

UCLA STAT 19
Order in the Stochastic Universe
A Fiat Lux Course

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University of California, Los Angeles, Fall 2003
http://www.stat.ucla.edu/~dinov/courses_students.html

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Announcement

- [Marschak Colloquium Series](#)
 - <http://www.anderson.ucla.edu/research/marschak>
- **October 31: *Dwight Read*,** Professor of Anthropology and Professor of Statistics, UCLA
- **Field/Subfield:** Mathematical Modeling of Human Conceptual Systems/Evolution of Symbolic Systems
Topic: "Four Major Events in the Universe: The Big Bang, the Origin of Life, the Origin of Sexual Reproduction and the Origin of Symbolic Thought"

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Experiments, Observations & Distributions

- SOCR Demos (all available online, see class web-page)
 - C:\Ivo.dir\UCLA_Classes\Applets.dir\SOCR\Prototype1.1\classes\TestDistribution.html
 - C:\Ivo.dir\UCLA_Classes\Applets.dir\SOCR\Prototype1.1\classes\TestExperiment.html
- Describing processes using distributions, instead of using precise numerical quantitative descriptions:
- **Examples:** Outcome of a coin-toss experiment, number of arrivals for a fixed time interval, DNA mutation rates, particle velocities/positions, light intensities, exam/test scores, length/weight measurements, etc.

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Discrete & Continuous Patterns of Disorder

- Examples of **discrete** stochastic processes:
- Examples of **continuous** processes:

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Mathematical/Statistical Modeling


- **Modeling is an attempt to see the wood for the trees.**
- A model is a **simplification or abstraction of reality** separating the *important* from the *irrelevant*. Actually, modeling is a part of our existence.
- We could say that we do not perceive reality as it is. We only realize a model our mind has designed from sensory stimuli and their interpretation. It seems that certain animal species perceive different models of reality which, compared to ours, are based more on hearing and smell than on sight.

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Mathematical/Statistical Modeling

- Many philosophers have had deeper thoughts on this problem; following Plato's famous allegory of the cave. We may say that we only see the shadows of reality, or, following Kant, that we see the **phenomena** rather than the **noumena** (ground of the phenomena apprehended by the thought process).

Prisoners chained in a cave, unable to turn their heads. All they can see is the wall of the cave. Behind them burns a fire. Between the fire and the prisoners there is a parapet, along which puppeteers can walk. The puppeteers, who are behind the prisoners, hold up puppets that cast shadows on the wall of the cave. The prisoners are unable to see these puppets, the real objects, that pass behind them. What the prisoners see and hear are shadows and echoes cast by objects that they do not see.



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Mathematical/Statistical Modeling

- *We obtain our knowledge from models, and we make our predictions on the basis of models.*
- Since we are always modeling, modeling in the strict sense is the purposeful attempt to replace one model (the so-called "real world," which we typically accept without questioning) by another, deliberate, model which may give us more insight.
- There are two incentives for modeling:
 - either the **real-world** model is too complex to obtain the desired insight and so is replaced by a simpler or more abstract one.

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Mathematical/Statistical Modeling

- Or the **real-world** model does not allow certain experiments for ethical, practical, resource-limitations or other reasons. So, real-world model is replaced by a model in which all kinds of changes can be readily made and their consequences studied efficiently without causing harm.
- The word **model** traces back to the Latin word *modulus*, which means "little measure" (Merriam-Webster, 1994), alluding to a small-scale physical representation of a large object (e.g., a model airplane).

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Mathematical/Statistical Modeling

- **(Theoretical) Modeling** uses symbolic rather than physical representations, unleashing the power of mathematical analysis to increase scientific understanding. It can be divided into three stages (cf. Lin, Segel, 1974, 1988).
1. **Model formulation**: the translation of the scientific problem into mathematical terms.
 2. **Model analysis**: the mathematical solution of the model thus created.
 3. **Model interpretation and verification**: the interpretation of the solution and its empirical verification (**validation**) in terms of the original problem.

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Mathematical/Statistical Modeling

- The first step – **model formulation** – can lead to considerable insight. For building a math/stat model, one makes assumptions about the operating mechanisms, but often the real-model – the **real-world** – is far less understood than we expected.
- In many cases the modeling procedure – at least if one chooses parameters that are meaningful – already teaches what further knowledge is needed in order to apply the mathematical model successfully;
- The **model analysis** and its interpretation help to determine to what extent and precision new information and new data have to be collected.

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Mathematical/Statistical Modeling

- Analytic and numerical tools allow the **extrapolation** of present states of the mathematical model into the future and, sometimes, into the past.
- Assumptions, initial states, and parameters can easily be changed and the different outcomes compared. So, models can be used to **identify trends** or to **estimate uncertainties** in forecasts.
- While the model analysis may require sophisticated analytic or computational methods, **mathematical modeling ideally leads to conceptual insight**, which can be expressed without elaborate mathematics.

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Mathematical/Statistical Modeling

- A model is a simplification or abstraction; very often it is an **oversimplification** or **over-abstraction**. Insight obtained from a model should be checked against empirical evidence and common sense.
- It can also be **checked against insight from other models**: how much does the model's behavior depend on the degree of complexity, on the form of the model equations, on the choice of the parameters?
- Dealing with a concrete problem, a modeler should work with a whole scale of models starting from one which is as simple as possible.

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Mathematical/Statistical Modeling

- The use of a range of models also educates the modeler on how critically qualitative and quantitative results depend on the assumptions one has made.
- When modeling concrete phenomena, there is typically a dilemma between incorporating enough complexity (or realism) on the one hand and keeping the model tractable on the other.
- Extremely complex mathematical models will be of limited value for quantitative and maybe even qualitative forecasts, but still have the other benefits of being realistic.

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Mathematical/Statistical Modeling

- Mathematical modeling has its place in all sciences.
- Deterministic models (as opposed to stochastic models), which neglect the influence of random events.
- To some degree one can dispute whether stochastic models are more realistic than deterministic models; there is still the possibility that everything is deterministic, but just incredibly complex. In this case, stochasticity would simply be a certain way to deal with the fact that there are many factors we do not know.

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Mathematical/Statistical Modeling

- While a typical tool of deterministic-model analysis consists of discussing large-time limits, stochastic models take account of the truism that *nothing lasts forever* and make it possible to analyze the expected time until extinction--a concept that has no counterpart in deterministic models.

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Mathematical/Statistical Modeling

- In many cases, deterministic models can theoretically be justified as approximations of stochastic models for large populations sizes; however, the population size needed to make the approximation good enough may be unrealistically large.
- Nevertheless, deterministic models have the values which we described above, as long as one keeps their limitations in mind. The latter particularly concerns predictions, which are of very limited use in this uncertain world if no confidence intervals for the predicted phenomena are provided.

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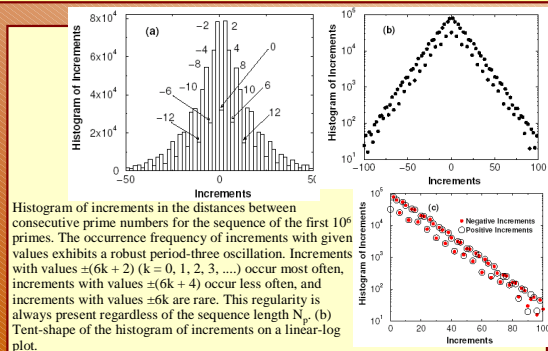
Are Prime Numbers randomly distributed?

- The difference between two consecutive prime numbers is called the distance between the primes. This study of the statistical properties of the distances and their increments is for a sequence comprising the first 5×10^7 prime numbers. Results: the histogram of the increments follows an exponential distribution with superposed periodic behavior of period three, similar to previously-reported period six oscillations for the distances.
- *Information Entropy and Correlations in Prime Numbers* by P. Kumar, P. Ivanov, H. E. Stanley (2003)

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Are Prime Numbers randomly distributed?



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Are Prime Numbers randomly distributed?

- **Why Care?**
- The findings might have implications in the real world, as some systems in physics and biology - such as interacting prey and predator species with different life cycles - show patterns that depend on prime numbers.
- Coding Theory (e.g., Internet Security)
- Riemann hypothesis in number theory is intimately related to the distribution of primes. In 2001 the Clay Institute in the USA offered a prize of a million dollars for a proof of the this conjecture.
- **Prime Number Th:** number of primes $\leq x$ is: $\pi(x) \sim x/\log x$

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Random Noise Generates 1-Way Spin

- A simple top converts foghorn noise to one-way spin. The device raises the hope that useful energy could be collected from ambient sounds. Normally, random vibrations, which physicists and engineers call noise, produce useless random motion. You can't move a cart from A to B by shoving it randomly in every direction.



- But in the new device, a flat plate encounters more friction when it spins in one direction than in the other, meaning it always rotates predictably.

•Norden, B., Zolotaryuk, Y., Christiansen, P.L. & Zolotaryuk, A.V. Ratchet device with broken friction symmetry. *Applied Physics Letters* **80**, 2601 - 2603 (2002).

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Noise breaks ice

- Natural randomness in the world's climate system may have caused the frequent, fast and fleeting returns to warm conditions during past ice ages.
- It's suggested that the events were caused by some kind of periodic influence on climate that repeated every 1,500 years. Perhaps a very weak periodic signal alters the ocean salt content every 1,500 years.
- There is evidence of a 1,500-year periodic forcing in many climate records. It is widely suspected to originate from repetitive changes in the activity of the Sun.



•Ganopolski, A. & Rahmstorf, S.
•Abrupt glacial climate changes due to noise-Infectious noise.
•*Physical Review Letters* **88**, 038501, (2002)

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Central Limit Theory and the Normal Distribution

- **SOCR Dice Demo + CLT Applet Demo**
Applets.dir/SamplingDistributionApplet.html

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Standard Normal Curve (cf. Modeling)

- The standard normal curve is described by the equation:

$$y = \frac{e^{-\frac{x^2}{2}}}{\sqrt{2\pi}}$$



Where remember, the natural number $e \sim 2.7182...$
We say: $X \sim \text{Normal}(\mu, \sigma)$, or simply $X \sim N(\mu, \sigma)$

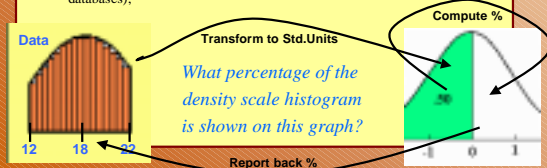
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Standard Normal Approximation

- The **standard normal curve** can be used to estimate the percentage of entries in an interval for any process. Here is the protocol for this approximation:

- Convert the interval (we need the assess the percentage of entries in) to **standard units**. We saw the algorithm already.
- Find the corresponding area under the normal curve (from tables or online databases);



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General Normal Curve

- The **general normal curve** is defined by:
 - Where μ is the **average** (of the symmetric) normal curve, and σ is the **standard deviation** (spread of the distribution).

$$y = \frac{e^{-\frac{(x-\mu)^2}{2\sigma^2}}}{\sqrt{2\pi\sigma^2}}$$

- Why worry about a **standard** and **general normal curves**?
- How to convert between the two curves?

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Areas under Standard Normal Curve – Normal Approximation

- Protocol:**
 - Convert the interval (we need to assess the percentage of entries in) to **Standard units**. Actually convert the end points in Standard units.
 - In general, the transformation $X \rightarrow (X-\mu)/\sigma$, **standardizes** the observed value X, where μ and σ are the **average** and the **standard deviation** of the distribution X is drawn from.
 - Find the corresponding area under the normal curve (from tables or online databases);
 - Sketch the normal curve and shade the area of interest
 - Separate your area into individually computable sections
 - Check the Normal Table and extract the areas of every sub-section
 - Add/compute the areas of all sub-sections to get the total area.

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Obtaining central range for symmetric distributions

What values contain the **central 50%**?

What does that say about the **lower tails**?

Obtain **b** from program

Obtain **a** from program

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Areas under Standard Normal Curve – Normal Approximation, Scottish Army Recruits

- The **mean height is 64 in** and the **standard deviation is 2 in**.
 - Only recruits shorter than 65.5 in will be trained for tank operation. What percentage of the incoming recruits will be trained to **operate armored combat vehicles** (tanks)?
 - $X \rightarrow (X-64)/2$
 - $65.5 \rightarrow (65.5-64)/2 = 1/4$
 - Percentage is **77.34%**
 - Recruits within $1/2$ standard deviations of the mean will have no restrictions on duties. About what percentage of the recruits will have **no restrictions** on training/duties?
 - $X \rightarrow (X-64)/2$
 - $65 \rightarrow (65-64)/2 = 1/2$
 - $63 \rightarrow (63-64)/2 = -1/2$
 - Percentage is **38.30%**

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Randomness in Biology, Genetics, Engineering & Physics

- Life is not ordered – life is organized.** Order is what a crystal (lattice) has.
- If you have 26 letters, as in English, you would expect a long sequence of (randomly chosen) characters to give each letter $1/26^{\text{th}}$ of the time. That would be random.
- Random sequences have a high informational content, using information theory. A sequence can have lots of information regardless of whether it has any meaning.
- Now comes the problem that most anti-evolutionists don't quite grasp. **Organized sequences are quite similar to random sequences.**

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Randomness in Biology, Genetics, Engineering & Physics

- Organisms are often characterized as being **highly ordered** and in the same time as being **highly organized**. Clearly these terms have opposite meanings
- The message **01010101010101010101** is **highly ordered** and has a low entropy. A message **highly organized** is **011011001101110001000**.
- Highly-organized** means that a long algorithm is needed to describe the sequence and therefore **highly organized systems** have a large entropy.
- Highly-ordered** systems and **highly-organized** ones occupy opposite ends of the entropy scale.

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Randomness in Biology, Genetics, Engineering & Physics

- Highly-organized systems are found embedded among random sequences, the latter occupying the high end of the entropy scale.
- Both, random sequences and highly organized sequences are complex (the shortest algorithm needed to compute a sequence is its complexity).
- Information theory shows that it is fundamentally undecidable whether a given sequence has been generated by a stochastic process or by a highly organized process.
- Algorithmic information theory shows that truth or validity may also be indeterminate or fundamentally undecidable.

High = Random
Low = Order
Entropy

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Randomness in Biology, Genetics, Engineering & Physics

- It is impossible (or at least not clear how to) to tell an organized (designed) sequence from one which is merely random.
- If you can't tell an organized sequence with high informational content from a random sequence, then you can't tell if the sequence arose through random processes or through an intelligence who designed it.
- Meaningful high informational content patterns are rare compared to meaningless sequences with a high info content. However, randomness can give rise to meaningful patterns.
- Difference between life and matter is information.

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Randomness in Biology, Genetics, Engineering & Physics

- Although humans have 30 times the DNA of some insects, there are insects that have more than double the DNA in humans.
- The amount of DNA is not a reliable measure of complexity because not all the DNA may have to do with complexity; part of a genome may be just many repeats of the same section, or random sections or just meaningless patterns.
- There are bacteria that are resistant to very high dosages or radiation – their DNA is mainly devoted to real time identification and correction of DNA breakage/mutations.

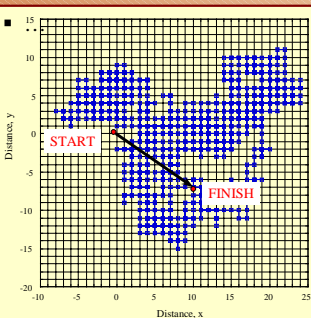
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Random Walks – The Gambler's Ruin

- Betting \$1 on a game with a 50/50 chance: If you win, you get \$2. If you lose, you get \$0.
- A gambler bets \$1 each round of a game random walk. However, he starts with n amount of money, whereas the bank/casino has unlimited funds.
- Let $P_N(n)$ denote the probability that, starting with n dollars, the gambler goes broke before winning $N > n$ dollars.
Previous Trial: Win Loose
- Solving $P_N(n) = (0.5)[P_N(n-1) + P_N(n+1)]$
- Boundary conditions: $P_N(0) = 1, P_N(N) = 0$.
- Solution: $P_N(n) = 1 - n/N$.

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Random Walks



Each step has 4 possibilities:

- East
- West
- North
- South

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Duality Principles: The Uncertainty Principle (momentum vs. position)

- Some physics experiments (such as blackbody radiation, the photoelectric effect, and Compton scattering) can be explained using the photon picture of light, and not with its wave properties.
- Other experiments such as diffraction and interference all need the wave characteristics of light, as a photon (particle) picture fails in these cases.
- We say that light exhibits a wave-particle duality: Light has a dual nature; in some cases it behaves as a wave, and in other cases it behaves as a photon.

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Duality Principles: The Uncertainty Principle (momentum vs. position)

- One important consequence of the wave-particle duality of nature was discovered by Heisenberg, and is called the (Heisenberg's) **uncertainty principle**.
- Imagine that we want to measure the position and the momentum of a particular particle. To do so we must see the particle, and so we shine some **light (as a wave)** of wavelength λ on it. There is a limit to the resolving power of the light used to see the particle given by the wavelength of light used. This gives an **uncertainty** in the **particle's position**: $\Delta x \sim \lambda$.

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Duality Principles: The Uncertainty Principle (momentum vs. position)

- However, viewed as a photon, the light strikes the particle and gives up some or all of its momentum to the particle. Since we don't know how much it gave up, as we don't measure the photon's properties, there is an uncertainty in the **momentum** of the particle; $\Delta p \sim h/\lambda$, there $h > 0$ is a constant.
- Hence, $\Delta x \times \Delta p \sim h$.
- A more refined treatment, developed by Heisenberg, results in the following relation:
 - $\Delta x \times \Delta p \geq h/4\pi$

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Duality Principles: The Uncertainty Principle (momentum vs. position)

$$\Delta x \times \Delta p \geq h/4\pi$$

- Note that this is independent of the wavelength used, and says there is a **limit as to how accurately one can simultaneously measure the position (Δx) and momentum of a particle (Δp)**.
- If one tries to measure the position more accurately by using light of a shorter wavelength, then the uncertainty in momentum grows.
- Whereas if one uses light of a longer wavelength in order to reduce the uncertainty in momentum, then the uncertainty in position grows.

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Balancing Quality vs Volume of Information

...

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Statistical vs. Practical Significance

- Is a second child gender influenced by the gender of the first child, in families with >1 kid?
- When analyzing real data, investigators frequently employ statistical analytic techniques to detect real signal/effects in the data. Hence **statistically significant effects** are determined by a statistical analysis.
- How **practically meaningful**, however, are these statistically significant effects? Answer: Not clear, in general.

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Is a second child gender influenced by the gender of the first child, in families with >1 kid?

First and Second Births by Sex

	Second Child		Total
	Male	Female	
First Child	Male	2,776	5,978
	Female	2,792	5,412
Total	5,822	5,568	11,390

- Research hypothesis needs to be formulated first before collecting/looking/interpreting the data that will be used to address it. Mothers whose 1st child is a girl are more likely to have a girl, as a second child, compared to mothers with boys as 1st children.
- Data: 20 yrs of birth records of 1 Hospital in Auckland, NZ.

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Analysis of the birth-gender data – data summary

Group	Second Child	
	Number of births	Number of girls
1 (Previous child was girl)	5412	2792 (approx. 51.6%)
2 (Previous child was boy)	5978	2776 (approx. 46.4%)

- Let p_1 =true proportion of girls in mothers with girl as first child, p_2 =true proportion of girls in mothers with boy as first child. Parameter of interest is $p_1 - p_2$.
- $H_0: p_1 - p_2 = 0$ (skeptical reaction). $H_a: p_1 - p_2 > 0$ (research hypothesis)

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Hypothesis testing as decision making

Decision Making

Decision made	Actual situation	
	H_0 is true	H_0 is false
Accept H_0 as true	OK	Type II error
Reject H_0 as false	Type I error	OK

- Sample sizes: $n_1=5412$, $n_2=5978$, Sample proportions (estimates) $\hat{p}_1 = 2792/5412 \approx 0.5159$, $\hat{p}_2 = 2776/5978 \approx 0.4644$.
- $H_0: p_1 - p_2 = 0$ (skeptical reaction). $H_a: p_1 - p_2 > 0$ (research hypothesis)

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Analysis of the birth-gender data

- Samples are large enough to use **Normal-approx.**. Since the two proportions come from totally diff. mothers they are **independent** → use formula 8.5.5.a

$$t_0 = \frac{\text{Estimate} - \text{Hypothesized Value}}{SE} = 5.49986 = \frac{\hat{p}_1 - \hat{p}_2 - 0}{SE(\hat{p}_1 - \hat{p}_2)} = \frac{\hat{p}_1 - \hat{p}_2}{\sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}}}$$

$$P\text{-value} = \Pr(T \geq t_0) = 1.9 \times 10^{-8}$$

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Analysis of the birth-gender data

- We have strong evidence to reject the H_0 , and hence conclude mothers with first child a girl a **more likely** to have a girl as a second child.

- How much more likely? A 95% CI:

$$CI(p_1 - p_2) = [0.033; 0.070]. \text{ And computed by: } \text{estimate} \pm z \times SE = \hat{p}_1 - \hat{p}_2 \pm 1.96 \times SE(\hat{p}_1 - \hat{p}_2) = \hat{p}_1 - \hat{p}_2 \pm 1.96 \times \sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}} = 0.0515 \pm 1.96 \times 0.0093677 = [3\% ; 7\%]$$

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Statistics of Extremes

- SOCR Demo:

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Interpolation vs. Extrapolation

- Interpolation** is the process of estimating a value for a point that lies on a curve between known data points
 - Linear interpolation assumes a straight line between the known data points
- One Method:
 - Select the two points with known coordinates
 - Determine the equation of the line that passes through the two points (Find m and b of the line)
 - Insert the X value of the desired point in the equation and calculate the Y value (knowing $y = mx + b$)

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Interpolation vs. Extrapolation

Linear Interpolation:

$$\text{Fractional Difference} = \left(\frac{x - x_1}{x_2 - x_1} \right) = \left(\frac{y - y_1}{y_2 - y_1} \right)$$

$$y = y_1 + \left(\frac{y_2 - y_1}{x_2 - x_1} \right) (x - x_1)$$

- Given the following set of points, find the dependent variable y_2 using linear interpolation.

$$(x_1, y_1) = (1.0, 18)$$

$$(x, y) = (2.4, y)$$

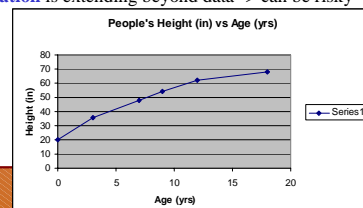
$$(x_2, y_2) = (4.0, 35)$$

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Interpolation vs. Extrapolation

- Interpolation** is extending between data points
-> usually safe
- Extrapolation** is extending beyond data -> can be risky



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Noise and Perception

- Types of Noise:

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Bayesian Theory – Statistical Inference

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Bayesian Theory – Statistical Inference

- Statistical inference is based on probability
 - To be useful probability must be **interpreted**.
 - Relative Frequency (Venn, Fisher, Neyman, etc.)
 - Degree of Belief (Bayes, Laplace, Gauss, Jeffreys, etc.)
 - Propensity (Popper, etc.)
 - The validity of these interpretations cannot be decided by an appeal to Nature.
 - Statistical inference is based on principles that can always be challenged by anyone who doesn't find all of them compelling. Again, Nature cannot help.
 - Statistical inference cannot be fully objective.

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Frequentist Inference

- The Good**
 - No **arbitrary priors**: Absence of prior anxiety!
 - Coverage property is powerful (some say beautiful)
 - There is a **badness-of-fit test**
 - One can play delightful MC games on a computer
- The Bad**
 - No systematic method to incorporate prior information
 - "Grosse Fuge" reasoning is difficult and unnatural
- The Ugly**
 - Difficult to teach
 - Doesn't do what we want: **Probability(Theory|Data)**

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Bayesian Inference

- **The Good**
 - Natural **model of inferential reasoning**
 - General theory for handling uncertainty in all its forms
 - Results depend only on data observed
 - Does what we want: **Probability(Theory|Data)**
 - Easy to teach and understand
- **The Bad**
 - Can be computationally demanding
 - Until recently, no goodness-of-fit test
- **The Ugly**
 - Choosing prior probabilities can be, well, a “Grosse Fuge”!

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Bayesian Theory – Statistical Inference

- “A **Frequentist** uses impeccable logic to answer the **wrong question**, while a **Bayesian** answers the **right question by making assumptions** that nobody can fully believe in.”

P.G. Hamer

- Do you see another version of the Duality-Principle in actions?

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