6/08/20

**Agenda for Math 5710 ♬ Meeting #27 ☻☺ 7/30/20 (8:00 a.m. – 9:10 a.m.)**

1. Hello:

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|---|---|---|---|---|
| Brigham City: | Adam Blakeslee | Ryan Johnson | Tyson Mortensen | |
| Logan: | David Allen | Natalie Anderson | Kameron Baird | Stephen Brezinski |
| | Zachary Ellis | Adam Flanders | Brock Francom | Xiang Gao |
| | Ryan Goodman | Janette Goodridge | Hadley Hamar | Phillip Leifer |
| | Brittney Miller | Jonathan Mousley | Erika Mueller | Shelby Simpson |
| | Steven Summers | Matthew White | Zhang Xiaomeng | |

2. Note the syllabus' activity list for today:

| | |
|---|---|
| 27:<br>H/7/30 | 1. Overview and interrelate topics to be studied in the remainder of our Math 5710 time.<br>2. Comprehend the development of the Central Limit Theorem and attributes of {Gaussian probability distributions}.<br>2. Take advantage of Quiz 27. |

3. Briefly raise issues and questions prompted by the following homework assignment:

   A. Study our notes from Meeting #26

   B. Study the sample responses to Quiz #26's prompts that are posted in the indicated page section of *Canvas*.

   C. Deeply comprehend Theorem 14 listed as Entry 048 in our *Glossary* and reflect on how we might prove it.

4. Briskly walk through the following entries from our *Glossary* for the purpose of gaining an overview of where we're headed:

048. Theorem 14 (the Principle of Large Numbers):

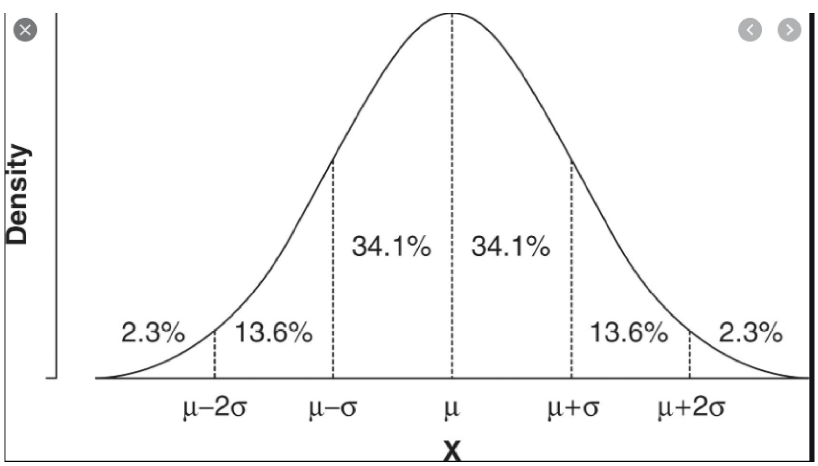
(( $n \in \mathbb{N} \wedge X_1, X_2, X_3, ..., X_n \in$ { independent trials process with continuous function $p$ } $\wedge$ ( $\mu \in \mathbb{R} \ni \mu$ is the expected value of $X_i \ \forall i \in \{1, 2, 3, ..., n\}$) $\wedge$
( $\sigma \in [0, \infty) \ni \sigma^2$ is the expected variance of $X_i \ \forall i \in \{1, 2, 3, ..., n\}$)) $\Rightarrow$

$$\lim_{n \to \infty} \left( p\left( \left| \frac{\sum_{i=1}^{n} X_i}{n} - \mu \right| \right) \right) = 0$$

049. The family of *normal* (i.e, *Gaussian* ) probability density functions:

A. Definition for normal probability density function: $f \in$ { normal probability density functions }
$\Leftrightarrow$ ( $f \in$ { probability density functions } $\wedge$ ( $f : \mathbb{R} \to \mathbb{R} \ni$ ( $f(x) =$
$\frac{1}{\sigma\sqrt{2\pi}} \cdot (e^{-(x-\mu^2)/2\sigma^2}) \ni$
( $\mu$ is the expected value of $f(x) \wedge \sigma^2$ is the expected variance of $f(x)$ )).

B. Note that the following graph of a normal probability density function, depicts some of the features of a the function that is particularly useful in the world of inferential statistics:



050: Theorem 15 (the Central Limit Theorem):

(( $n \in \mathbb{N} \wedge X_1,\ X_2,\ X_3, ...,\ X_n \in$ { independent trials process with continuous function $p$ } $\wedge$ ( $\mu \in \mathbb{R} \ni \mu$ is the expected value of $X_i\ \forall\, i \in \{ 1, 2, 3, ..., n \}$) $\wedge$ ( $\sigma \in [\,0, \infty\,) \ni$ $\sigma^2$ is the expected variance of $X_i\ \forall\, i \in \{ 1, 2, 3, ..., n \}$)) $\Rightarrow$ ( $\exists\ f \ni$ ( $f \in$ { normal probability density functions } $\ni$ ( $\mu$ is the expected value of $f(x)$ $\wedge\ \sigma^2$ is the expected variance of $f(x)$ $\wedge$ ( as $n$ increases without limit (i.e, $n \to \infty$), $p$ varies so it is a closer and closer approximation of $f$ ( i.e, $p \to f$ ).

051. Population means, population standard deviations, sample means, sample standard deviations, and $z$-scores:

A. Given $t \in$ { data strings resulting from measurements of entire populations }, note the following:

i. "$\mu_t$" is read "the population mean of $t$."

ii. Definition for *population mean*: $\mu_t = \dfrac{\sum_{i=1}^{N} t(i)}{N}$ where $N = |\ t\ |$

iii. "$\sigma_t$" is read "the population standard deviation of $t$."

iv. Definition for *population standard deviation*: $\sigma_t = \sqrt{\dfrac{\sum_{i=1}^{N} (t(i) - \mu_t)^2}{N}}$ where $N = |\ t\ |$

v. "$z_{t(i)}$" is read "the z-score associated with $t(\ i\ )$."

vi. Definition for $z_{t(i)}$: $z_{t(i)} = \dfrac{t(i) - \mu_t}{\sigma_t}$

B. Given $t \in$ { data strings resulting from measurements of samples drawn from sample drawn from populations }, note the following:

i. "$\overline{x}_t$" is read "the sample mean of $t$."

ii. Definition for *sample mean*: $\overline{x}_t = \dfrac{\sum_{i=1}^{n} t(i)}{n}$ where $n = |\ t\ |$

iii. "$s_t$" is read "the sample standard deviation of $t$."

iv. Definition for *sample standard deviation*: $s_t = \sqrt{\dfrac{\sum_{i=1}^{n} (t(i) - \overline{x}_t)^2}{n-1}}$ where $n = |\ t\ |$

052. Population statistics and inferential statistics:

A. Definition for *population data*: Data gathered via measurements employed on an entire population of interest are population data.

B. Definition for *population parameter*: Population parameters are statistics (e.g., $\mu$ or $\sigma$ ) computed from population data.

C. Definition for *sample data*: Data gathered via measurements employed on a sample randomly drawn from a population of interest are sample data.

D. Definition for *inferential statistics*: Inferential statistics are statistics (e.g., $\bar{x}$ or $s$ ) computed from sample data for the purpose of assessing hypotheses with respect of population parameters.

053. Null hypotheses, type I error, and type II error:

A. Definition of a *null hypothesis*: A null hypothesis ( symbolized "$H_o$") is a supposition about the value of a population parameter.

B: Note: In the world of inferential statistics, the supposition that $H_o$ is true establishes a probability density function (e.g., a normal distribution) to help assess whether or not $H_o$ (e.g., $\mu_t = \mu_{\bar{x}}$ ) should be rejected. The underlying logic is somewhat similar to that of mathematical proofs by contradiction; however, instead of deducing an absolute logical contradiction, the probability about the truth value of $H_o$ is computed.

C. Note: A *type I* error occurs whenever a true null hypothesis is rejected. A *type II* error occurs whenever a false null hypothesis is not rejected.

D. Note: In an experiment that employs inferential statistics, statistical test $A$ of a null hypothesis has greater *statistical power* than statistical test $B$ iff the likelihood of a Type II is lower for $A$ than it is for $B$ (i.e., the likelihood of a Type I error using statistical test A is greater than the likelihood of a Type I error using statistical test $B$).

054. *Pearson product-moment correlation coefficient*:

$$\rho_{(a,b)} = \frac{1}{N}\sum_{i=1}^{N} z_{a_i} z_{b_i}$$

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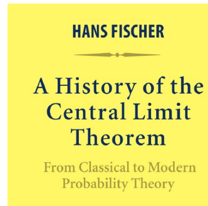
5. Reintroduce ourselves to the family of *normal* (i.e, *Gaussian* ) probability density functions:

   A. A touch of history




   B. Attributes

6. Take advantage of Quiz 27.

7. Complete the following assignments prior to Meeting #28:

   A. Study our notes from today's meeting.

   B. Study the sample responses to Quiz #27's prompts that are posted in the indicated page section of *Canvas*.

   C. Comprehend Entries 049A–B & 050 from our *Glossary*.

   D. From the Video Page of *Canvas*, view with comprehension the videos named "intro normal distributions kahn ," "central limit theorem intro, and "central limit theorem animation." Please take care of *intro normal distributions kahn* first.

8. And from Karl Pearson (1857–1936);

   *Statistics is the grammar of science.*