

Hypothesis testing

We have talked about point estimation, say estimating μ .
and bit about confidence intervals
(like $P(\bar{X} - 1.96 \frac{\sigma}{\sqrt{n}} \leq \mu \leq \bar{X} + 1.96 \frac{\sigma}{\sqrt{n}}) = 95\%$),
which is related to interval estimation.

In hypothesis testing, we are saying yes or no to some hypothesis, when presented with an alternative hypothesis.

$X \sim$ normal variable, σ known

$$H_0: \mu = \mu_0$$

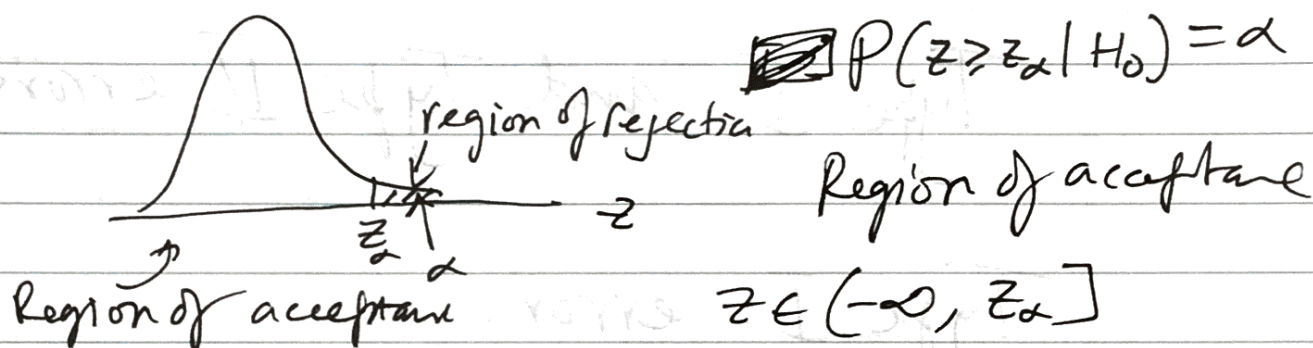
$$H_1: \mu > \mu_0$$

(In fact this is a whole class of hypothesis)

Traditionally we define a region of acceptance for a test statistic. If the statistic observed falls in the region H_0 is accepted,

Otherwise, it is rejected

For example, if we knew σ (a tall order),
 $\bar{X} = \frac{X_1 + \dots + X_N}{N}$ is distributed as $N(\mu_0, \frac{\sigma^2}{N})$
according to H_0 . Let $Z = \frac{\bar{X} - \mu_0}{\sigma/\sqrt{N}}$. $Z \sim N(0, 1)$ then



Region of rejection complementary to that.

This is a one tailed one sample z -test.

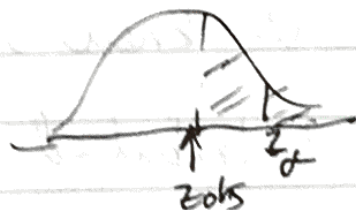
The prob. α is called level of significance.

In this version you get an yes/no answer.

Alternative: Convert Z_{obs} to a p -value

$P(Z \geq Z_{obs} | H_0)$. If this value is greater

than α , then accept:



Type I and Type II errors.

Type I error.

H_0 true but rejected

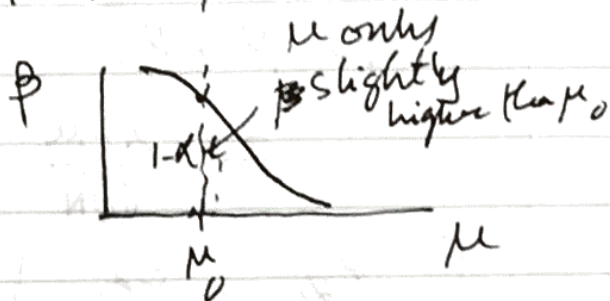
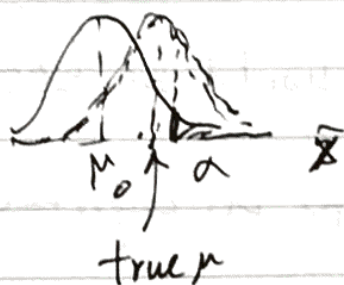
Type II error

H_a true but H_0 accepted.

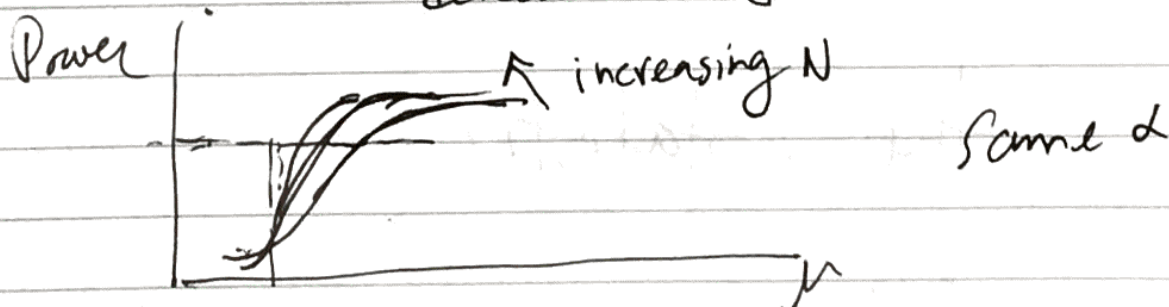
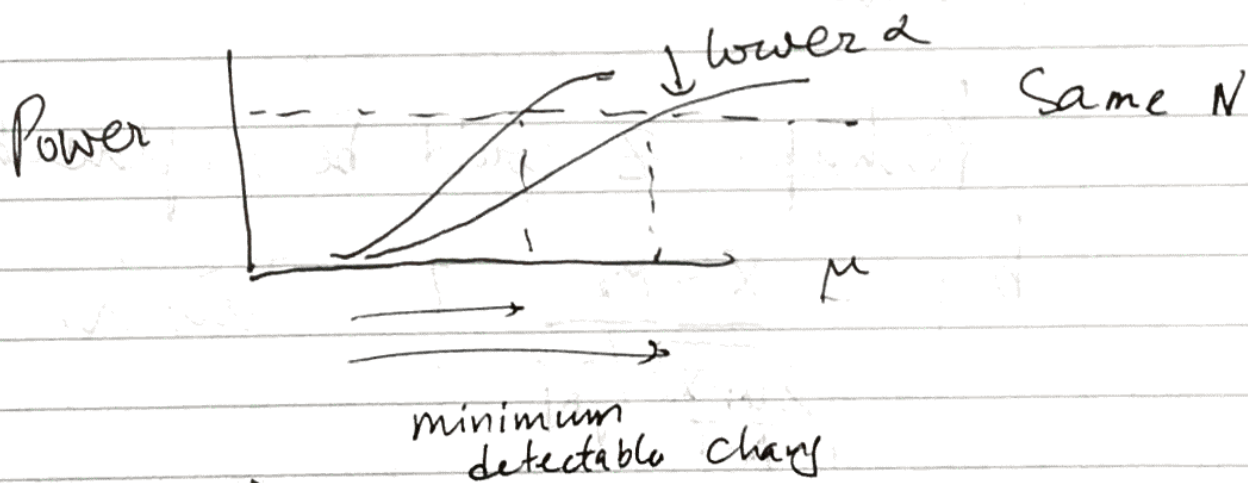
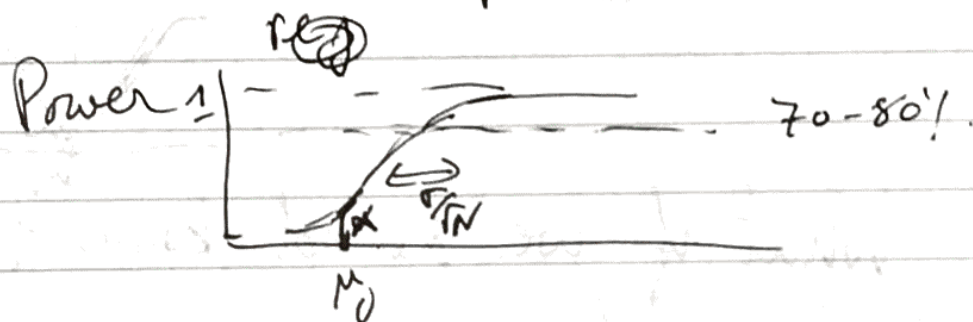
Prob of Type I error $\rightarrow \alpha$

Prob of type II error $\rightarrow \beta$
is more complicated.

β depends on true μ



Power = $1 - \beta$ = Prob if H_a is true H_0 would be rejected

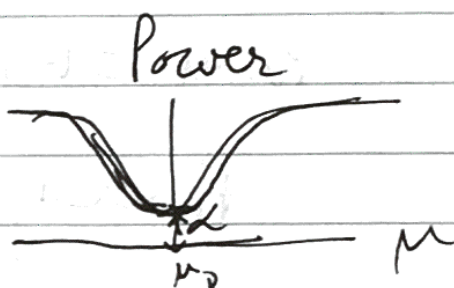
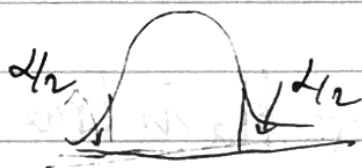


Two sided tests for $\mu = \mu_0$
vs $\mu \neq \mu_0$

$$Z = \frac{\bar{X} - \mu}{\sigma/\sqrt{N}}$$

should be ~~between~~ ^{in the interval}

$[-z_{\alpha/2}, z_{\alpha/2}]$ for acceptance.

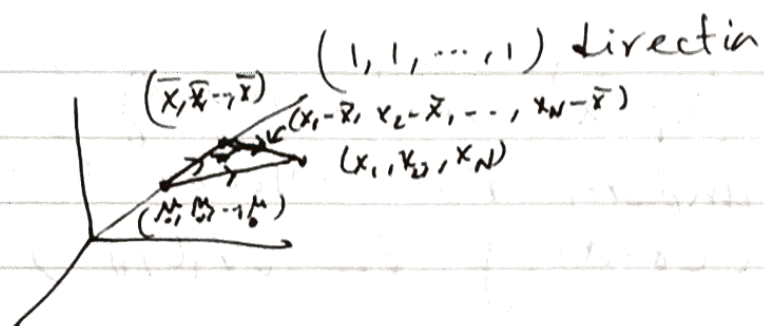


What if we do not know the variance?

Perhaps Z could be replaced
by $\frac{\bar{X} - \mu_0}{\sqrt{\frac{\sum (x_i - \bar{x})^2}{N-1}} / \sqrt{N}}$? This is

the t statistic.

Quite remarkably, we know the exact distribution of t .



Consider the vector $(x_1 - \bar{x}, \dots, x_N - \bar{x})$
with entries i.i.d $N(0, \sigma^2)$

It's projection along the $(1, 1, 1, \dots)$ direction
is obtained by taking the dot product
with $(\frac{1}{\sqrt{N}}, \frac{1}{\sqrt{N}}, \dots, \frac{1}{\sqrt{N}})$.

That dot product is $\frac{x_1 + \dots + x_N - N\bar{x}}{\sqrt{N}}$

$$= \frac{N(\bar{x} - \mu_0)}{\sqrt{N}} = \sqrt{N}(\bar{x} - \mu_0)$$

The component perpendicular to $(1, 1, \dots)$
lives in an $N-1$ dimensional space
call $N-1 = v$. That is the degree
of freedom of $x_i - \bar{x}$ components.

With a change of coordinates, we can write

$(x_i - \bar{x})$ in terms of $N-1$ independent random normal variables distributed according to $N(0, \sigma^2)$.

$$\prod_i e^{-\frac{(x_i - \bar{x})^2}{2\sigma^2}} \sim e^{-\frac{Y_0^2}{2\sigma^2}} e^{-\sum_{j=1}^N \frac{Y_j^2}{2\sigma^2}}$$

$$Y_0 = \sqrt{N} (\bar{x} - \mu_0)$$

$Y_0, Y_1, \dots, Y_N$ in $(1, 1, \dots)$ direction.

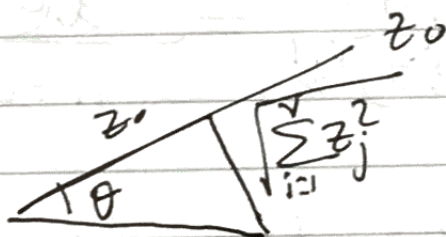
$$\sum_{i=1}^N (x_i - \bar{x})^2 = \sum_{j=1}^N Y_j^2$$

$$\text{So } t = \frac{\bar{x} - \mu_0}{\sqrt{\sum_{i=1}^N (x_i - \bar{x})^2 / N}} = \frac{Y_0}{\sqrt{\sum_{j=1}^N Y_j^2 / N}}$$

We could write $Y_0 = \sigma Z_0$, $Y_j = \sigma Z_j$, and Z_0, Z_j would all be independent standard normal variates.

$$\text{So } t = \frac{z_0}{\sqrt{\sum_{j=1}^v z_j^2 / v}}$$

$\sum_{j=1}^v z_j^2$ is called a χ^2 variate of degree of freedom v
 [Sum of ~~squares of~~ v independent ~~norm~~ standard normal variates.]

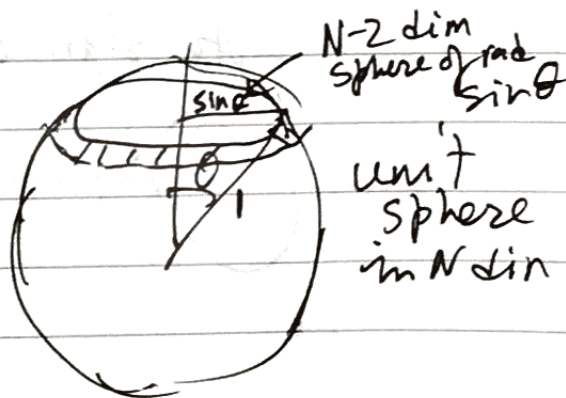


$$\frac{z_0}{\sqrt{\sum_{j=1}^v z_j^2}} = \cos \theta = \frac{t}{\sqrt{v}}$$

It depends only on a random angle

In $N = v + 1$ dimension θ distribution goes as $\sin^{v-1} \theta d\theta$

$$\text{Vol} \sim \sin^{N-2} \theta d\theta \\ \sim \sin^{v-1} \theta d\theta$$



$$1 + \cot^2 \theta = \frac{\sin^2 \theta + \cos^2 \theta}{\sin^2 \theta} = \frac{1}{\sin^2 \theta}$$

$$\text{So } \sin \theta = \frac{1}{\sqrt{1 + \cot^2 \theta}}$$

$$\begin{aligned} d \cot \theta &= -\csc^2 \theta d\theta \\ &= -\frac{1}{\sin^2 \theta} d\theta = -(1 + \cot^2 \theta) d\theta \end{aligned}$$

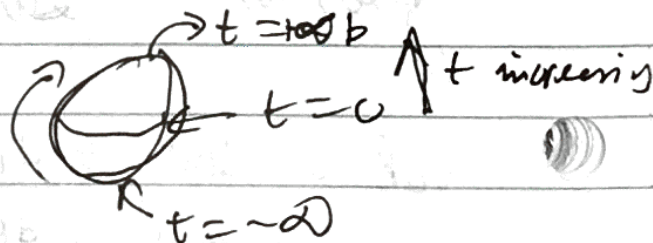
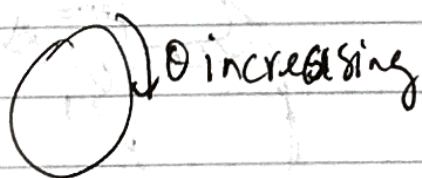
$$\sin^{\nu+1} \theta d\theta = (1 + \cot^2 \theta)^{\frac{\nu+1}{2}} d\theta$$

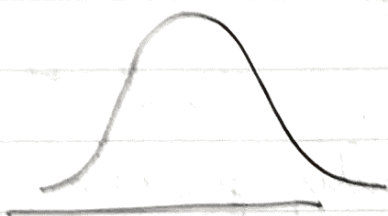
$$= + \frac{(1 + \cot^2 \theta) d\theta}{(1 + \cot^2 \theta)^{\frac{\nu+1}{2}}} = - \frac{d(\cot \theta)}{(1 + \cot^2 \theta)^{\frac{\nu+1}{2}}}$$

Changing to $\cot \theta = \frac{t}{\sqrt{\nu}}$

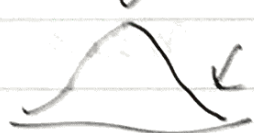
$$\sin^{\nu+1} \theta d\theta \rightarrow \frac{dt}{\left(1 + \frac{t^2}{\nu}\right)^{\frac{\nu+1}{2}}}$$

upto sign and constants.





$$C_1 \int_0^\pi d\theta \sin^{v-1} \theta = C_2 \int_{-\infty}^{\infty} \frac{dt}{\left(1 + \frac{t^2}{v}\right)^{\frac{v+1}{2}}}$$



Powerlaw tail $\frac{z_0}{\sqrt{z_0^2}}$ ← The z^2 variable fluctuates and can be small occasionally.

~~Step~~ We can do one and two sided test with t .

If we have two samples of size n_1, n_2 and we know σ_1, σ_2 , a two

sample z test could decide if the means are the same or not. $H_0: \mu_1 = \mu_2, H_a: \mu_1 > \mu_2$ or $\mu_1 \neq \mu_2$

$$z = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}$$

The corresponding thing for t test is fricky.

Paired t-test.

If ~~the~~ $n_1 = n_2$ and the x 's are naturally paired, take difference

$$d_i = x_{1i} - x_{2i}$$

Do a t-test on d_i mean being zero or not.

Pooled t-test

If we don't know σ 's but $\sigma_1 = \sigma_2$

$$t = \frac{\bar{x}_1 - \bar{x}_2}{S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \quad \text{is a } t \text{ statistic}$$

of degree $n_1 + n_2 - 2$,

$$\text{where } S_p = \sqrt{\frac{\sum_i (x_{1i} - \bar{x}_1)^2 + \sum_j (x_{2j} - \bar{x}_2)^2}{n_1 + n_2 - 2}}$$

Two sample-t test

This is an approximate test

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}}$$

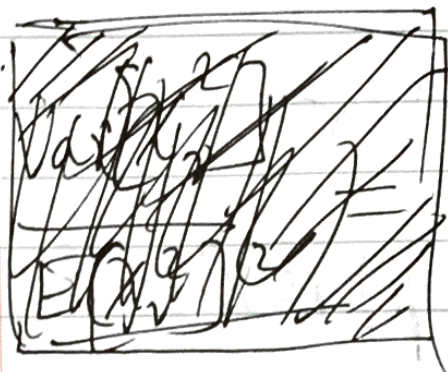
$$S_\alpha^2 = \sum_{i=1}^{n_\alpha} (X_{\alpha i} - \bar{X}_\alpha)^2 / (n_\alpha - 1) = \frac{\sigma_\alpha^2}{n_\alpha - 1} \sum_{j=1}^{n_\alpha - 1} Z_{\alpha j}^2$$

We need to know how does $\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}$ fluctuate compared to the mean.

$$\text{For } \sum_{j=1}^v Z_j^2 \quad E\left[\sum_{j=1}^v Z_j^2\right] = v$$

$$\text{Var}\left[\sum_{j=1}^v Z_j^2\right] = \sum_{j=1}^v \text{Var}[Z_j^2] = 2v$$

$$\text{Var}[Z^2] = E[Z^4] - E[Z^2]^2 = 3 - 1^2 = 2$$



$$\frac{2E[x_v^2]^2}{\text{Var}[x_v^2]} = v$$

If we compute that for

$$\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}, \text{ we get}$$

$$\text{Expectation} \quad \frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}$$

$$\text{Var} \quad \frac{2\sigma_1^4}{(n_1-1)n_1^2} + \frac{2\sigma_2^4}{(n_2-1)n_2^2}$$

So we  should use

$$\frac{2\left(\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}\right)^2}{\frac{2\sigma_1^4}{(n_1-1)n_1^2} + \frac{2\sigma_2^4}{(n_2-1)n_2^2}}$$

as the effective d.f.

We use its estimate

$$\text{d.f.} \approx \frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\frac{s_1^4}{(n_1-1)n_1^2} + \frac{s_2^4}{(n_2-1)n_2^2}}$$

Enough about means, what about hypotheses regarding variances?

Say $X_i \sim \text{i.i.d. } N(\mu, \sigma^2) \quad i=1, \dots, N$

Remember that $\sum_{i=1}^N (X_i - \bar{X})^2 = \sum_{j=1}^v Y_j^2$

with $v = N-1$. If we set $Y_j = \sigma Z_j$ then

Z_j 's are i.i.d. $N(0, 1)$.

The hypothesis $\sigma = \sigma_0$ against some alternative hypothesis could be decided by the statistic

$$\frac{\sum_{i=1}^N (X_i - \bar{X})^2}{\sigma_0^2}$$

To test these hypotheses we need to know the distribution of $\chi^2 = \sum_{j=1}^v Z_j^2$

$$P(\mathbf{z}) d^v \mathbf{z} \sim e^{-\sum_{j=1}^v z_j^2 / 2} dz_1 \dots dz_v$$

$$\text{Let } \sum_{j=1}^v z_j^2 = \chi^2$$

The radius in the $\mathbf{z}$ space

is χ .

$$\boxed{P(z_1, \dots, z_\nu)} \rightarrow e^{-\chi^2/2}$$

If I go to polar ~~coordinates~~ coordinates

$$dz_1 \cdots dz_\nu \rightarrow \chi^{\nu-1} d\chi d\Omega$$

↑
angular
degrees of freedom

Integrate out Ω 's

$$C e^{-\chi^2/2} \chi^{\nu-1} d\chi$$

$$\text{Normaliz'n} \int_0^\infty e^{-\chi^2/2} \chi^{\nu-1} d\chi$$

$$= \int_0^\infty e^{-y} (2y)^{\frac{\nu-2}{2}} dy = 2^{\frac{\nu-2}{2}} \int_0^\infty y^{\frac{\nu-1}{2}-1} e^{-y} dy$$

$$= 2^{\frac{\nu-2}{2}} \Gamma\left(\frac{\nu}{2}\right)$$

$$S_0 C = \frac{1}{2^{\frac{\nu-2}{2}} \Gamma\left(\frac{\nu}{2}\right)}$$

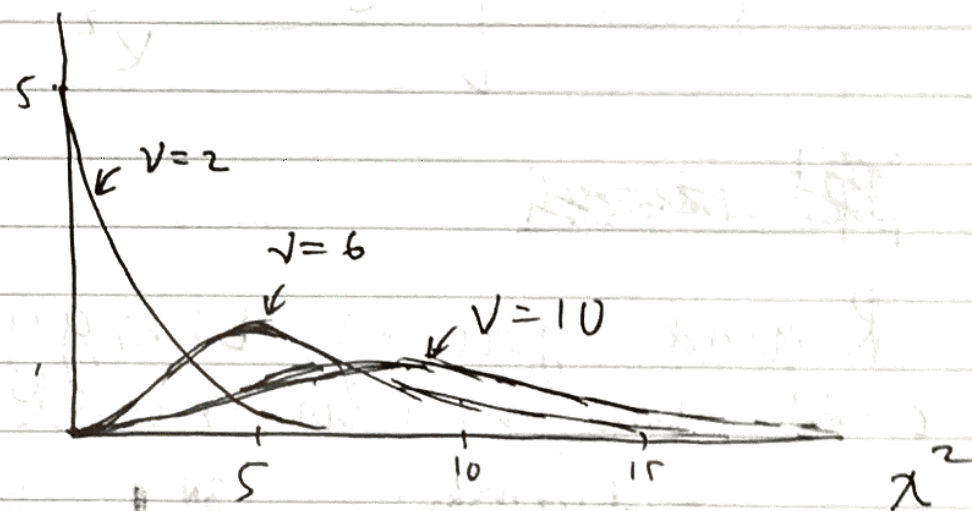
If we call $x^2 = x$

$$\frac{1}{2^{\frac{\nu}{2}-1} \Gamma\left(\frac{\nu}{2}\right)} e^{-x^2/2} x^{\nu-1} dx$$

$$= \frac{1}{2^{\frac{\nu}{2}} \Gamma\left(\frac{\nu}{2}\right)} e^{-x^2/2} (x^2)^{\frac{\nu-2}{2}} dx^2$$

$$= \frac{1}{2^{\frac{\nu}{2}} \Gamma\left(\frac{\nu}{2}\right)} e^{-\frac{x}{2}} x^{\frac{\nu}{2}-1} dx$$

$x(x^2)$ p.d.f.



Mode for x : take log and diff $\frac{d}{dx} \left(-\frac{x}{2} + \left(\frac{\nu}{2}-1\right) \log x \right) = 0$
 $\Rightarrow x_m = \nu - 2$

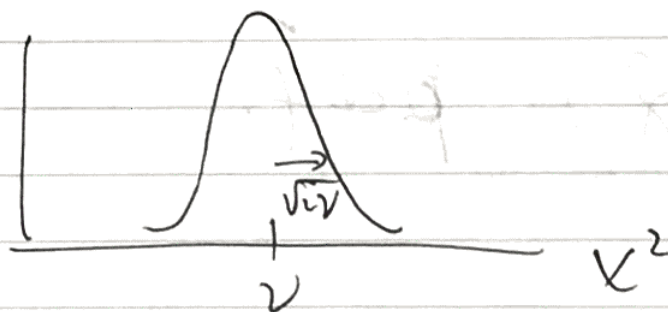
Since $\chi^2 = \sum_{i=1}^v z_i^2$

$$E[\chi^2] = v$$

$$\text{Var}[\chi^2] = 2v$$

So for large v , we expect

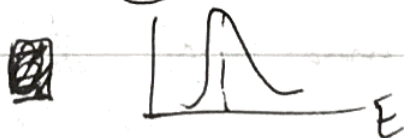
$\frac{\chi^2 - v}{\sqrt{2v}}$ to behave like a standard normal variate



~~Chi-squared distribution~~

Reminds you of Energy of ideal gas in canonical ensemble

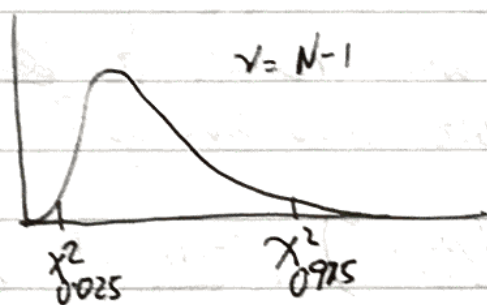
$$\left(\sum \frac{1}{2} m \overline{v_i^2} \right) \rightarrow \frac{3N}{2} k_B T = \frac{3N}{2} \frac{1}{\beta} = \frac{3N}{2\beta} = \bar{E}$$



$$\bar{E} \approx \frac{3N}{2\beta} = \frac{3Nk_B T}{2} = \text{Equipartition law.}$$

Back to practical things!

First we can generate confidence intervals of σ .



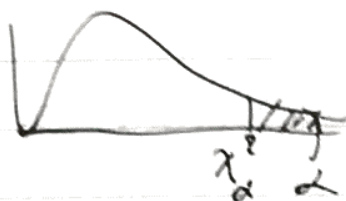
$$\text{Prob} \left[\chi^2_{0.025} \leq \frac{\sum (x_i - \bar{x})^2}{\sigma^2} < \chi^2_{0.975} \right] = 95\%$$

Let us call $s^2 = \frac{1}{N-1} \sum (x_i - \bar{x})^2$

$$\text{Prob} \left[\frac{(N-1)s^2}{\chi^2_{0.975}} < \sigma^2 < \frac{(N-1)s^2}{\chi^2_{0.025}} \right] = 95\%$$

Similarly we could do hypothesis testing.

$$H_0: \sigma = \sigma_0 \quad H_1: \sigma > \sigma_0$$



Reject H_0 if $\frac{(N-1)s^2}{\sigma_0^2} > \chi^2_\alpha$.

What if we need to ~~consider~~ compare two variances?

i.i.d $X_{1i} \sim N(\mu_1, \sigma_1^2), i=1, \dots, N_1,$

i.i.d $X_{2j} \sim N(\mu_2, \sigma_2^2), j=1, \dots, N_2,$

$$H_0: \sigma_1 = \sigma_2$$

$$H_a: \sigma_1 > \sigma_2$$

$$\text{Note that } \frac{\sum_{i=1}^{N_1} (X_{1i} - \bar{X}_1)^2 / (N_1 - 1)}{\sum_{j=1}^{N_2} (X_{2j} - \bar{X}_2)^2 / (N_2 - 1)} = \frac{S_1^2}{S_2^2} = \frac{\chi_1^2 / \nu_1}{\chi_2^2 / \nu_2} = F$$

Where χ_1^2, χ_2^2 are independently distributed χ^2 's with d.f. $\nu_1 = N_1 - 1, \nu_2 = N_2 - 1$.

What is the distribution of F for degrees of freedom ν_1, ν_2

Construct standard normal variables

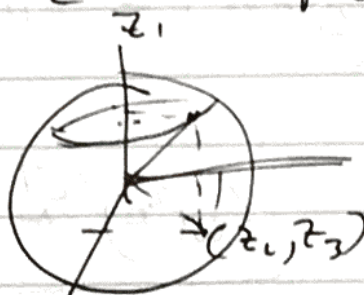
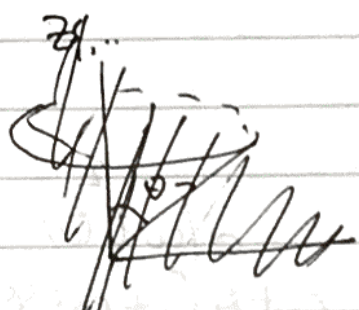
$$\boxed{\text{Z}} \quad z_1, \dots, z_{v_1}, z_{v_1+1}, \dots, z_{v_1+v_2}$$

$$z_1^2 + \dots + z_{v_1}^2 = \chi_1^2$$

$$z_{v_1+1}^2 + \dots + z_{v_1+v_2}^2 = \chi_2^2$$

$$F \propto \chi_1^2 / \chi_2^2$$

has to
do
with
angle



Consider $\chi_1^2 + \chi_2^2 = \chi^2$. χ is the $v_1 + v_2$ dim radius
 $\chi_1 = \chi \cos \theta$
 $\chi_2 = \chi \sin \theta$

$$\text{Phase space} \sim \chi_1^{v_1-1} d\chi_1 \chi_2^{v_2-1} d\chi_2$$

$$\sim \chi_1^{v_1-1} \chi_2^{v_2-1} d\theta d\chi$$

χ magnitude does not matter

$$\chi_1^{v_1-1} \chi_2^{v_2-1} d\theta$$

[Note that the χ distribution calculation had $v_1=1, v_2=N-1$]

$$\text{Also } \frac{\chi_1}{\chi_2} = \frac{\cos \theta}{\sin \theta} = \cot \theta$$

Once more $\cot^2 \theta + 1 = \frac{1}{\sin^2 \theta}$

$$\left(\frac{\cot^2 \theta}{\cot^2 \theta + 1} \right)^{\frac{\nu_1 - 1}{2}} \left(\frac{1}{\cot^2 \theta + 1} \right)^{\frac{\nu_2 - 1}{2}} d\theta$$

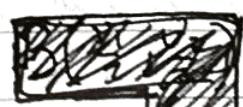
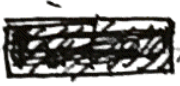
$$d(\cot \theta) = -(1 + \cot^2 \theta) d\theta$$

So
$$\frac{(\cot^2 \theta)^{\frac{\nu_1 - 1}{2}}}{(1 + \cot^2 \theta)^{\frac{\nu_1 + \nu_2}{2} - 1}} \frac{d(\cot^2 \theta)}{\cot \theta (1 + \cot^2 \theta)}$$

$$\propto \frac{F^{\frac{\nu_1}{2} - 1} dF}{\left(1 + \frac{\nu_1 F}{\nu_2}\right)^{\frac{\nu_1 + \nu_2}{2}}}$$

$$\propto \frac{F^{\frac{\nu_1}{2} - 1} dF}{(\nu_1 F + \nu_2)^{\frac{\nu_1 + \nu_2}{2}}}$$

I will leave finding the normalization constant using

 Beta  function as an  exercise.

Note that the mode is at

$$\left(\frac{v_1}{2} - 1\right) \frac{1}{F_m} = \frac{v_1 + v_2}{2} \frac{v_1}{v_1 F_m + v_2}$$

$$\Rightarrow \frac{v_1 F_m}{v_1 F_m + v_2} = \frac{v_1 - 2}{v_1 + v_2}$$

$$\Rightarrow \frac{v_1 F_m}{v_2} = \frac{v_1 - 2}{v_2 + 2} \Rightarrow F_m = \frac{v_2(v_1 - 2)}{v_1(v_2 + 1)}$$

For large v_1, v_2 $F_m \rightarrow 1$

we expect that since $\frac{v_1^2}{v_1}$ and $\frac{v_2^2}{v_2}$ would both self average to 1; making the ratio F to be 1 as well

