Stat 431 Midterm Review Guide, Hyunseung Kang

All of Stat 431 starts by (i) **collecting i.i.d. samples**, $X_1, ..., X_n$ from a distribution and (ii) **studying its properties** of the distribution. The main focus is studying its **mean**, μ , and **variance**, σ^2 .

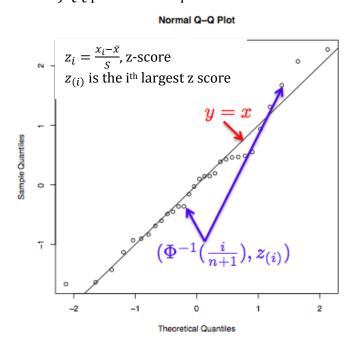
1. Sampling Distribution

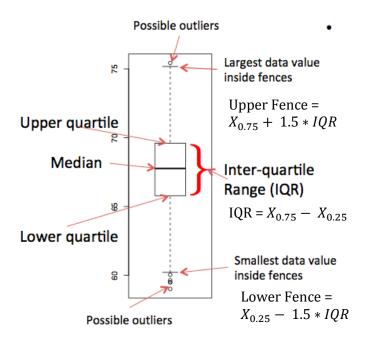
The most natural thing to do once we collected our sample is to compute its sample mean, $\bar{X} = \frac{1}{n} \sum_{i=1}^{n} X_i$, and sample variance, $S^2 = \frac{1}{n-1} \sum_{i=1}^{n} (X_i - \bar{X})$. In addition, we can identify the distributions of them

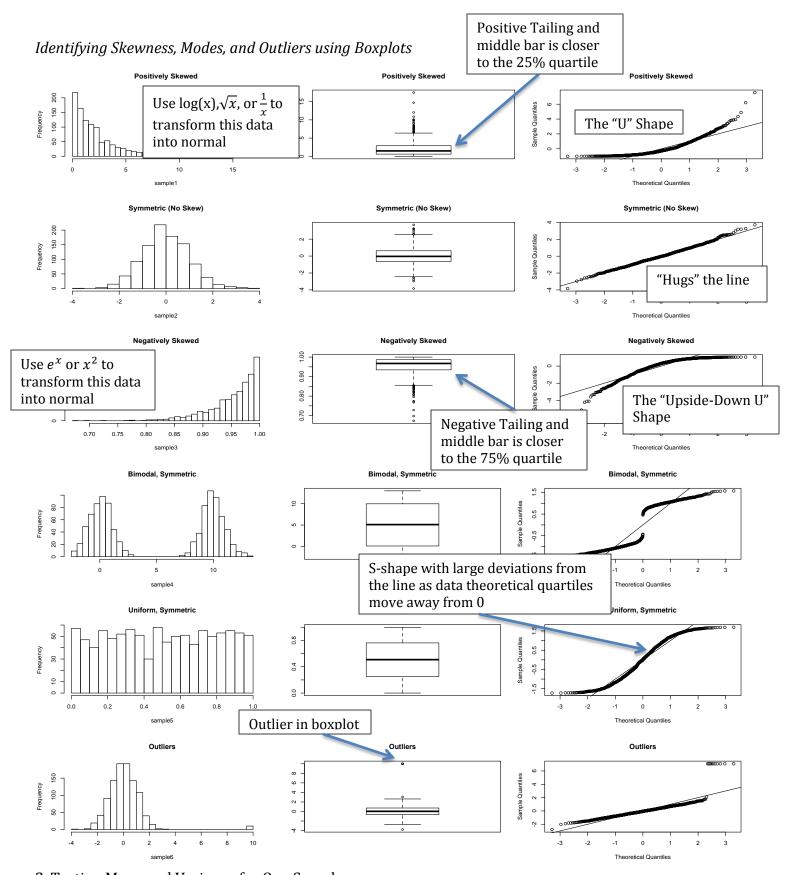
	Normal Distribution	t Distribution	Chi-Square Distribution
Parameters of Interest (for testing and CI)	μ with known σ	μ with unknown σ	σ
Examples	$1. \overline{X} \sim N\left(\mu, \frac{\sigma^2}{n}\right)$ $2. \frac{\overline{X} - \mu}{\sigma/\sqrt{n}} \sim N(0, 1)$ $3. Z \sim N(0, 1)$	$1. \frac{\bar{X} - \mu}{s / \sqrt{n}} \sim t_{n-1}$ $2. \frac{Z}{\sqrt{\frac{U}{n}}} \sim t_n \text{ where } Z \sim N(0,1), U \sim \chi_n^2,$ and U and Z are indep.	$1. \frac{(n-1)S^2}{\sigma^2} \sim \chi_{n-1}^2$ $2. \sum_{i=1}^n Z_i^2 \sim \chi_n^2,$ where $Z_i \sim N(0,1)$ and are i.i.d.
Properties	1. If $n \ge 30$, then regardless of the original distribution of X_i , \bar{X} is normally distributed by Central Limit Theorem. Otherwise, $X_i \sim N(\mu, \sigma^2)$ assumption is needed	1. If df (i.e. $n-1$) gets larger, (i.e. $df \ge 30$) then $t \sim N(0,1)$ 2. t Distribution has a "FATTER" tail than the normal distribution \rightarrow the 95% intervals using t are LARGER than those using normal	

Also, we can use boxplots/qq plots to summarize the sampling distribution

Basics of QQ plots and Boxplots







2. Testing Mean and Variance for One Sample

In addition to using summary statistics and graphical tools, we can hypothesize about what the true μ or σ may entail and test our hypothesis. In particular, the procedure of hypothesis testing is as follows:

- 1. We hypothesis whether it's a **two-sided** or a **one-sided test**.
- 2. We create a **test statistic,T(X),** to test (a). All of our test statistics have to be **pivotal** (i.e. the probabilities of our test statistics CANNOT depend on the true unknown parameters).

3. We test our hypothesis with the test statistic. In particular, a natural testing procedure would be to **reject the null is the probability of rejecting it is small** given that the null is indeed true (i.e. Type I error is small). For example, for the two-sided case we reject the null whenever $P_{\mu_0}(|T(X)| > t(x)) < \alpha$ where t(x) is the observed value of the test statistic and α is the **maximum probability of Type I Error.**

The truth	H_0 is actually true	H_a is actually true		
		Note : Type II + Power = 1		
Our conclusion from data				
We conclude: H_0 is correct (i.e.	Note : We don't care about this	Type II Error or		
H_0 is retained)	box since we always control for	$P(retain null \mid H_a is true)$		
	Type I Error (aka this term is also			
	controlled by $1 - \alpha$)			
We conclude: H_a is correct (i.e. H_0	Type I Error or	Power or		
is rejected)	$P(reject null H_0 is true)$	$P(reject null H_a is true)$		
	Note : always controlled by α			

We can also reject the null through a variety of methods, as listed below.

- a. **P-values**: If the maximum probability of Type I error from the sample (i.e. p-value) is less than the allowed probability of Type I Error (i.e. $P\left(|Z| > \frac{\bar{X} \mu_0}{\frac{\sigma}{\sqrt{n}}}\right) < \alpha$), we reject the null
- b. **Rejection Region**: We reject the null whenever our observed test statistic is in a spec. region. c. **Confidence Intervals**: If the interval DOES NOT contains μ_0 , we REJECT the null. Note that
- c. **Confidence intervals**: If the interval DOES NOT contains μ_0 , we REJECT the null. Note that confidence intervals are random and it covers μ under repeated sampling 1α amount of times.

	Testing μ with known σ^2	Testing μ with unknown σ^2	!	Testing σ^2
Hypothesis	1. H_0 : $\mu = \mu_0$, H_a : $\mu \neq \mu_0$ (two-sided)			1. H_0 : $\sigma = \sigma_0$, H_a : $\sigma \neq \sigma_0$
Setup	2. $H_0: \mu \le \mu_0, H_a: \mu > \mu_0$ (one-sided)			$2. H_0: \sigma \leq \sigma_0, H_a: \sigma > \sigma_0$
	3. $H_0: \mu \ge \mu_0, H_a: \mu < \mu_0$ (one-sided)			$3. H_0: \sigma \geq \sigma_0, H_a: \sigma < \sigma_0$
	Note : The direction of the inequality sign in the rejection			
	region is identical to the direction of the inequality sign			
	in the alternative			
Assumptions	i.i.d. sample from a norma	al distribution*		
Test Statistic	$\frac{\bar{X} - \mu_0}{\sigma / \sqrt{n}} \sim N(0,1)$ $1. \bar{x} - \mu_0 > z_{\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}}$	$\frac{\bar{X} - \mu_0}{S/\sqrt{n}} \sim t_{n-1}$ $1. \bar{x} - \mu_0 > t_{\frac{\alpha}{2}, n-1} \frac{s}{\sqrt{n}}$		$\frac{(n-1)S^2}{\sigma_0^2} \sim \chi_{n-1}^2$ $\frac{\sigma_0^2}{\sigma_{n-1}^2} \chi_{\frac{\alpha}{2}, n-1}^2 \text{ or }$
Rejection	1 15 1 > - 0	1 15 1 > t S		σ_0
Region	$ 1. x - \mu_0 > \frac{2\alpha}{2} \sqrt{n}$		1.5^2	$\frac{2}{n-1}\chi_{\frac{\alpha}{n-1},n-1}^{\alpha}$ or
Region	$2. \bar{x} > \mu_0 + z_\alpha \frac{\sigma}{\sqrt{n}}$	$2. \bar{x} > \mu_0 + t_{\alpha, n-1} \frac{s}{\sqrt{n}}$	S ² <	$\leq \frac{\sigma_0^2}{n-1} \chi_{1-\frac{\alpha}{2},n-1}^2$
	$3. \bar{x} < \mu_0 - z_\alpha \frac{\sigma}{\sqrt{n}}$	3. $\bar{x} < \mu_0 - t_{\alpha, n-1} \frac{s}{\sqrt{n}}$		2
	$\int d^{2} d^$	$\int \int $	$2. S^2$	$\frac{\sigma^2}{n-1}\chi^2_{\alpha,n-1}$
				$\frac{\sigma^2}{\sigma^2} < \frac{\sigma_0^2}{n-1} \chi^2_{1-\alpha,n-1}$
Confidence	1. $(\bar{x} - z_{\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}}, \bar{x} + z_{\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}})$	1. $(\bar{x} - t_{\frac{\alpha}{2},n-1} \frac{s}{\sqrt{n}}, \bar{x} +$	1 ($(n-1)S^2$ $(n-1)S^2$
Intervals	$2.(\bar{x}-z_{\alpha}\frac{\sigma}{\sqrt{n}},\infty)$	$t_{\underline{\alpha},n-1}\frac{s}{\sqrt{n}}$	1.	$\left(\frac{(n-1)S^2}{\chi_{\frac{\alpha}{2},n-1}^2}, \frac{(n-1)S^2}{\chi_{1-\frac{\alpha}{2},n-1}^2}\right)$
	$3. \left(-\infty, \bar{x} + z_{\alpha} \frac{\sigma}{\sqrt{n}}\right)$	$2. (\bar{x} - t_{\frac{\alpha}{2}, n-1} \frac{s}{\sqrt{n}}, \infty)$	$2.\left(\frac{C}{C}\right)$	$\frac{n-1)S^2}{\chi^2_{\alpha,n-1}}$, ∞
		$3. \left(-\infty, \bar{x} + t_{\frac{\alpha}{2}, n-1} \frac{s}{\sqrt{n}}\right)$	3. (0	$\left(1, \frac{(n-1)S^2}{\chi^2_{1-\alpha, n-1}}\right)$
Power: NOTE : Need a	$1. P_{\mu \in H_a} \left(\frac{ \bar{X} - \mu_0 }{\sigma / \sqrt{n}} > Z_{\frac{\alpha}{2}} \right)$	$1. P_{\mu \in H_a} \left(\frac{ \bar{X} - \mu_0 }{S / \sqrt{n}} > t_{\frac{\alpha}{2}, n-1} \right)$	1 D	$\left(\frac{S^2(n-1)}{\sigma_0^2} > \chi_{\frac{\alpha}{2},n-1}^2 \right)$
pre-specified	$2. P_{\mu \in H_a} \left(\frac{\bar{X} - \mu_0}{\sigma / \sqrt{n}} > z_{\alpha} \right)$	$2. P_{\mu \in H_a} \left(\frac{\bar{x} - \mu_0}{S / \sqrt{n}} > t_{\alpha, n - 1} \right)$	1. P _o	$\sigma^{2} \in H_{a} \left(\begin{array}{c} \frac{S^{2}(n-1)}{\sigma_{0}^{2}} > \chi_{\frac{\alpha}{2}, n-1}^{2} \\ \cup \frac{S^{2}(n-1)}{\sigma_{0}^{2}} < \chi_{1-\frac{\alpha}{2}, n-1}^{2} \end{array} \right)$

value from the	$3. P_{\mu \in H_a} \left(\frac{\bar{X} - \mu_0}{\sigma / \sqrt{n}} < z_\alpha \right)$	$3. P_{\mu \in H_a} \left(\frac{\bar{X} - \mu_0}{S / \sqrt{n}} < t_{\alpha, n-1} \right)$	$2. P_{\sigma^2 \in H_a} \left(\frac{S^2(n-1)}{\sigma_0^2} > \chi_{\alpha,n-1}^2 \right)$
alternative			$3. P_{\sigma^2 \in H_a} \left(\frac{S^2(n-1)}{\sigma_s^2} < \chi_{1-\alpha,n-1}^2 \right)$

^{*}You can check for normality using the QQ plot and make transformations as needed. Also, if the sample size is greater than 30, then by the CLT, we can assume it came from a normal distribution ou

3. Testing Mean for Two Samples

Suppose we collect $X_1, ..., X_{n_1}$ i.i.d. from sample 1 and $Y_1, ..., Y_{n_2}$ i.i.d. from sample 2. We want to test whether the two samples have the same means (i.e. $\mu_1 = \mu_2$)

	Equal Variance Assumption	Without Equal Variance Assumption	
Hypothesis Setup	$1. \ H_0: \mu_1 - \mu_2 = \mu_0, H_a: \mu_1 - \mu_2 \neq \mu_0 \ (\text{two-sided})$ $2. \ H_0: \mu_1 - \mu_2 \leq \mu_0, H_a: \mu_1 - \mu_2 > \mu_0 \ (\text{one-sided})$ $3. \ H_0: \mu_1 - \mu_2 \geq \mu_0, H_a: \mu_1 - \mu_2 < \mu_0 \ (\text{one-sided})$ Note : The direction of the inequality sign in the rejection region is identical to the direction of the inequality sign in the alternative		
Assumptions	i.i.d samples from two normal distribution* AND independent samples from each other		
Test Statistic	A. $\frac{(\bar{X} - \bar{Y}) - \mu_0}{S\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \sim t_{n_1 + n_2 - 2}, \text{ we don't know } \sigma^2$ B. $\frac{(\bar{X} - \bar{Y}) - \mu_0}{\sigma\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \sim N(0, 1), \text{ we know } \sigma^{2**}$ $S^2 = \frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}$	A. $\frac{(\bar{X} - \bar{Y}) - \mu_0}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \sim t_v$, we don't know σ^2 B. $\frac{(\bar{X} - \bar{Y}) - \mu_0}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}} \sim N(0,1)$, we know σ^{2**} $\min(n_1, n_2) - 1 \le v \le n_1 + n_2 - 2$	
Rejection Region	1. $ \bar{x} - \bar{y} - \mu_0 > t_{n_1 + n_2 - 2, \frac{\alpha}{2}} S \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}$ 2. $\bar{x} - \bar{y} > \mu_0 + t_{n_1 + n_2 - 2, \alpha} S \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}$ 3. $\bar{x} - \bar{y} < \mu_0 - t_{n_1 + n_2 - 2, \alpha} S \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}$	$\begin{aligned} 1. & \bar{x} - \bar{y} - \mu_0 > t_{v,\frac{\alpha}{2}} \sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}} \\ 2. & \bar{x} - \bar{y} > \mu_0 + t_{v,\alpha} \sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}} \\ 3. & \bar{x} - \bar{y} < \mu_0 - t_{v,\alpha} \sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}} \end{aligned}$	
Confidence Intervals	$1. \bar{x} - \bar{y} \pm t_{n_1 + n_2 - 2, \frac{\alpha}{2}} S \sqrt{\frac{1}{n_1} + \frac{1}{n_2}} $ $2. \left(\bar{x} - \bar{y} - t_{n_1 + n_2 - 2, \alpha} S \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}, \infty \right)$ $3. \left(-\infty, \bar{x} - \bar{y} + t_{n_1 + n_2 - 2, \alpha} S \sqrt{\frac{1}{n_1} + \frac{1}{n_2}} \right)$	1. $\bar{x} - \bar{y} \pm t_{v,\frac{\alpha}{2}} \sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}$ 2. $(\bar{x} - \bar{y} - t_{v,\alpha} \sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}, \infty)$ 3. $(-\infty, \bar{x} - \bar{y} + t_{v,\alpha} \sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}})$	

**If σ^2 is known, then use z's instead of t's (see the case for known variance for one sample for details) *Power*: Same as the one-sample case. For example, for the case (1) for equal variance assumption

Power=
$$P_{\mu_1 - \mu_2 \in H_a} \left(\left| \frac{(\bar{X} - \bar{Y} - \mu_0)}{S \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \right| > t_{n_1 + n_2 - 2, \frac{\alpha}{2}} \right)$$

Paired Samples: If the samples are paired, take the difference and use one-sample testing procedure. For example, H_0 : $\delta=0$ and H_a : $\delta\neq 0$ where δ represent the differences. Your n should be the number of pairs, S^2 should be the sample variance of the differences , and \bar{X} is the mean of the differences