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### 16.1 Random Sampling

Definition 16.1. A random variable $X$ which can take any real number value from a population.
Definition 16.2. A sample is a subset of a population A sampling procedure which produces inferences that consistently over or underestimate some characteristic of the population are said to be biased. A random sample is chosen so that the observations are independent and at random. A random sample of size $n$ is

$$
X_{1}, X_{2}, \ldots, X_{n}
$$

with numerical values $x_{1}, x_{2}, \ldots, x_{n}$. Random variables in a random sample are said to be independent and identically distributed (iid).

### 16.2 Some Important Statistics

An estimate of a population parameter is given the hat as an identifier. For example, the estimate of a population proportion $p$ is $\hat{p}$, read " p hat".

Definition 16.3. any function of the random variables from a random sample is a statistics Recall the following sample statistics of the location

Definition 16.4. The sample mean $\bar{X}$ is

$$
\bar{X}=\frac{1}{n} \sum_{i=1}^{n} X_{i} .
$$

Definition 16.5. The sample median is

$$
\tilde{x}= \begin{cases}x_{(n+1) / 2} & \text { if } n \text { is odd } \\ \frac{1}{2}\left(x_{n / 2}+x_{n / 2+1}\right) & \text { if } n \text { is even }\end{cases}
$$

Definition 16.6. The sample mode is the value of the sample which occurs most often.
Definition 16.7. The sample variance $S^{2}$ is

$$
S^{2}=\frac{1}{n-1} \sum_{i=1}^{n}\left(X_{i}-\bar{X}\right)^{2}
$$

Definition 16.8. The sample standard deviation is $S=\sqrt{S^{2}}$.
Definition 16.9. The sample range is $X_{\max }-X_{\min }$.

### 16.3 Sampling Distributions

Given a random sample of size $n$ from a population with mean $\mu$ and variance $\sigma^{2}$, what is the mean and variance of $\bar{X}$ ?

$$
\begin{gathered}
E(\bar{X})=E\left(\frac{1}{n}\left(X_{1}+\cdots+X_{n}\right)\right)=\frac{1}{n}\left(E\left(X_{1}\right)+\cdots+E\left(X_{n}\right)\right)=\frac{1}{n} n E\left(X_{1}\right)=\mu \\
\operatorname{Var}(\bar{X})=\operatorname{Var}\left(\frac{1}{n}\left(X_{1}+\cdots+X_{n}\right)\right)=\frac{1}{n^{2}}\left(\operatorname{Var}\left(X_{1}\right)+\cdots+\operatorname{Var}\left(X_{n}\right)\right)=\frac{1}{n^{2}} n \operatorname{Var}\left(X_{1}\right)=\frac{\sigma^{2}}{n}
\end{gathered}
$$

Definition 16.10. The probability distribution of a statistic is a sampling distribution.

### 16.3.1 Properties of Some Distributions

Theorem 16.11. If $X_{1}, \ldots, X_{n}$ are independent, and $X_{i} \sim N\left(\mu_{i}, \sigma_{i}^{2}\right)$, then

$$
\sum_{i=1}^{n} X_{i} \sim N\left(\sum \mu_{i}, \sum \sigma_{i}^{2}\right)
$$

Theorem 16.12. If $X_{1}, \ldots, X_{n}$ are independent, and $X_{i} \sim \operatorname{Gamma}\left(\alpha_{i}, \beta\right)$, then

$$
\sum_{i=1}^{n} X_{i} \sim \operatorname{Gamma}\left(\sum \alpha_{i}, \beta\right)
$$

Corollary 16.13. If $X_{1}, \ldots, X_{n} \sim \operatorname{Exp}(\beta)$ are iid, then

$$
\sum_{i=1}^{n} X_{i} \sim \operatorname{Gamma}(n, \beta)
$$

### 16.3.2 The Central Limit Theorem

Theorem 16.14. Central Limit Theorem: If $\bar{X}$ is the sample mean of a sample of size n, from a population with mean $\mu$ and variance $\sigma^{2}$, then

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

follows a standard normal distribution as $n \rightarrow \infty$.
Example 16.15. At a pencil company the machines are supposed to produce pencils of average length 20 cm . The pencils have a standard deviation $\sigma^{2}=.2 \mathrm{~cm}$. A random sample of 100 pencils is found to have a mean length of 20.13 cm . Is there reason to believe that the machines are not calibrated correctly?

Example 16.16. A punk band's songs are on average $1: 44$ with a standard deviation of 10 seconds. If you make a random mix of 40 of their songs, what is the probability it will last longer than 75 minutes?

### 16.3.3 Difference of Sample Means

Corollary 16.17. If independent random samples of sizes $n_{1}$ and $n_{2}$ are drawn from two populations with respective means $\mu_{1}, \mu_{2}$ and variances $\sigma_{1}^{2}, \sigma_{2}^{2}$, the difference of the sample means $\bar{X}_{1}-\bar{X}_{2}$ is approximately normal (moreso as $n_{i} \rightarrow \infty$ ) with

$$
\mu_{\bar{X}_{1}-\bar{X}_{2}}=\mu_{1}-\mu_{2}, \quad \sigma_{\bar{X}_{1}-\bar{X}_{2}}^{2}=\frac{\sigma_{1}^{2}}{n_{1}}+\frac{\sigma_{2}^{2}}{n_{2}}
$$

so

$$
Z=\frac{\left(\bar{X}_{1}-\bar{X}_{2}\right)-\left(\mu_{1}-\mu_{2}\right)}{\sqrt{\sigma_{1}^{2} / n_{1}+\sigma_{2}^{2} / n_{2}}}
$$

### 16.3.4 Sampling Distribution of $S^{2}$

Recall that

$$
S^{2}=\frac{1}{n-1} \sum_{i=1}^{n}(X-\bar{X})^{2}
$$

By Adding and subtracting $\bar{X}$, we can write

$$
\begin{aligned}
\sum_{i=1}^{n}\left(X_{i}-\mu\right)^{2} & =\sum_{i=1}^{n}\left[\left(X_{i}-\bar{X}\right)+(\bar{X}-\mu)\right]^{2} \\
& =\sum_{i=1}^{n}\left(X_{i}-\bar{X}\right)^{2}+\sum_{i=1}^{n}(\bar{X}-\mu)^{2}+2(\bar{X}-\mu) \sum_{i=1}^{n}\left(X_{i}-\bar{X}\right) \\
& =\sum_{i=1}^{n}\left(X_{i}-\bar{X}\right)^{2}+n(\bar{X}-\mu)^{2}
\end{aligned}
$$

We substitute $(n-1) S^{2}=\sum\left(X_{i}-\bar{X}\right)$ and divide both sides by $\sigma^{2}$.

$$
\frac{1}{\sigma^{2}} \sum_{i=1}^{n}\left(X_{i}-\mu\right)^{2}=\frac{(n-1) S^{2}}{\sigma^{2}}+\frac{(\bar{X}-\mu)^{2}}{\sigma^{2} / n}
$$

Left hand side follows a Chi-Squared distribution with $n$ degrees of freedom. The second term on the right is $Z^{2}$ which is Chi-Squared with 1 degree of freedom. It takes a little more theory than this course contains, but we get the following conclusion:

Theorem 16.18. Given $X_{1}, \ldots, X_{n}$ iid from a Normal population with variance $\sigma^{2}$,

$$
\chi^{2}=\frac{(n-1) S^{2}}{\sigma^{2}}
$$

follows a Chi-Squared distribution with $n-1$ degrees of freedom.
Example 16.19. Car batteries have a lifetime that is normally distributed, with a supposed standard deviation of 1 year. If 5 batteries are sampled with lifetimes of $1.9,2.4,3,3.5$ and 4.2 years, should we suspect that the standard deviation has changed?

## 16.4 t-Distribution

Often the population variance is unknown, so it is natural to use $S^{2}$ as an estimate. So we use

$$
T=\frac{\bar{X}-\mu}{S / \sqrt{n}}
$$

But for small samples, the value of $S$ may vary quite a bit from sample to sample. This statistic follows what is known as a $t$-distribution.

Theorem 16.20. If $X_{1}, \ldots, X_{n}$ are iid $N\left(\mu, \sigma^{2}\right)$, then

$$
T=\frac{\bar{X}-\mu}{S / \sqrt{n}}
$$

follows a t-distribution with $v=n-1$ degrees of freedom.
Even when the population is not normal, if it is approximately normal (bell shaped, symmetric) then the distribution will be approximately a $t$-distribution.

