Purpose and Nature of Sampling

- Nature: only incomplete view of a true picture available in real life
- **Purpose:** to describe a clearly defined population on the basis of sample information
- **Statistics:** Various functions of the data may be used to calculate measures, each of which is a reflection of some special feature of the population. These sample measure are called **statistics**

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Measure of Central Tendency (Location)

• Sample Mean: of a set of numbers (lower case in expressions) $x_1, x_2, ..., x_n$ is given by

$$\bar{x} = \frac{x_1 + \dots + x_n}{n} = \frac{\sum_{i=1}^n x_i}{n}$$

• Note:

sample mean is a "statistic" and is not a <u>true</u>
 mean but an estimate of mean

Measure of Dispersion

• Sample Variance of the set $x_1, x_2, ..., x_n$ of numerical observations, denoted by s^2 is given by

 $s^{2} = \frac{\sum_{i=1}^{n} (x_{i} - \overline{x})^{2}}{n-1}$ Degree of freedom=*n*-1
Why not *n*?

- Sample variance is a statistic used to estimate variance
- The **sample standard deviation**, denoted by *s*, is the positive square root of the sample variance

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Degree of Freedom (DoF)

- DoF: the number of independent pieces of information
- DoF=the number of values free to vary in calculation of a statistic
- Suppose there are n observations x_i , i=1,...,n. To calculate the sample mean, there are n independent pieces of information available for calculation of the statistic:

$$\bar{x} = \frac{x_1 + \dots + x_n}{n} = \frac{\sum_{i=1}^n x_i}{n} \quad \text{DoF}=n$$

DoF of $x_i - \overline{x}$

- x_i —average is called *residual* or *centered-measure* and $\Sigma(x_i$ —average)=0
- Let n=3; $x_1=1$, $x_2=2$, $x_3=3$; average=(1+2+3)/3=2
- That is, if we know x_1 -average(=-1) and x_2 -average(=0), then x_3 -average must be known(= 1)
 - \rightarrow If you know two of x_i -average, you know the third. The number of values free to vary is 2!
- How many independent pieces of information do we have about (x_i -average)? Answer: 2
- For x_i —average, i=1,...,n, there are only n-1 pieces of independent information that are free to vary because the average has taken one piece of information and the nth value is subject to zero sum.

Taking average of $(x_i$ —average)²

- Again, let n=3 and $x_1=1, x_2=2, x_3=3$
- x_1 -average=-1; x_2 -average=0, and x_3 -average=1
- What is the good estimate of $E(x-mean)^2$? $\Sigma(x_i-average)^2/3$ or $\Sigma(x_i-average)^2/2$?
- $\Sigma(x_i$ -average)²/3=2/3 or $\Sigma(x_i$ -average)²/2=1 more plausible? $\Sigma(x_i$ -average)²/2!

More on the DoF of $(x_i$ -average)²

- Average is used to estimate the mean
- What if "median" is used to estimate of mean?
- Again, let n=3 and $x_1=1$, $x_2=2$, $x_3=3$:median= x_2
- DoF of $(x_i$ -median)²?
- Since x_2 has been used to estimate the mean, only x_1 -median=-1 and x_3 -median=1 are left to estimate the distance from the center!
- The estimate of E(x-mean)²? $\Sigma(x_i$ -median)²/2

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Sample Covariance

- There must be correlations among measurements. For example, the higher blood pressure level often comes with the higher cholesterol level.
- The co-variation of two measurements is measured by sample covariance: (the trend that one is larger then the other is larger or one is smaller then the other is smaller)

$$Cov(x,y) = s_{xy} = \frac{\sum_{i=1}^{n} (x_i - \overline{x})(y_i - \overline{y}_i)}{n-1}$$

• $X \uparrow$, $Y \uparrow \Rightarrow \text{Cov} > 0$: positively correlated

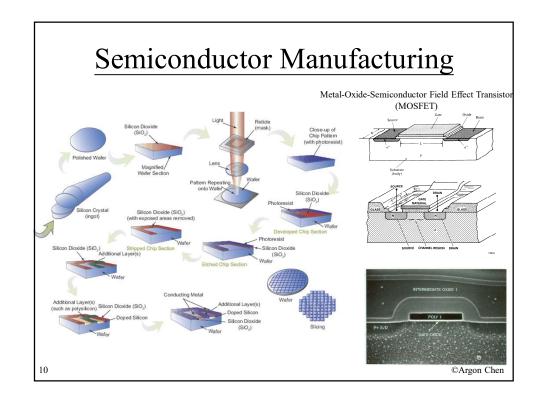
• $X \uparrow$, $Y \downarrow \Rightarrow$ Cov<0: negatively correlated

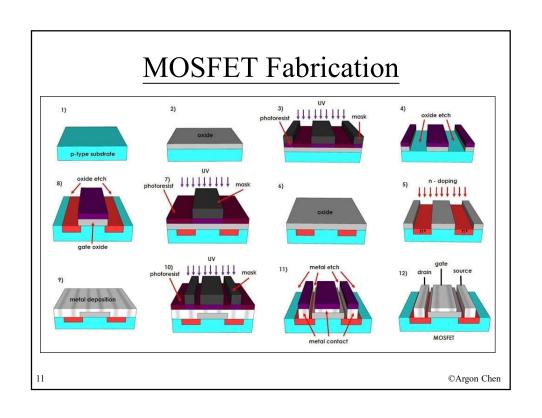
Sample Correlation Coefficient

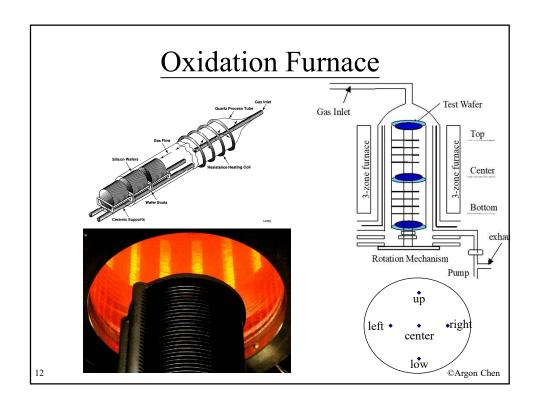
• Correlation coefficient is defined a σ (-1 $\leq \rho_{xy} \leq 1$):

$$\rho_{xy} = \frac{S_{xy}}{S_x S_y} = \frac{\sum_{i=1}^{n} (x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \overline{x})^2} \sqrt{\sum_{i=1}^{n} (y_i - \overline{y})^2}}$$

- $-1 \le \rho_{xy} < 0$: negatively correlated; $0 < \rho_{xy} \le 1$: positively correlated
- ρ_{xy} =0: no correlation; ρ_{xy} =±1: perfect correlation
 Let x'=(x-x-bar)/s_x and y'=(y-y-bar)/s_y
- Let $x'=(x-x-bar)/s_x$ and $y'=(y-y-bar)/s_y$ $\rightarrow Cov(x', y')=\rho_{xy}$

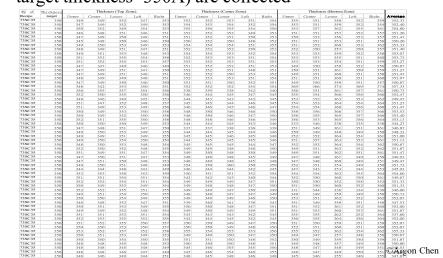








• Example: 85 readings of SiO₂ average thickness (with target thickness=350Å) are collected



Frequency Distribution

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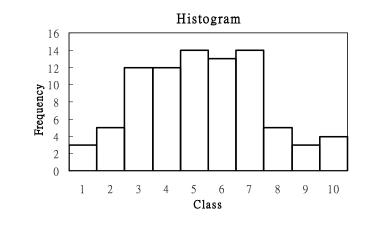
• Example: frequency distribution is calculated for 85 readings of SiO₂ average

	Class Interval	Frequency=fi	Relative Freq.= fi/Tota
1	~346.5	3	0.0353
2	346.6~347.5	5	0.0588
3	347.6~348.5	12	0.1412
4	348.6~349.5	12	0.1412
5	349.6~350.5	14	0.1647
6	350.6~351.5	13	0.1529
7	351.6~352.5	14	0.1647
8	352.6~353.5	5	0.0588
9	353.6~354.5	3	0.0353
10	354.6~	4	0.0471
	Total	85	

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Histograms

• Example: 350Å SiO₂ thickness data



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The Box Plot

The Five-Number Summary:

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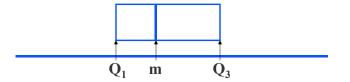
 $Min ---- Q_1 ---- Median ---- Q_3 ---- Max$

- •Divides the data into 4 sets containing an equal number of measurements.
- •A quick summary of the data distribution.
- •Use to form a **box plot** to describe the **shape** of the distribution and to detect **outliers**.

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Constructing a Box Plot

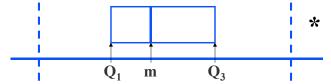
- ✓ Calculate Q_1 , the median, Q_3 and $IQR(=Q_3-Q_1)$.
- ✓Draw a horizontal line to represent the scale of measurement.
- ✓ Draw a box using Q_1 , the median m, Q_3 .



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Constructing a Box Plot

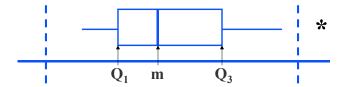
- ✓ Isolate outliers by calculating
 - ✓ Lower fence: Q_1 -1.5 IQR (or Q_1 -3(m- Q_1))
 - ✓Upper fence: $Q_3+1.5$ IQR (or $Q_3+3(Q_3-m)$)
- ✓ Measurements beyond the upper or lower fence are outliers and are marked with *.



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Constructing a Box Plot

✓Draw "whiskers" connecting the largest and smallest measurements that are NOT outliers to the box.

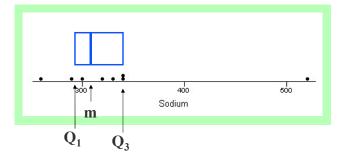


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Example

Amt of sodium in 8 brands of cheese:

260 290 300 320 330 340 340 520
$$\begin{matrix} \uparrow & & \uparrow \\ Q_1 = 292.5 & m = 325 \end{matrix} \qquad Q_3 = 340$$



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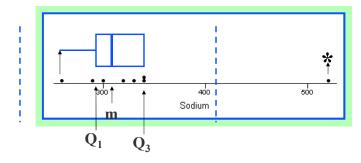
Example

$$IQR = 340-292.5 = 47.5$$

Lower fence =
$$292.5 - 1.5(47.5) = 221.25$$

Upper fence =
$$340 + 1.5(47.5) = 411.25$$

Outlier: x = 520



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Interpreting Box Plots

- ✓ Median line in center of box and whiskers of equal length—symmetric distribution
- ✓ Median line left of center and long right whisker—skewed right
- ✓ Median line right of center and long left whisker—skewed left



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Statistic

• A **statistic** is any function of the random variables constituting one or more samples, provided that the function does not depend on any unknown parameter values

Examples: sample mean, sample variance

- Sample data:
 - A sample = A set of sample observations $[x_1, x_2,...,x_i,...,x_n]$ and sample size=n
 - A sample **observation** = A piece of data vector $\mathbf{x}_i = [x_{i1}, x_{i2}, ..., x_{ii}, ..., x_{im}]$

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What does Statistics do?

- Point estimate:
 - To estimate the parameters of the probability models with sample data
 - To evaluate how good the estimators are
- Hypothesis test:
 - To check/test whether the model parameter(s) has changed.
 - To evaluate how good the tests are (two types errors?)
- Mathematical modeling of sampling statistics for performance evaluation:
 - Modeling the "point estimate" and "hypothesis testing" for their performance evaluation

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Point Estimate

• A **point estimate** of a parameter θ is a single number that can be regarded as the most plausible value of θ . A point estimate is obtained by selecting **a suitable statistic** and computing its value from the given sample data. The selected statistic is called the **point estimator** of θ

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A Point Estimate of Mean: Sample Mean (Average)

• A statistic of point estimate, say sample mean, is a random variable. For example

1st sampling:
$$\overline{x}_{1st} = \frac{\sum_{i=1}^{n} x_{1st,i}}{n}$$
 2nd: $\overline{x}_{2nd} = \frac{\sum_{j=1}^{n} x_{2nd,j}}{n}$ $\Rightarrow \overline{x}_{1st} \neq \overline{x}_{2nd}$

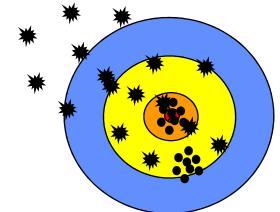
• Modeling sample mean by random variables: Assuming iid $X_1, X_2, ..., X_n$ $\sum_{i=1}^{n} X_i$

 $\overline{X} = \frac{\sum_{i=1}^{n} x_i^{n}}{n}$

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Performance of Point Estimate and Bull's Eye Aiming

- Parameter to be estimated: bull's eye Center
- Two estimators: 57 Rifle and M16 Rifle



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Unbiased Point Estimate

- A point estimator is itself a random variable with a distribution \Rightarrow Probability model of $\hat{\theta}$
- A point estimator $\hat{\theta}$ is said to be an **unbiased estimator** of θ if $E(\hat{\theta}) = \theta$ for every possible value of θ . If not unbiased, the difference $E(\hat{\theta}) \theta$ is called the **bias** of θ
- Example: Is sample mean \overline{X} the unbiased estimate of μ ?

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Is sample mean an Unbiased Estimator of mean?

We model our observations $x_1, x_2, ..., x_n$ as independent and identically distributed (iid) $X_1, X_2, ..., X_n$ with μ and σ and sample mean can be modeled as a random variable:

$$\overline{X} = \frac{\sum_{i=1}^{n} X_i}{n}$$

Recall Mean and Variance of sample mean:

$$E(\overline{X}) = \mu \text{ and } V(\overline{X}) = \frac{\sigma^2}{n}$$

$$\overline{X} \text{ with } n_1$$

$$\overline{X} \text{ with } n_1$$

$$\overline{X} \text{ with } n_1$$

Is Sample Variance an Unbiased Estimator of Variance? $E(S^2) = \sigma^2$?

Assuming iid $X_1, X_2, ..., X_n$ with mean= μ and

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

$$=\frac{1}{n-1}\left\{\sum_{i=1}^{n}E[X_{i}^{2}]-E\left[2n\frac{\sum_{i=1}^{n}X_{i}}{n}\bar{X}-\sum_{i=1}^{n}\bar{X}^{2}\right]\right\} = \frac{1}{n-1}\left\{nE[X_{i}^{2}]-E\left[2n\bar{X}^{2}-n\bar{X}^{2}\right]\right\}$$

$$=\frac{1}{n-1}\left\{n[\sigma^{2}+\mu^{2}]-nE\left[\bar{X}^{2}\right]\right\} = \frac{1}{n-1}\left\{n\sigma^{2}+n\mu^{2}-n\left[\frac{\sigma^{2}}{n}+\mu^{2}\right]\right\}$$

$$=\frac{1}{n-1}[(n-1)\sigma^{2}+n\mu^{2}-n\mu^{2}] = \sigma^{2}$$
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Example: Point Estimate of Binomial Distribution Parameter

• Let *x* be the number of heads observed from *n* tosses of coin. What would be the most plausible estimate of p for the Binomial distribution model?

$$\hat{p} = \frac{x}{n}$$

 To evaluate the performance of \(\hat{p}\), we model x to be a random variable X following a \((n, p)\) Binomial distribution. Is \(\hat{p}\) an unbiased estimate of \(p?\)

$$E(\hat{p}) = E(\frac{X}{n}) = \frac{E(X)}{n} = \frac{np}{n} = p$$

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Standard Error

- **Remember:** an estimator is itself a random variable with a distribution
- Standard Error of an estimator $\hat{\theta}$ is its S.D.

$$\sigma_{\hat{\theta}} = \sqrt{V(\hat{\theta})}$$

- Estimated Standard Error is the estimate of $\sigma_{\hat{\theta}}$ often denoted by $\hat{\sigma}_{\hat{\theta}}$ or $s_{\hat{\theta}}$
- Example: standard error of \bar{X} : $\sqrt{V(\bar{X})} = \sqrt{\frac{\sigma^2}{n}} = \frac{\sigma}{\sqrt{n}}$
- Example: Binomial experiment

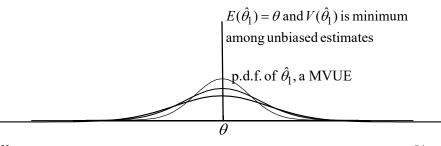
$$\sigma_{\hat{p}} = \sqrt{V(\hat{p} = X/n)} = \sqrt{\frac{V(X)}{n^2}} = \sqrt{\frac{np(1-p)}{n^2}} = \sqrt{\frac{p(1-p)}{n}}$$

$$\hat{\sigma}_{\hat{p}} = s_{\hat{p}} = \sqrt{\frac{\hat{p}(1-\hat{p})}{n}} = \sqrt{\frac{(x/n)(1-x/n)}{n}} = \sqrt{\frac{x(n-x)}{n}}$$

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Performance of Point Estimate

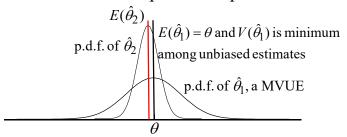
- How good is an estimate?
 - On target? Unbiased?
 - Very certain? Minimum variance?
- Minimum Variance Unbiased Estimator (MVUE)
 - Among all unbiased estimators, the one with the minimum variance
- Example: sample mean is a MVUE for normally distributed populations



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Preferable Point Estimate

• Is a MVUE the most preferable point estimate?



- There are different point estimates for the same model parameter
- Different models requires different estimates
- Different point estimates serve different needs

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Example: Different Point Estimates of

- Point estimates: \overline{X} , \widetilde{X} , \overline{X}_e , $\overline{X}_{tr(m)}$
- \overline{X} is the arithmetic average called sample mean
- \widetilde{X} is the median that is the center observation of the entire sample
- \overline{X}_e is the extreme mean (an average of two extreme observations)
- $\bar{X}_{tr(m)}$ is a trimmed mean that trims m\% of observations from each end of the sample

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Different Mean Point Estimates for Different Distributions

- Point estimates: $\overline{X}, \widetilde{X}, \overline{X}_e, \overline{X}_{tr(m)}$
- \overline{X} is the best for Normal distribution
- How about an estimator for Cauchy distribution: $f(x) = \frac{1}{\pi[1 + (x \mu)^2]}$

$$f(x) = \frac{1}{\pi[1 + (x - \mu)^2]}$$

Cauchy is bell-shaped with heavier tails

- \overline{X} , \overline{X}_{ρ} are terrible since they are sensitive to outlying observations; \widetilde{X} is quite good
- For Uniform distribution (no tails), \overline{X}_e is the best
- $\overline{X}_{tr(m)}$ is not the best in all three situations, but it works reasonably well in all three!

Methods of Point Estimate

- Most often used methods:
 - moment estimator
 - maximum likelihood estimator (MLE)
- Where do you learn all these? Theories of Statistical Inference
- BUT don't worry! Most of reasonable estimators are from your intuitions
- Example: Binomial experiment

$$\hat{p} = X / n$$

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Moment Estimator

- Moments of distribution models:
 - 1st moment=E(X), 2nd moment= $E(X^2)$,... m^{th} moment= $E(X^m)$
- Let $X_1, X_2, ..., X_n$ are *independent* random sample observations from a population following an *identical* probability model with p.m.f. or p.d.f. $f(X=x; \theta_1, \theta_2, ..., \theta_m)$. Then, the moment estimator of $\theta_1, \theta_2, ..., \theta_m$ are obtained by equating the first m sample moments to the corresponding first m model moments and solve for the estimators

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Example of Moment Estimator: Gamma Distribution

• To estimate the α and β of the Gamma distribution, equating the 1st and 2nd sample and model moments:

sample mean=
$$\alpha\beta = E(X)$$

sample variance= $\alpha\beta^2 = E(X^2) - E^2(X)$
 $\Rightarrow \hat{\beta} = (\text{sample variance})/(\text{sample mean})$
 $= S^2/\bar{X}$
 $\hat{\alpha} = (\text{sample mean})^2/(\text{sample variance})$
 $= \bar{X}^2/S^2$

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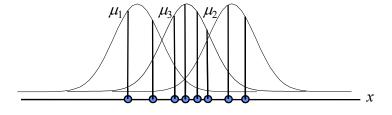
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Maximum Likelihood Estimate (MLE)

- The better the estimate of the parameter of a distribution model, the higher the value of the likelihood function substituted by the observed sample value.
- Let $X_1, X_2, ..., X_n$ are *independent* random sample observations from a population following an *identical* probability model with likelihood function P(X) (discrete) or f(X). Then, the joint joint likelihood for $X_1 = x_1, X_2 = x_2, ..., X_n = x_n$ is:

$$P(X_1=x_1,X_2=x_2,\dots,X_n=x_n)=P(X=x_1)P(X=x_2)\cdots P(X=x_n) \text{ or } f(X_1=x_1,X_2=x_2,\dots,X_n=x_n)=f(X=x_1)f(X=x_2)\cdots f(X=x_n)$$

• MLE is the estimate of a parameter that maximizes the joint likelihood function:



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MLE for p of Binomial Distribution

- Let *X* follow a (*n*, *p*) binomial distribution and *p* is unknown.
 - we observe the number of successes x from n trials.
 - What is the MLE of *p*?

$$P(X=x)=C_{x}^{n}p^{x}(1-p)^{n-x}$$

• To maximize P(x) w.r.t. p, take derivative of P(x) w.r.t. p and set it to zero:

$$x\hat{p}^{x-1}(1-\hat{p})-(n-x)\hat{p}^{x}(1-\hat{p})^{n-x-1}=0$$

$$\Rightarrow x(1-\hat{p})=(n-x)\hat{p}$$

$$\Rightarrow \hat{p}=x/n$$

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MLE for μ of Normal Distribution

- Let X follow a (μ, σ^2) normal distribution and μ is unknown.
 - we take a sample of *n* observed values $x_1, x_2, ..., x_n$.
 - the joint likelihood function

$$f(x_1,...,x_n \mid \mu) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi}\sigma} \exp\left[\frac{-(x_i - \mu)^2}{2\sigma^2}\right] = \left(\frac{1}{2\pi}\right)^{n/2} \frac{1}{\sigma^n} \exp\left[\frac{-\sum (x_i - \mu)^2}{2\sigma^2}\right]$$

• Maximizing $f(x_1,...,x_n)$ is equivalent to maximizing $\log f(x_1,...,x_n)$. Take derivative of $\log f(x_1,...,x_n)$ and set it to zero:

$$\frac{d}{d\mu}\log f(x_1,\ldots,x_n\mid\mu) = \frac{\sum_{i=1}^n (x_i - \hat{\mu})}{\sigma^2} = 0 \Rightarrow \hat{\mu} = \frac{\sum_{i=1}^n x_i}{n}$$

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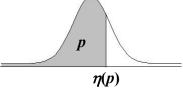
Which Probability Model Fits Best?

- Sample observations can be used to estimate parameters of any given probability model.
 - MLE can be used to estimate p of Geometric distribution as well as λ of Poisson distribution
- Which probability distribution model fits best to the sample observed data?
 - Goodness-of-Fit Tests
 - Q-Q (P-P) plot: an effective visualized goodness of fit

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Percentile and Sample Percentile

• Cumulative probability $F(\eta(p))=p$ $\eta(p)$ is called the (100p)th percentile (Quantile) $= F^{-1}(p)$



- Sort the *n* sample observations from the smallest to the largest and the *sample cumulative probability* of the *i*th smallest observation=100(i-0.5)/n
- The *i*th smallest observation = [100(i-0.5)/n]th sample percentile is an estimate of [100(i-0.5)/n]th percentile

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Probability Plot (Q-Q Plot)

Step 1: Sort the data from the smallest to the largest

Step 2: Calculate the sample cumulative probabilities = 100(i-0.5)/n

Step 3: Assume a probability distribution model (F) and estimate probability distribution parameters

Step 4: Calculate the percentiles of the sample cumulative probabilities = $F^{-1}((i-0.5)/n)$

Step 5: Plot ([100(i-.5)/n]th percentile, *i*th smallest of the distribution sample observation

on the X-Y plane. If the observations follow the assumed distribution, the points form roughly a 45° line

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Example: 350Å SiO2 Assumed to Follow Normal Distribution

Step 1: Sort the thickness data from 345.6 to 355.6 (X_i)

Step 2: Calculate the sample cumulative probabilities

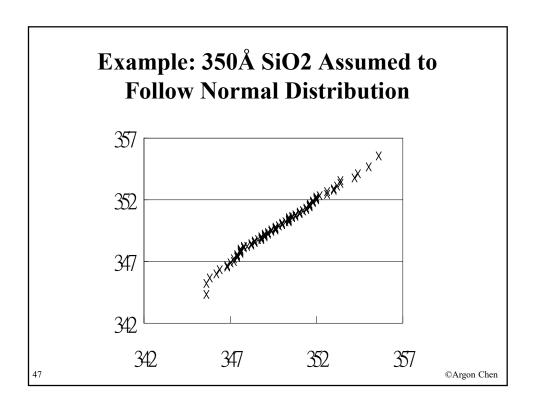
$$\hat{p}_i = (i - 0.5)/n$$

Step 3: Assume a **normal** probability distribution and estimated mean=349.91 and sample s.d.=2.235

Step 4: Calculate the *percentiles* of the sample cumulative probabilities $N^{-1}(\hat{p}_i;349.91,2.235)$

Step 5: Plot $[N^{-1}(\hat{p}_i;349.91, 2.235), X_i]$

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Normal Probability Plot

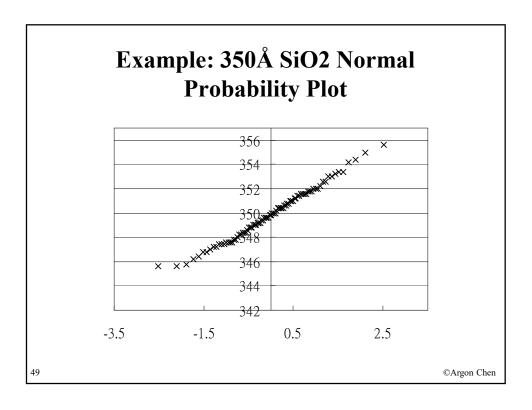
- $X \sim N(\mu, \sigma)$
- $Z=(X-\mu)/\sigma \sim N(0, 1)$

([100(i-.5)/n]th z percentile, ith smallest obs. x)

 \Rightarrow form a line: $X = \sigma Z + \mu$

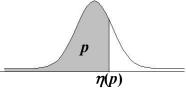
is a line with slop σ and intercept μ

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Percentile and Sample Percentile

• Cumulative probability $F(\eta(p))=p$ $\eta(p)$ is called the (100p)th percentile (Quantile) $= F^{-1}(p)$



- Sort the n sample observations from the smallest to the largest and the *sample cumulative probability* of the ith smallest observation=100(i-0.5)/n
- The *i*th smallest observation = [100(i-0.5)/n]th sample percentile is an estimate of [100(i-0.5)/n]th percentile

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Probability Plot (Q-Q Plot)

Step 1: Sort the data from the smallest to the largest

Step 2: Calculate the sample cumulative probabilities =100(i-0.5)/n

Step 3: Assume a probability distribution model (*F*) and estimate probability distribution parameters

Step 4: Calculate the percentiles of the sample cumulative probabilities = $F^{-1}(100(i-0.5)/n)$

Step 5: Plot

([100(i-.5)/n]th percentile, *i*th smallest of the distribution sample observation

on the X-Y plane. If the observations follow the assumed distribution, the points form roughly a 45° line

Example: 350Å SiO2 Assumed to Follow Normal Distribution

Step 1: Sort the thickness data from 345.6 to 355.6 (X_i)

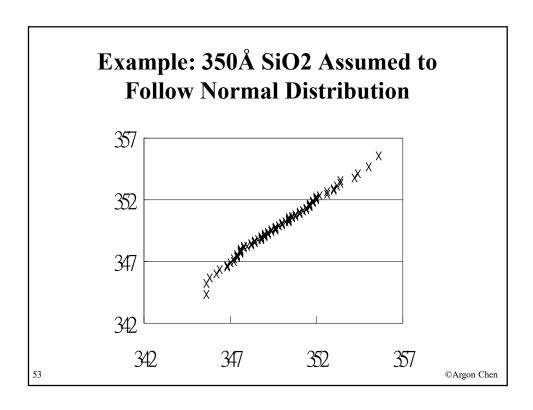
Step 2: Calculate the sample cumulative probabilities $\binom{p_i}{i}$

Step 3: Assume a **normal** probability distribution and estimated mean=349.91 and sample s.d.=2.235

Step 4: Calculate the *percentiles* of the sample cumulative probabilities $N^{-1}(\hat{p}_i;349.91,2.235)$

Step 5: Plot $[N^{-1}(\hat{p}_i;349.91,2.235),X_i]$

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Normal Probability Plot

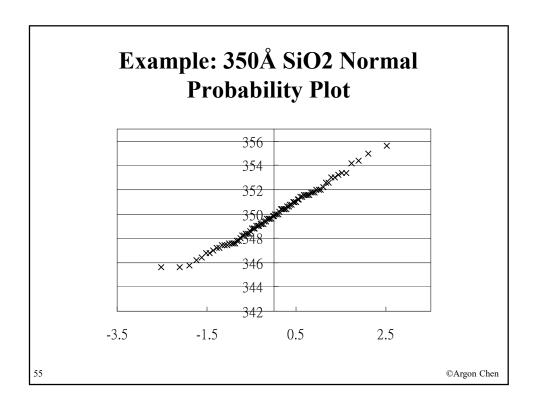
- $X \sim N(\mu, \sigma)$
- $Z=(X-\mu)/\sigma \sim N(0, 1)$

([100(i-.5)/n]th z percentile, ith smallest obs. x)

 \Rightarrow form a line: $X = \sigma Z + \mu$

is a line with slop σ and intercept μ

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Probability Interval of Normal Sample Mean

- Actual sample observations $x_1, x_2, ..., x_n$ from random sample $X_1, X_2, ..., X_n$ following $N(\mu, \sigma)$. Then, \overline{X} follows $N(\mu, \sigma/\sqrt{n})$
- Standardization:

Standardization.
$$Z = \frac{\overline{X} - \mu}{\sigma / \sqrt{n}}$$

$$\Rightarrow P(-1.96 < \frac{\overline{X} - \mu}{\sigma / \sqrt{n}} < 1.96) = .95$$

Confidence Interval (C.I.) of Normal Mean

$$P(-1.96 < \frac{\overline{X} - \mu}{\sigma / \sqrt{n}} < 1.96) = .95$$

$$\Rightarrow P(\overline{X} - 1.96 \frac{\sigma}{\sqrt{n}} < \mu < \overline{X} + 1.96 \frac{\sigma}{\sqrt{n}}) = .95$$

- What does this mean?
- Remember that the sample mean is an estimator of the mean and is itself a *random variable* with uncertainty.
- With confidence interval, you are about 95% sure that the true mean will be in the range of

$$(\bar{x}-1.96\frac{\sigma}{\sqrt{n}}, \bar{x}+1.96\frac{\sigma}{\sqrt{n}})$$

• What if I would like to be 99% sure?

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$100(1-\alpha)\%$ Confidence Interval

• a $100(1-\alpha)\%$ confidence interval for the mean μ of a normal population when the value of σ is known is given by

$$(\overline{x}+z_{\alpha/2}\frac{\sigma}{\sqrt{n}},\overline{x}+z_{1-\frac{\alpha}{2}}\frac{\sigma}{\sqrt{n}})$$

- Example: 99%, $Z_{\alpha/2}$ =?
- In reality, what is the difficulty? σ is usually unknown!

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Large-sample Confidence Interval

• If sample size *n* is sufficiently large

$$Z \cong \frac{\overline{X} - \mu}{S/\sqrt{n}}$$
 (S: sample S.D.)

• Z is then approximately N(0, 1)

$$(\overline{x} + z_{\alpha/2} \frac{s}{\sqrt{n}}, \overline{x} + z_{1-\frac{\alpha}{2}} \frac{s}{\sqrt{n}})$$

is a **large-sample confidence interval** for μ with confidence level approximately $100(1-\alpha)\%$

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Example: 350Å SiO₂ Thickness

- Sample size *n*=85
- Sample mean=349.91 and sample s.d.=2.235
- 95% confidence interval of the thickness mean?
- $95\%=100(1-0.05)\% \Rightarrow \alpha=0.05$
- Thickness mean 95% confidence interval:

$$(349.91 + z_{0.025} \frac{2.235}{\sqrt{85}}, 349.91 + z_{0.975} \frac{2.235}{\sqrt{85}}) =$$

$$(349.91 - 1.96 \cdot 0.2424, 349.91 + 1.96 \cdot 0.2424) =$$

$$(349.435, 350.385)$$

• What if *n* is considered small or the sample s.d. is not considered reliable?

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t statistics: C.I. Interval for Unknown σ

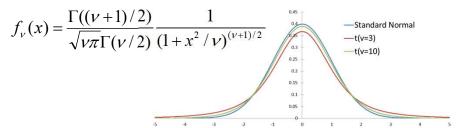
• \overline{X} is the average of a random sample of size n from a normal distribution with mean μ , Then, the random variable

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

follows a probability distribution called a t distribution with n-1 degrees of freedom

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t-Distribution



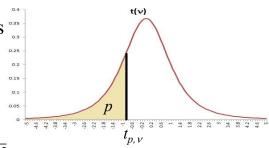
- Bell-shaped & centered at 0
- $v \uparrow$ distribution spread \downarrow
- The distribution spreads wider than the normal distribution (heavier tails)
- $v \rightarrow \infty$ $t_v \rightarrow \text{standard normal } N(0, 1)$

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Confidence Interval using t-Statistic

• Let $t_{p, \nu}$ denotes os



$$\Rightarrow P(t_{\alpha/2,\nu} < \frac{\overline{X} - \mu}{S/\sqrt{n}} < t_{1-\alpha/2,\nu}) = 1 - \alpha$$

Then a $100(1-\alpha)\%$ confidence interval for μ

is:
$$(\overline{x} + t_{\alpha/2,n-1} \frac{s}{\sqrt{n}}, \overline{x} + t_{1-\alpha/2,n-1} \frac{s}{\sqrt{n}})$$

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Example: 350Å SiO₂ Thickness

- Sample size *n*=85
- Sample mean=349.91 and sample s.d.=2.235
- 95% confidence interval of the thickness mean?
- $95\%=100(1-0.05)\% \Rightarrow \alpha=0.05$
- Thickness mean 95% confidence interval using Z:

$$(349.91 + z_{0.025} \frac{2.235}{\sqrt{85}}, 349.91 + z_{0.975} \frac{2.235}{\sqrt{85}}) =$$

$$(349.91 - 1.96 \cdot 0.2424, 349.91 + 1.96 \cdot 0.2424) = (349.435, 350.385)$$

• Thickness mean 95% confidence interval using t:

$$(349.91 + t_{0.025,84} \frac{2.235}{\sqrt{85}}, 349.91 + t_{0.975,84} \frac{2.235}{\sqrt{85}}) =$$

 $(349.91 - 1.9886 \cdot 0.2424, 349.91 + 1.9886 \cdot 0.2424) = (349.428, 350.392)$

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Tests of Hypotheses

- The motivation: to reject an initial claim and to statistically prove that a scientific effort really makes differences
- Example: Medical experiment
- Initial claim

Null hypothesis H_{θ}

• Claim otherwise

Alternative hypothesis H_1

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Errors in Hypothesis Tests

- Type I error: rejecting the null hypothesis H_{θ} when it is true
- Type II error: not rejecting H_{θ} when H_{θ} is false
- Probability of type I error (α)
- Probability of type II error (β)

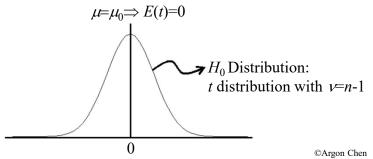
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Test Statistic and Distribution under H_0 (Example: Testing Normal Mean)

$$H_0: \mu = \mu_0$$

Test statistic: t -test = $\frac{\overline{x} - \mu_0}{s / \sqrt{n}}$

Distribution under H_0 : *t*-Distribution with $\nu=n-1$

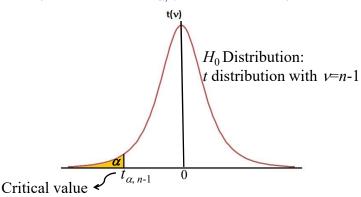


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Criteria to Reject H_0 : Reject Region

 $H_0: \mu = \mu_0$ Test statistic: t-test = $\frac{\overline{x} - \mu_0}{s / \sqrt{n}}$ Distribution under H_0 : t-distribution

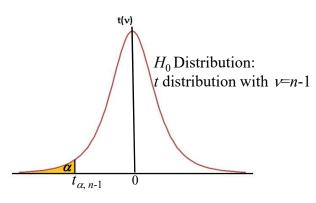
Reject H_0 when t-test $\leq t_{\alpha, n-1} \Rightarrow H_1$: $\mu < \mu_0$



Type I Error Probability of Rejecting the Null Hypothesis

Reject H_0 when t-test $\leq t_{1-\alpha, n-1} \Rightarrow H_1$: $\mu < \mu_0$ Probability ($\mu = \mu_0$ but you reject H_0 and accept H_1)

 $=\alpha$



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Hypothesis Test Procedure

- 1 Choose a test statistic: a function of the sample data with a known probability distribution model under H_{θ}
- 2 Choose the Type I error probability (significance level) α to find the reject region and critical value based on the distribution of the test statistic under H_0
- 3 The H_{θ} will then be rejected if and only if the observed or computed test statistic values falls in the reject region

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Test about Population Mean

*H*₀:
$$\mu = \mu_0$$

Test statistic: $t = \frac{\overline{x} - \mu_0}{s / \sqrt{n}}$

Reject Region	Reject Region	
$t \ge t_{1-\alpha,n-1}$ or	ne-tailed	
$t \le t_{\alpha, n-1}$	test	
$t \ge t_{1-\alpha/2}, n-1$ ft	wo-tailed	
or $t \le t_{\alpha/2, n-1}$	test ©Argon Ch	
	<u> </u>	

Another View of Reject Region

Let H_1 be $\mu \neq \mu_0$ then reject H_0 when $t \leq t_{\frac{\alpha}{2},n-1}$ or $t \geq t_{1-\frac{\alpha}{2},n-1}$

$$\Rightarrow \frac{\overline{x} - \mu_0}{s / \sqrt{n}} \le t_{\alpha/2, n-1} \text{ or } \frac{\overline{x} - \mu_0}{s / \sqrt{n}} \ge t_{1 - \alpha/2, n-1}$$

$$\mu_0 \le \overline{x} - t_{1-\frac{\alpha}{2}, n-1} \frac{s}{\sqrt{n}}$$
 or $\mu_0 \ge \overline{x} - t_{\frac{\alpha}{2}, n-1} \frac{s}{\sqrt{n}}$

$$\mu_0 \le \overline{x} + t_{\frac{\alpha}{2}, n-1} \frac{s}{\sqrt{n}}$$
 or $\mu_0 \ge \overline{x} + t_{1-\frac{\alpha}{2}, n-1} \frac{s}{\sqrt{n}}$

 \Rightarrow when μ_0 is outside the 100(1- α)% confidence interval of mean estimated by \bar{x} :

$$(\overline{x}+t_{\alpha/2,n-1}\frac{s}{\sqrt{n}},\overline{x}+t_{1-\alpha/2,n-1}\frac{s}{\sqrt{n}})$$

we reject it and accept $\mu \neq \mu_0$ with Type I error probability = α

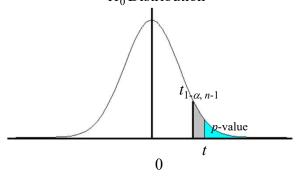
p-value in Hypothesis Tests

- Another way of presenting the test result
- The *p*-value is the smallest level of significance at which H_0 would be rejected when a specified test procedure is used on a given data set. Once the *p*-value has been determined, the conclusion at any particular level α results from comparing the *p*-value to α :

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p-value in one-tailed Hypothesis Tests

• *p*-value for one-tailed test: (example: $H_1: \mu > \mu_0$) H_0 Distribution

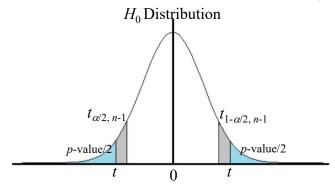


a. $t > t_{1-\alpha,n-1} \Rightarrow P(t\text{-test} \ge t) = p\text{-value} \le \alpha \Rightarrow \text{Reject } H_0$ b. $p\text{-value} > \alpha \Rightarrow \text{Accept } H_0$

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p-value in two-tailed Hypothesis Tests

• *p*-value for two-tailed test: (example: H_1 : $\mu \neq \mu_0$)



a. $t \ge t_{1-\alpha/2,n-1} \Rightarrow P(t\text{-test} \ge t) \le \alpha/2 \Rightarrow 2P(t\text{-test} \ge t) = p\text{-value} \le \alpha$ or $t \le t_{\alpha/2,n-1} \Rightarrow P(t\text{-test} \le t) \le \alpha/2 \Rightarrow 2P(t\text{-test} \le t) = p\text{-value} \le \alpha$ $\Rightarrow \text{Reject } H_0$

 75 b. *p*-value > α ⇒Accept H_0

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Testing 350Å SiO₂ Thickness Mean

- Null hypothesis: Thickness Mean= Target H_0 : μ =350
- Sample size *n*=85
- $\bar{x} = 349.91$ and $s = 2.235 \Rightarrow H_1$: $\mu < 350$

• Test statistic=
$$\frac{349.91-350}{2.235/\sqrt{85}} = -0.37$$

- Type I error prob.= $0.05 \Rightarrow \alpha = 0.05$
- Reject μ =350 if *t*-test \leq t_{0.05,84}=-1.663 but -0.37>-1.663 \Rightarrow μ =350 can't be rejected
- p-value=0.356157 > 0.05 \Rightarrow do not reject H_0

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Testing A Pair of Means

- Testing problem: are the means the same?
 - That is: H_0 : $\mu_x = \mu_y \implies \mu_x \mu_y = 0$
- Choice of the test statistic:
 - Compare two sample means \bar{X} with sample size m and \bar{Y} with sample size n: $\bar{X} \bar{Y}$
 - Question: what would be the distribution of $\bar{X} \bar{Y}$?
 - Assuming X and Y are normally distributed with the same mean and a common variance σ^2 , then $\overline{X} \overline{Y}$ follows a normal distribution with mean= $\mu_x \mu_y$ and variance= $\sigma^2/_m + \sigma^2/_n = \sigma^2(\frac{1}{m} + \frac{1}{n})$
- S.D. of $\bar{X} \bar{Y} : \sigma \sqrt{\frac{1}{m} + \frac{1}{n}}$, how to estimate σ ?

Pooled Estimator of σ^2

• The pooled estimator of the common variance σ^2 , denoted by S_p^2 , is the weighted average of the individual sample variances weighted by the degree of freedom, i.e., m-1 and n-1:

$$S_p^2 = \frac{m-1}{m-1+n-1} S_x^2 + \frac{n-1}{m+n-2} S_y^2$$

• Estimate of $\bar{X} - \bar{Y}$ S.D.: $S_p \sqrt{\frac{1}{m} + \frac{1}{n}}$

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Testing Mean Difference

 H_0 : $\mu_x - \mu_y = \Delta$ ($\Delta = 0$ for testing the same means)

Test statistic:
$$t = \frac{(\bar{x} - \bar{y}) - \Delta}{s_p \sqrt{\frac{1}{m} + \frac{1}{n}}}$$

$$\begin{array}{ll} H_1 & \text{Reject Region} \\ \hline \mu_x - \mu_y > \Delta & t \geq t_{1-\alpha,m+n-2} \text{ one-tailed} \\ \mu_x - \mu_y < \Delta & t \leq t_{\alpha,m+n-2} \text{ test} \\ \mu_x - \mu_y \neq \Delta & t \geq t_{1-\frac{\alpha}{2},m+n-2} \text{ two-tailed} \\ & \text{or } t \leq t_{\frac{\alpha}{2},m+n-2} \text{ test} \\ \hline \end{array}$$

Testing 350Å SiO₂ Means at Different Sites

• Null hypothesis:

$$H_0$$
: $\mu_{center} = \mu_{top}$

• Sample size *m*=*n*=86

•
$$\bar{x}_{center}$$
 =349.09 and s_{center}^2 =5.12 \bar{x}_{top} =348.48 and s_{top}^2 =5.52

•	Pooled estimate of σ : $s_p = \sqrt{\frac{s_p}{s_p}}$	$85s_{center}^2 + 85s_{top}^2$	$\frac{9}{2} = 2.31$	
	Pooled estimate of σ : $s_p = \sqrt{\frac{1}{2}}$	86+86-2	-2.31	

• Test statistic =
$$\frac{349.09 - 348.48}{2.31\sqrt{\frac{1}{86} + \frac{1}{86}}} = 1.752$$

- Type I error prob.=0.05 \Rightarrow two-tailed $\alpha/2=0$. 025; 1- $\alpha/2=0$. 975
- Do not reject $\mu_{center} = \mu_{top}$ as t-test = 1.752 < $t_{0.975,86+86-2} = 1.974$ \Rightarrow do not accept $\mu_{center} \neq \mu_{top}$
- p-value=2× Prob $(t_{86+86-2} > 1.752) = 0.0816 > 0.05 \Rightarrow$ do not reject H₀

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Testing Variance

- Testing problem: is the variance unchanged?
 - That is: H_0 : $\sigma^2 = \sigma_0^2$
- Choice of the test statistic:
 - Sample variance S^2 seems to be a good test statistics since it's an unbiased estimate of variance
 - Question: what would be the distribution of S² under H₀ ($\sigma^2 = \sigma_0^2$)?

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Distribution of Sample Variance

- To establish a hypothesis, one must know the assumed distribution model behind the sample. What would be the distribution model behind the variance?
- Recall: If $X_i \sim N(0, 1)$ then $\Sigma_n X_i^2 \sim \chi^2(n)$
- Recall: $(X-\mu)/\sigma \sim N(0, 1)$
- Therefore: $\Sigma_n[(X_i \mu)/\sigma]^2 = \Sigma_n(X_i \mu)^2/\sigma^2 \sim \chi^2(n)$
- Recall: $S^2 = \sum_n (X_i \overline{X})^2 / (n-1)$
- Result: $(n-1) S^2/\sigma^2 = \sum_n (X_i \overline{X})^2/\sigma^2 \sim \chi^2(n-1)$
- If $X_1, X_2, ..., X_n$ is a sample from a normal population with mean μ and variance σ^2 , then (n-1) S^2/σ^2 follows a χ^2 distribution with $\nu=n-1$.

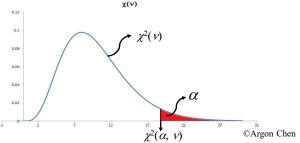
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Testing H_0 : $\sigma^2 = \sigma_0^2$

- Test statistic: $(n-1)S^2/\sigma_0^2$
- Under H₀ ($\sigma^2 = \sigma_0^2$), $(n-1)S^2/\sigma_0^2$ follows $\chi^2(n-1)$
- Reject region: determine critical value $\chi^2(\alpha, \nu)$ (CHISQ.INV.RT(α, ν) in Excel) and reject region based on $\alpha_{\tau(\nu)}$
- $H_1: \sigma^2 > \sigma_0^2$



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Testing 350Å SiO₂ Thickness Variance

- Null hypothesis: H_0 : $\sigma_{top}^2 = 5.0$
- Sample size n=86
- $\bar{x}_{top} = 348.48$ and $s_{top}^2 = 5.52$
- Test statistic = $(86 1) \frac{5.52}{5.0} = 93.89$
- Type I error prob. α =0.05
- $\chi^2(0.05, 86-1)=107.52$
- Do not reject $\sigma_{top}^2 = 5.0$ as test-stat = $93.89 < 107.\overline{52}$ \Rightarrow do not accept $\sigma_{top}^2 > 5.0$
- *p*-value= Prob($\chi_{85}^2 > 93.89$)=0.238 > 0.05 \Rightarrow do not reject H_0

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Testing A Pair of Variances

- Testing problem: are the variances the same?
 - That is: H_0 : $\sigma_x^2 = \sigma_y^2$
- Choice of the test statistic:
 - Compare two sample variances S_x^2 with sample size n_1 and S_y^2 with sample size n_2 :

$$S_x^2/S_y^2$$

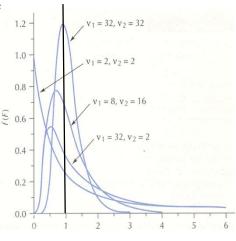
– Question: what would be the distribution of S_x^2/S_y^2 under H_0 ($\sigma_x^2 = \sigma_y^2$)?

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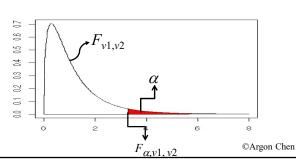
Distribution of Sample Variance Ratio

- Two *normal* populations have the *same variance*
- S_x^2 : sample variances from population 1 with sample size n_1
- S_y^2 : sample variances from population 2 with sample size n_2
- Then, S_x^2/S_y^2 follows $F_{v1, v2}$ distribution with $v_1=n_1-1$; $v_2=n_2-1$
- $E(S_x^2/S_y^2)=v_2/(v_2-2)$ if $v_2>2$
- $E(S_x^2/S_v^2) \rightarrow 1$ as $v_2 \rightarrow large$ number



Testing H_0 : $\sigma_x^2 = \sigma_v^2$

- Test statistic: S_x^2/S_y^2
- Under H₀ ($\sigma_x^2 = \sigma_y^2$), S_x^2/S_y^2 follows $F_{v1,v2}$
- Reject region: determine critical value F_{α,ν_1,ν_2} (F.INV.RT(α,ν_1,ν_2) in Excel) and reject region based on α
- $H_1: \sigma_x^2 > \sigma_y^2$



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Testing Variances at Different Sites

- Null hypothesis: $H_0: \sigma^2_{bottom} = \sigma^2_{center}$
- Sample size m=n=86
- $s_{bottom}^2 = 7.88$ $s_{center}^2 = 5.12$
- F-test statistic = $\frac{7.88}{5.12}$ = 1.538
- Type I error prob. α =0.05
- $F_{0.05, 86-1, 86-1} = 1.432$
- Reject $\sigma^2_{bottom} = \sigma^2_{center}$ as F-test =1.538 > 1.432 \Rightarrow accept $\sigma^2_{bottom} > \sigma^2_{center}$
- p-value=Prob($F_{86-1, 86-1} > 1.538$)=0.024<0.05 \Rightarrow Reject H₀

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347

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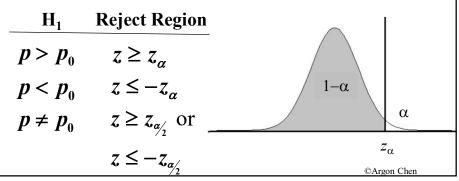
Testing a Proportion

- Testing problem: is the proportion of occurrences equal to p_0 ?
 - That is: $H_0: p = p_0$
- Choice of the test statistic:
 - -X: number of occurrences in n trials
 - -X follows Binomial distribution $b(x; p_0, n)$ under null hypothesis
- Given significance level (type I error prob.) α and H_1 : $p > p_0$
 - Reject region: $x > k^*$ where k^* is the smallest value of k for which $\sum_{i=k}^{n} C_i^n p_0^i (1 p_0)^{n-i} \le \alpha$.

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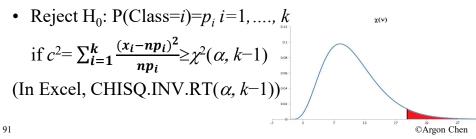
Testing the Proportion with Large n

- $H_0: p = p_0$
- Test statistic: $Z = \frac{X np_0}{\sqrt{np_0(1 p_0)}} \sim \text{standard normal}$ with a large n (recall: E(X) = np, Var(X) = np(1-p)) under null hypothesis



Testing Proportions

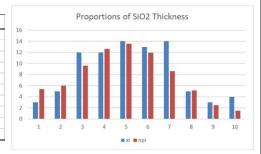
- Testing problem: do the occurrences of different classes agree with the hypothesis that the occurrence probability of class i (for i=1,...,k) equals to p_i and $\Sigma p_i=1$
- Let observed occurrences of class i be X_i (for i=1,...,k) in a total of n observations ($\sum X_i = n$)
- Test statistic: $C^2 = \sum_{i=1}^k \frac{(X_i np_i)^2}{np_i}$ follows $\chi^2(v = k-1)$ under null hypothesis



Testing the Frequency Distribution

• Example: Is the frequency distribution for 85 readings of SiO₂ average fit the proportions based on Normal distribution *N*(349.91, 2.235)?

	Class Interval	x_i	Relative Freq.	np i
1	~346.5	3	0.0353	5.40
2	346.6~347.5	5	0.0588	6.05
3	347.6~348.5	12	0.1412	9.64
4	348.6~349.5	12	0.1412	12.61
5	349.6~350.5	14	0.1647	13.54
6	350.6~351.5	13	0.1529	11.93
7	351.6~352.5	14	0.1647	8.63
8	352.6~353.5	5	0.0588	5.13
9	353.6~354.5	3	0.0353	2.50
10	354.6~	4	0.0471	1.53



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Testing the Proportions

• H_0 : $P(Class=i)=p_i i=1,...., 10$

	Class Interval	x_i	Relative Freq.	np i	$(x_i-np_i)^2/np_i$
1	~346.5	3	0.0353	5.40	1.067
2	346.6~347.5	5	0.0588	6.05	0.181
3	347.6~348.5	12	0.1412	9.64	0.580
4	348.6~349.5	12	0.1412	12.61	0.029
5	349.6~350.5	14	0.1647	13.54	0.016
6	350.6~351.5	13	0.1529	11.93	0.096
7	351.6~352.5	14	0.1647	8.63	3.340
8	352.6~353.5	5	0.0588	5.13	0.003
9	353.6~354.5	3	0.0353	2.50	0.101
10	354.6~	4	0.0471	1.53	4.008
	Total	85		c^2	9.421
				p-value	0.399
				$\chi^2(0.05, 10-1)$	16.919

- $c^2=9.421 < \chi^2(0.05, 10-1)=16.919$
- Do not reject the H_0 : the SiO_2 thickness proportions are the same as the normal distribution proportions.