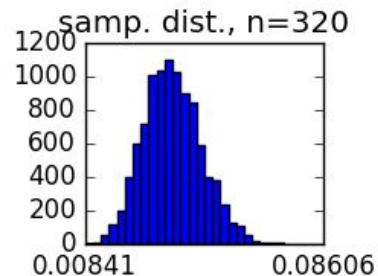
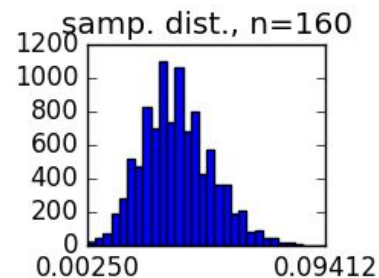
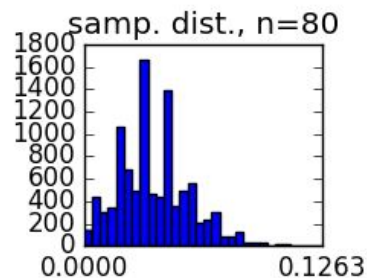
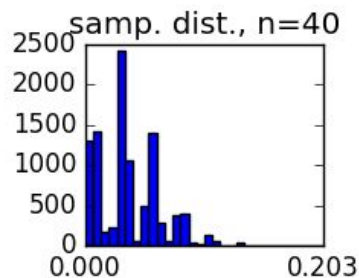
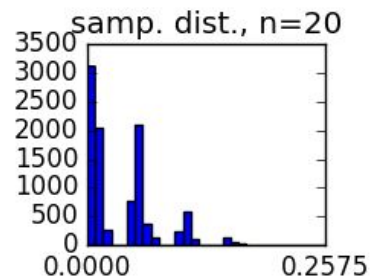
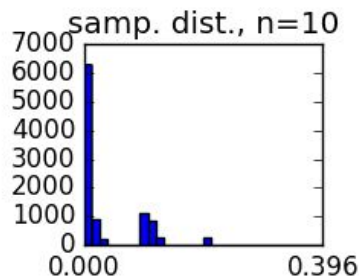
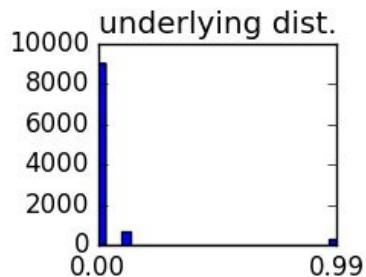
Collect n samples from the website revenue distribution, calculate the sample mean \bar{x}

Repeat 10,000 times, we get:

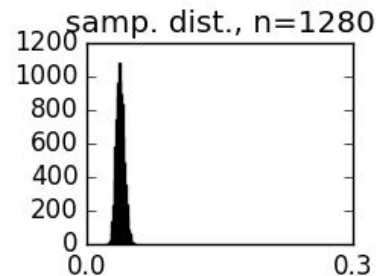
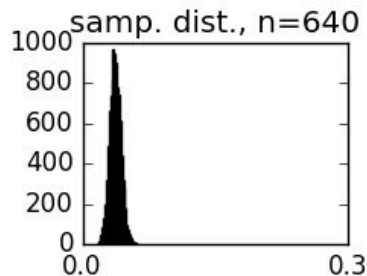
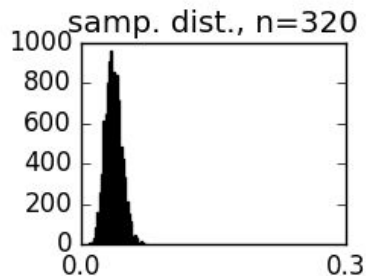
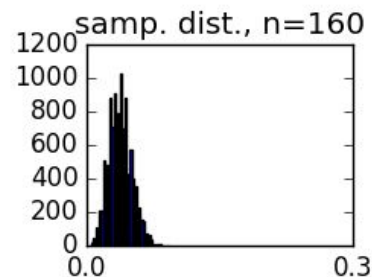
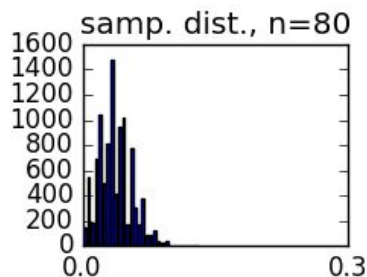
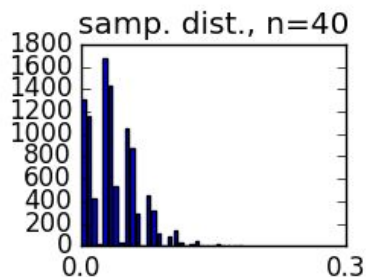
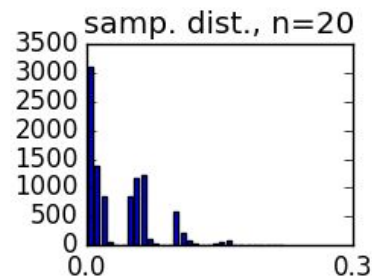
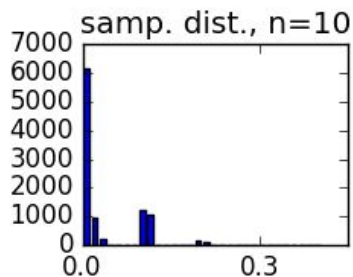
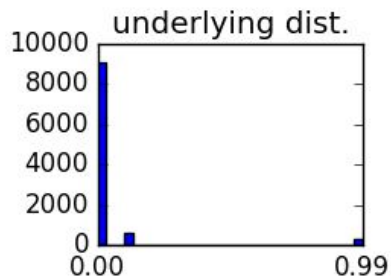
$\bar{x}_0, \bar{x}_1, \dots, \bar{x}_{9999}$

Plot all 10,000 sample means.





Central Limit Theorem: What happens when the sample size increases?



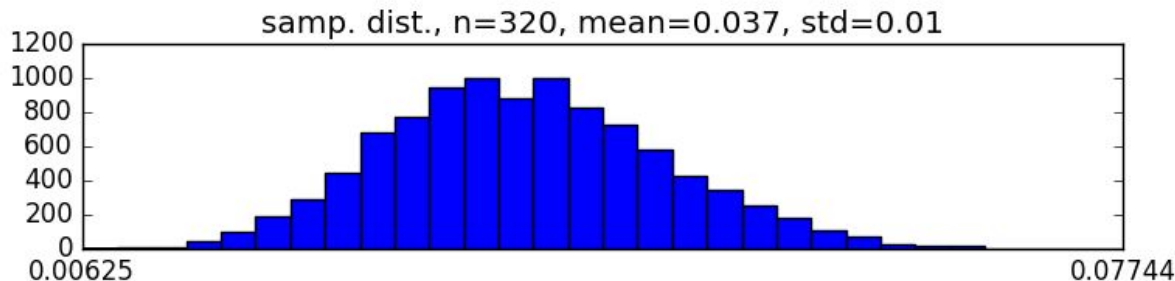
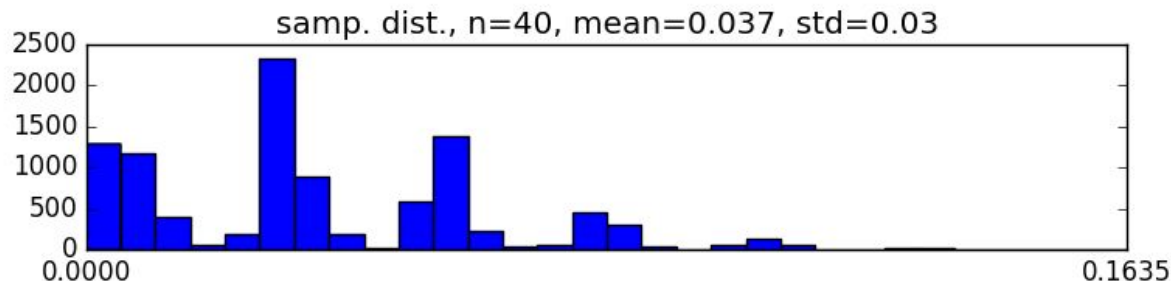
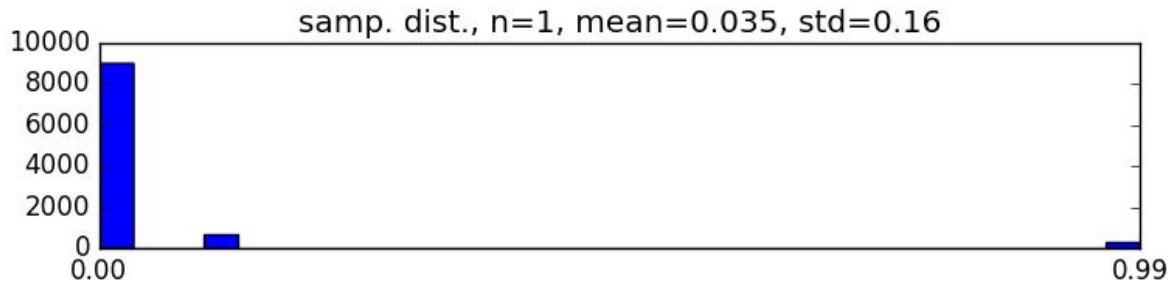
Let the underlying distribution have mean and std. dev.

μ and σ

The sampling distribution's mean and std. dev. will equal:

$$\mu' = \mu$$

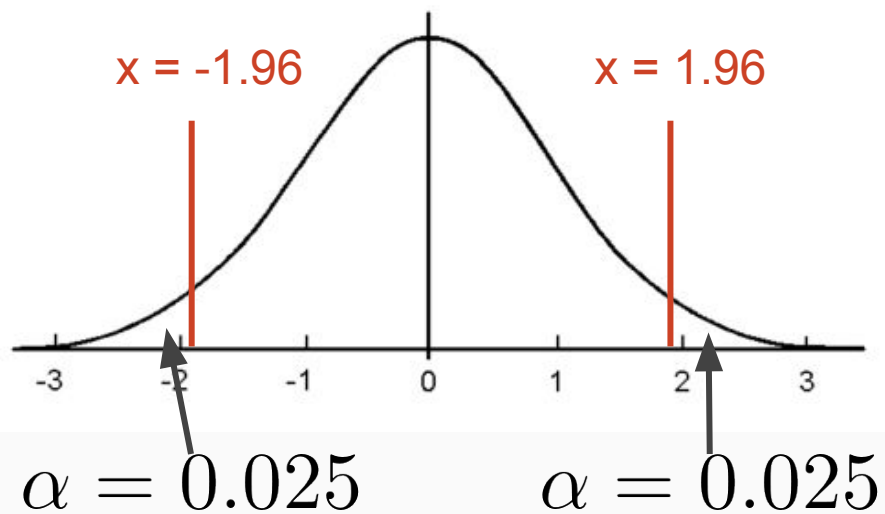
$$\sigma' = \sigma / \sqrt{n}$$



Two-sided test:

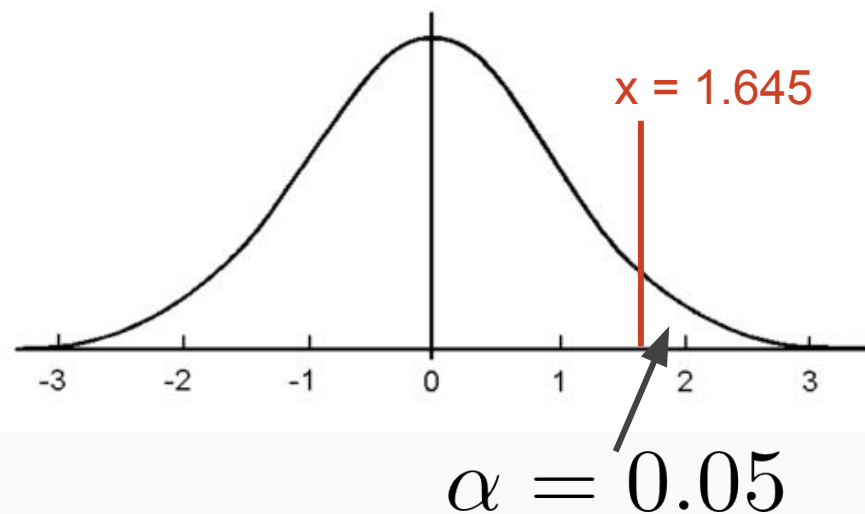
$$H_0 : \mu = 0$$

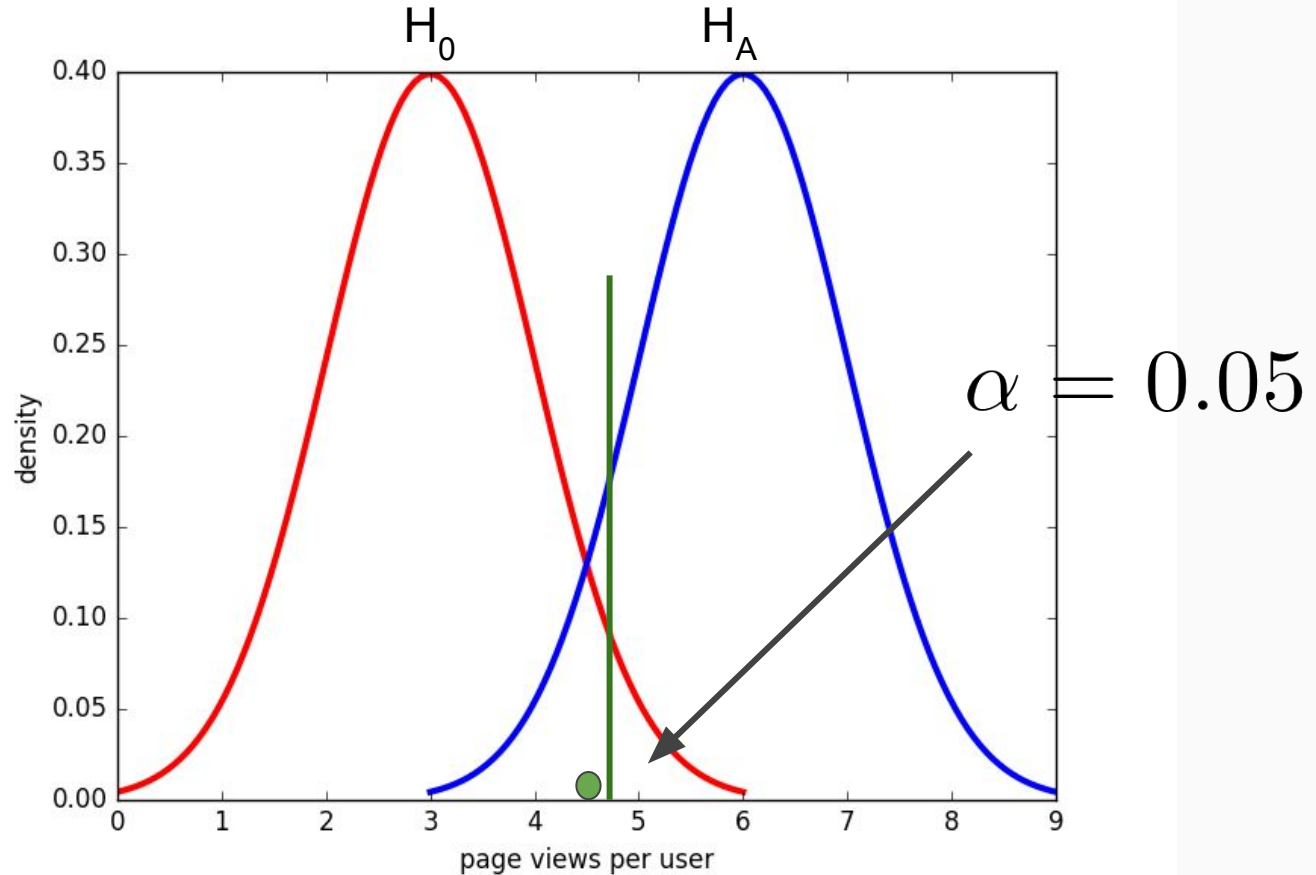
$$H_A : \mu \neq 0$$

**One-sided test:**


$$H_0 : \mu = 0$$

$$H_A : \mu > 0$$





	H_0 is true	H_0 is false
Accept H_0	Correct Decision ($1-\alpha$)	Type II Error (β)
Reject H_0	Type I Error (α)	Correction Decision ($1-\beta$)

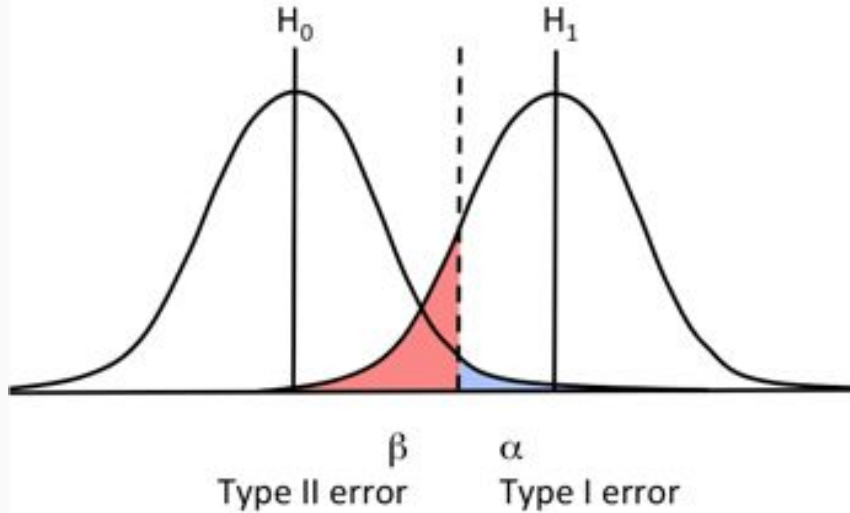


We call this the experiment's "Power". It is the probability that we **correctly reject H_0** when the null hypothesis is false.

	H_0 is true true -	H_0 is false true +
Accept H_0 predict -	Correct Decision ($1-\alpha$)	Type II Error (β)
Reject H_0 predict +	Type I Error (α)	Correction Decision ($1-\beta$)

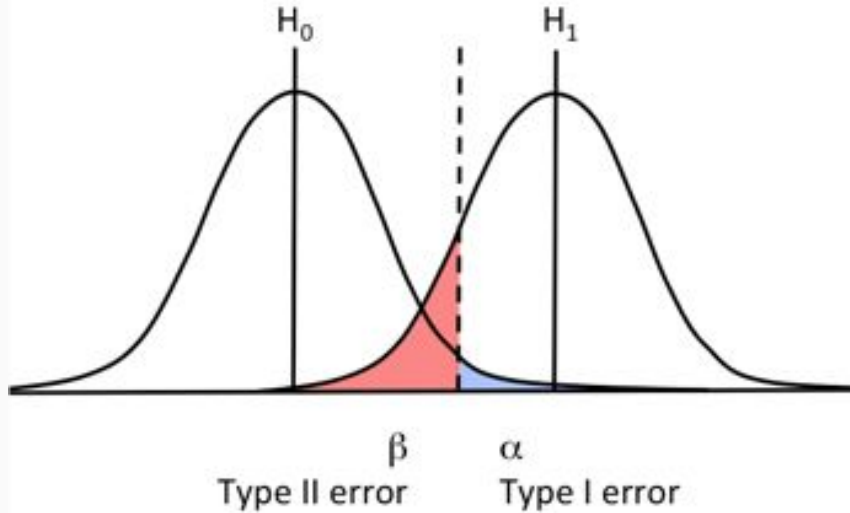
false positive rate
(aka, 1 - specificity)

true positive rate
(aka, sensitivity)



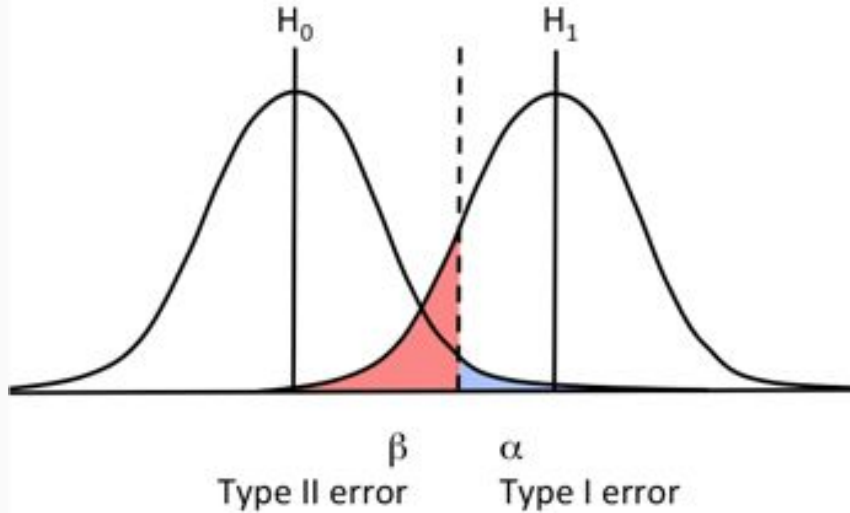
	H_0 is true	H_0 is false
Accept H_0	Correct Decision ($1 - \alpha$)	Type II Error (β)
Reject H_0	Type I Error (α)	Correction Decision ($1 - \beta$)

The *power* measurement is in relationship to a specific alternative hypothesis. Think of it as the *power* to detect a particular “effect size”.



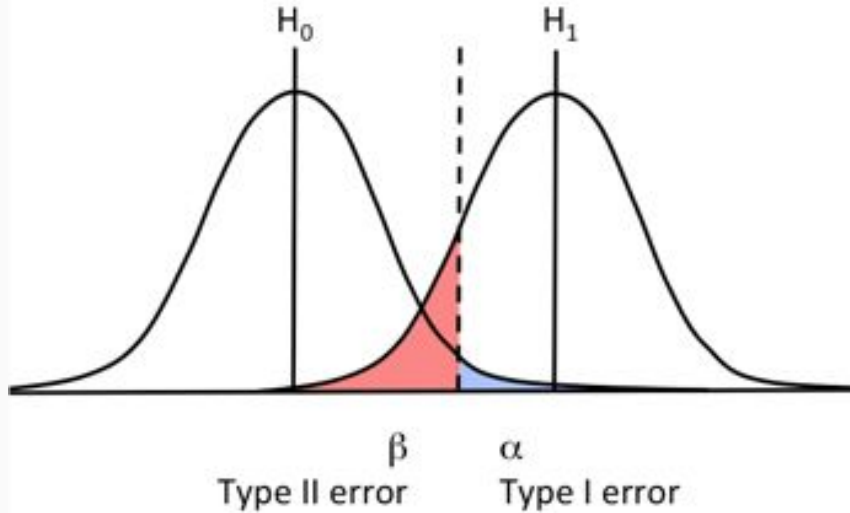
	H_0 is true	H_0 is false
Accept H_0	Correct Decision ($1-\alpha$)	Type II Error (β)
Reject H_0	Type I Error (α)	Correction Decision ($1-\beta$)

What happens to *power* when we increase alpha?



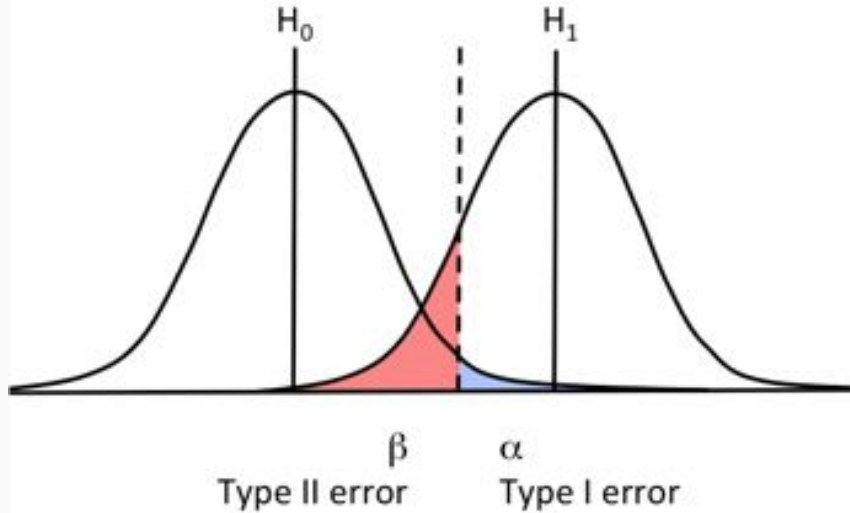
	H_0 is true	H_0 is false
Accept H_0	Correct Decision ($1-\alpha$)	Type II Error (β)
Reject H_0	Type I Error (α)	Correction Decision ($1-\beta$)

What happens to *power* when we increase the effect size?



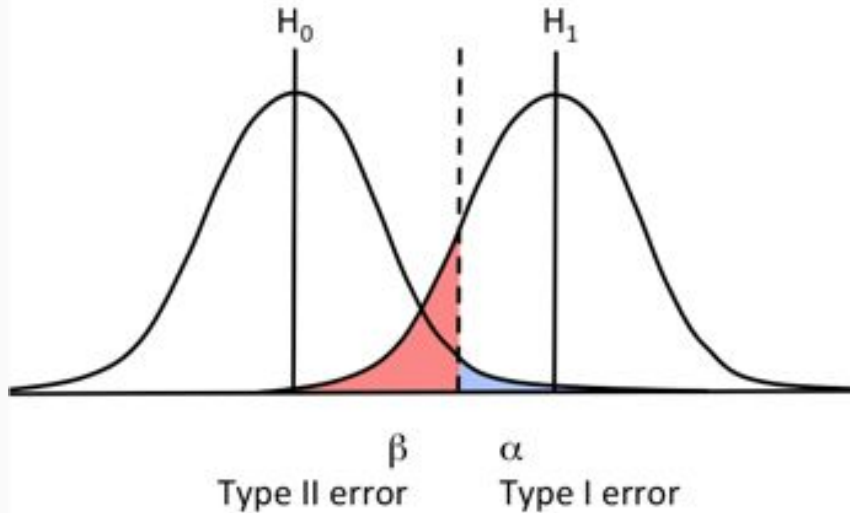
	H_0 is true	H_0 is false
Accept H_0	Correct Decision ($1-\alpha$)	Type II Error (β)
Reject H_0	Type I Error (α)	Correction Decision ($1-\beta$)

What happens to *power* when we increase the sample std. deviation?



	H_0 is true	H_0 is false
Accept H_0	Correct Decision ($1-\alpha$)	Type II Error (β)
Reject H_0	Type I Error (α)	Correction Decision ($1-\beta$)

What happens to *power* when we increase the sample size?

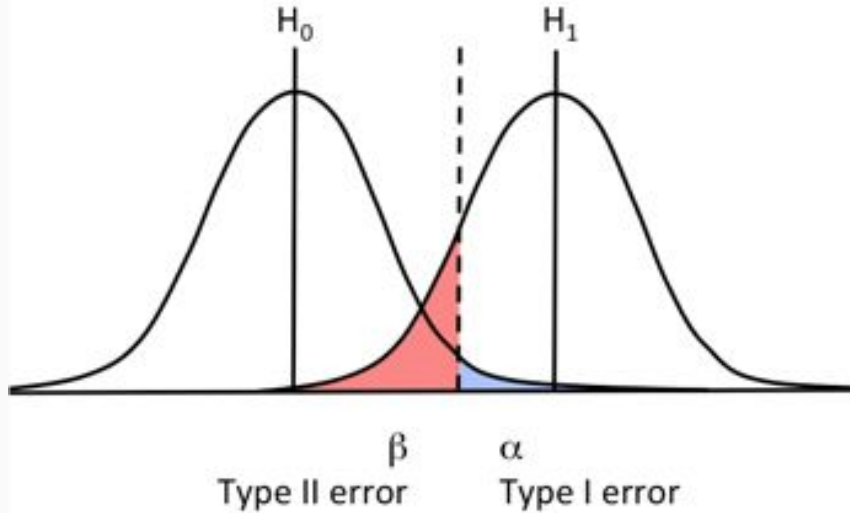


	H_0 is true	H_0 is false
Accept H_0	Correct Decision ($1-\alpha$)	Type II Error (β)
Reject H_0	Type I Error (α)	Correction Decision ($1-\beta$)

Often, we know:

1. The “effect size” that we want to detect, and
2. The *power* that we want to achieve.

We then calculate the *sample size* needed to get what we want!



	H_0 is true	H_0 is false
Accept H_0	Correct Decision ($1-\alpha$)	Type II Error (β)
Reject H_0	Type I Error (α)	Correction Decision ($1-\beta$)

1. Decide to run an experiment, choose α and $(1 - \beta)$
2. Calculate required sample size n
3. Take sample, obtain \bar{x} and s
4. Reject or “fail to reject” H_0

(new steps)

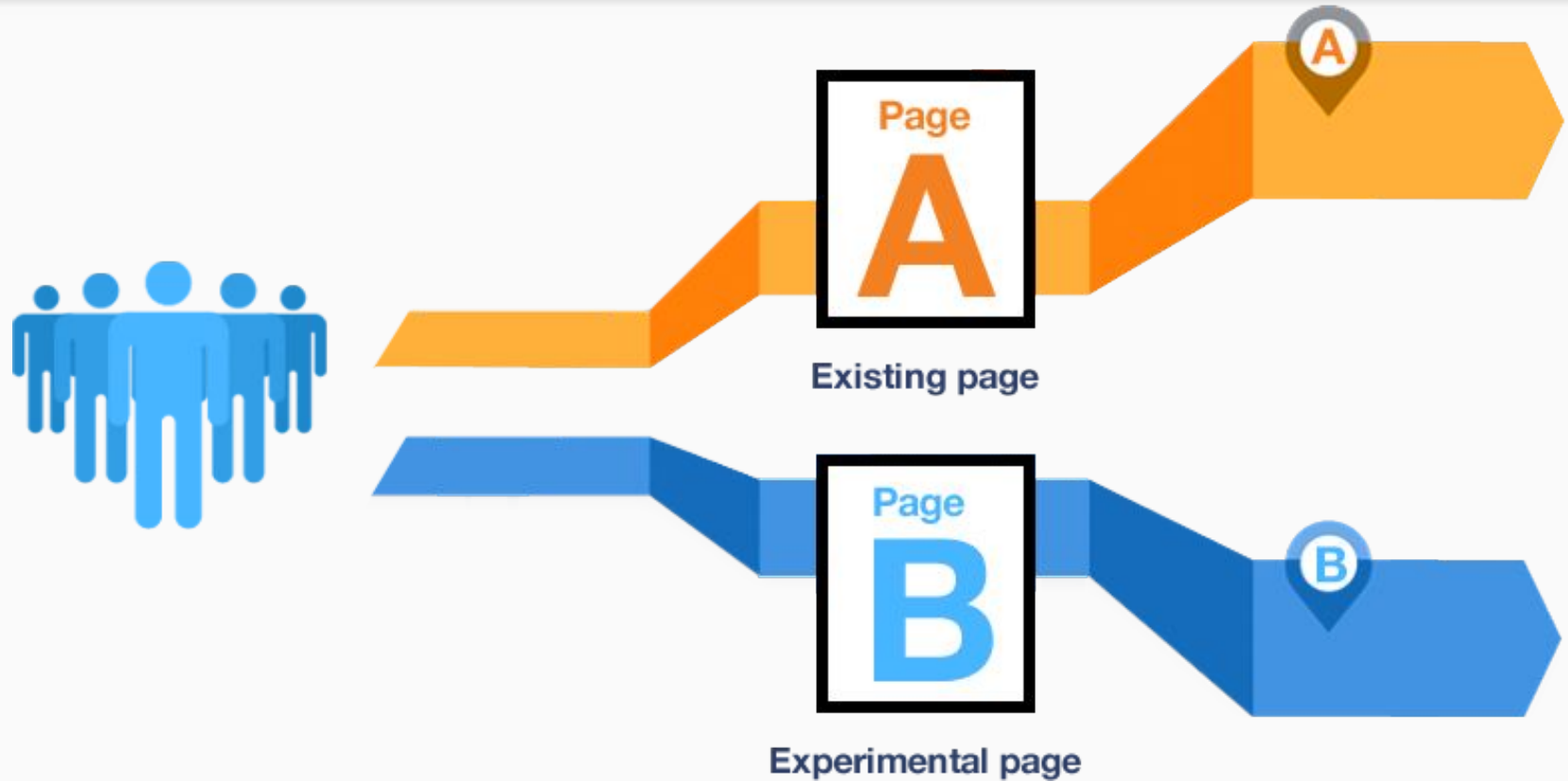
Calculating the required sample size

$$n > \left((Z_{(1-\beta)} - Z_{\alpha}) \frac{s}{\mu_b - \mu_a} \right)^2$$

```
import scipy.stats as st
```

```
st.norm.ppf(alpha)
```

```
st.norm.ppf(1 - beta)
```



Setup: A/B Test our website's homepage.

Our current homepage has a signup conversion rate of 6%. (The standard deviation would be 0.24.)

We want to test a new homepage design to see if we can get a 7% signup rate. We'll want an experiment where alpha is 1% and power is 95%.

How many visitors must visit the new homepage in order to fulfill the requirements of this experiment?

$$n \geq 9,084$$

Setup: A/B Test our website's homepage.

Our current homepage has a signup conversion rate of 1%. (The standard deviation would be 0.099.)

We want to test a new homepage design to see if we can get a 1.2% signup rate. We'll want an experiment where alpha is 1% and power is 95%.

How many visitors must visit the new homepage in order to fulfill the requirements of this experiment?

$$n \geq 39,427$$

Setup: A/B Test our website's homepage.

Our current homepage has a signup conversion rate of 20%. (The standard deviation would be 0.4.)

We want to test a new homepage design to see if we can get a 30% signup rate. We'll want an experiment where alpha is 1% and power is 95%.

How many visitors must visit the new homepage in order to fulfill the requirements of this experiment?

$$n \geq 253$$