

## UCLA STAT 110 A Applied Probability & Statistics for Engineers

- **Instructor:** Ivo Dinov,  
Asst. Prof. In Statistics and Neurology
  - **Teaching Assistant:** Maria Chang, UCLA Statistics
- University of California, Los Angeles, Spring 2003  
<http://www.stat.ucla.edu/~dinov/>

Stat 110A, UCLA, Ivo Dinov Slide 1

### Course Organization

**Software:** No specific software is required. SYSTAT, R, SOCR resource, etc.

**Text:** *Probability and Statistics for Engineering and the Sciences 5<sup>th</sup> edition* -- Jay Devore

**Course Description,  
Class homepage,  
online supplements,  
VOH's, etc.**

[http://www.stat.ucla.edu/~dinov/courses\\_students.html](http://www.stat.ucla.edu/~dinov/courses_students.html)

Slide 2 Stat 110A, UCLA, Ivo Dinov

### What is Statistics? A practical example

- **Demography:** *Uncertain population forecasts* by Nico Keilman, Wolfgang Lutz, *et al.*, Nature 412, 490 - 491 (2001)
- Traditional population forecasts made by statistical agencies **do not quantify uncertainty**. But demographers and statisticians have developed methods to calculate **probabilistic forecasts**.
- The demographic future of any human population is uncertain, but some of the many **possible trajectories** are **more probable** than others. So, forecast demographics of a population, e.g., **size** by 2100, should include **two elements**: a **range of possible outcomes**, and a **probability attached to that range**.

Stat 110A, UCLA, Ivo Dinov Slide 3

### What is Statistics?

- Together, ranges/probabilities constitute a **prediction interval** for the population. There are trade-offs between **greater certainty** (higher odds) and **better precision** (narrower intervals). Why?
- For instance, the next table shows an estimate that the odds are **4 to 1** (an 80% chance) that the world's population, now at **6.1 billion**, will be in the **range [5.6 : 12.1]** billion in the year 2100. Odds of **19 to 1** (a 95% chance) result in a **wider interval: [4.3 : 14.4]** billion.

Stat 110A, UCLA, Ivo Dinov Slide 4

Year	Median world and regional population sizes (millions)				
	2000	2025	2050	2075	2100
World total	6,055	7,827	8,797	9,351	8,414
North Africa	173	257	311	336	333
Sub-Saharan Africa	611	(228-285)	(249-378)	(238-443)	(215-484)
North America	314	976	1,319	1,522	1,500
Latin America	515	(856-1,100)	(1,010-1,701)	(1,021-2,194)	(878-2,450)
Central Asia	56	379	422	441	454
Middle East	172	(351-410)	(358-498)	(343-565)	(313-631)
South Asia	1,367	709	840	904	934
China region	1,408	(643-775)	(679-1,005)	(647-1,202)	(565-1,383)
Pacific Asia	476	625	100	107	106
Pacific OECD	150	(73-90)	(80-121)	(76-145)	(66-159)
Western Europe	456	285	368	413	413
Eastern Europe	121	(282-318)	(301-445)	(298-544)	(259-597)
European part of the former USSR	236	1,940	2,249	2,242	1,958
		(1,735-2,154)	(1,795-2,778)	(1,528-3,085)	(1,186-3,035)
		1,808	1,580	1,422	1,250
		(1,494-1,714)	(1,305-1,849)	(1,003-1,854)	(765-1,870)
		625	702	702	654
		(569-682)	(575-842)	(509-937)	(410-949)
		148	135	123	123
		(144-165)	(125-174)	(102-175)	(79-173)
		478	470	433	392
		(445-508)	(399-549)	(321-562)	(257-568)
		117	104	87	74
		(109-125)	(89-124)	(61-119)	(44-115)
		218	187	159	141
		(203-234)	(154-225)	(110-216)	(85-218)

Stat 110A, UCLA, Ivo Dinov Slide 5

Table 1 Forecasted population sizes and proportions over

Year	Median	
	2000	2025
World total	6,055	7,827
North Africa	173	(7,219-8,459)
Sub-Saharan Africa	611	257
North America	314	(228-285)
Latin America	515	976
Central Asia	56	(856-1,100)
Middle East	172	379
		(351-410)
		(643-775)
		81
		(73-90)
		285
		(252-318)

Large view

## What is Statistics?

### Demography: Uncertain population forecasts

by Nico Keilman, Nature 412, ,2001

Traditional population forecasts made by statistical agencies **do not quantify uncertainty**. But lately demographers and statisticians have developed methods to calculate **probabilistic forecasts**.

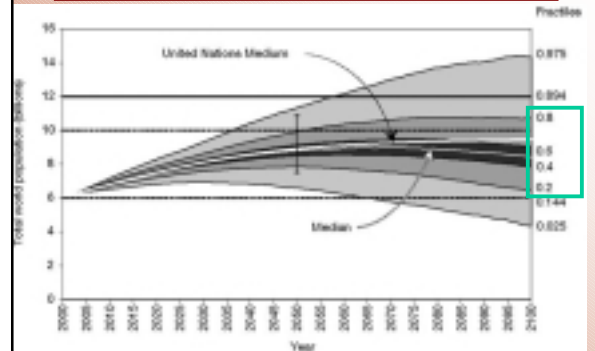
Proportion of population over 60yrs.

Proportion of population over age 60		
2000	2050	2100
0.10	0.22	0.34
0.06	(0.18-0.27)	(0.25-0.44)
0.05	0.19	0.32
0.16	(0.15-0.25)	(0.23-0.44)
0.08	0.07	0.20
0.08	(0.05-0.09)	(0.14-0.27)
0.07	0.30	0.40
0.10	(0.23-0.37)	(0.28-0.52)
0.06	0.22	0.33
0.07	(0.17-0.28)	(0.23-0.45)
0.08	0.20	0.34
0.06	(0.15-0.25)	(0.24-0.46)
0.07	0.18	0.35
0.10	(0.14-0.23)	(0.24-0.47)
0.08	0.18	0.35
0.22	(0.14-0.24)	(0.25-0.48)
0.20	0.30	0.39
0.18	(0.24-0.37)	(0.27-0.53)
0.19	0.23	0.36
0.19	(0.18-0.29)	(0.26-0.49)
	0.39	0.49
	(0.32-0.47)	(0.35-0.61)
	0.35	0.45
	(0.29-0.43)	(0.32-0.58)
	0.38	0.42
	(0.30-0.46)	(0.28-0.57)
	0.35	0.36
	(0.27-0.44)	(0.23-0.50)

Stat 110A, UCLA, Ivo Dinov

Slide 7

## What is Statistics?



Stat 110A, UCLA, Ivo Dinov

Slide 8

## What is Statistics?

There is concern about the **accuracy of population forecasts**, in part because the **rapid fall in fertility in Western countries in the 1970s** came as a surprise. Forecasts made in those years predicted **birth rates** that were up to **80% too high**.

The rapid reduction in mortality after the Second World War **was also not foreseen**; life-expectancy forecasts were too low by 1-2 years; and the **predicted number of elderly**, particularly the oldest people, was **far too low**.

Stat 110A, UCLA, Ivo Dinov

Slide 9

## What is Statistics?

So, during the 1990s, researchers developed methods for making **probabilistic population forecasts**, the **aim** of which is to **calculate prediction intervals for every variable of interest**. Examples include population forecasts for the USA, AU, DE, FIN and the Netherlands; these forecasts comprised prediction intervals for **variables** such as **age structure**, **average number of children per woman**, **immigration flow**, **disease epidemics**.

We need accurate probabilistic population forecasts for the whole world, and its 13 large division regions (see Table). The **conclusion** is that there is an estimated 85% chance that the **world's population will stop growing before 2100**. Accurate?

Stat 110A, UCLA, Ivo Dinov

Slide 10

## What is Statistics?

There are **three main methods of probabilistic forecasting**: **time-series extrapolation**; **expert judgement**; and **extrapolation of historical forecast errors**.

**Time-series** methods rely on statistical models that are fitted to historical data. These methods, however, seldom give an accurate description of the past. If many of the historical facts remain unexplained, time-series methods result in **excessively wide prediction intervals** when used for **long-term forecasting**.

**Expert judgement** is subjective, and **historic-extrapolation** alone may be near-sighted.

Stat 110A, UCLA, Ivo Dinov

Slide 11

## Chapter 1: Intro to Data Analysis

- Variation in data
- Data Distributions
- Stationary and (dynamic) non-stationary processes
- Causes of Variation

Stat 110A, UCLA, Ivo Dinov

Slide 12

### Newtonial science vs. chaotic science

- Article by Robert May, *Nature*, vol. 411, June 21, 2001
- Science we encounter at schools deals with **crisp certainties** (e.g., prediction of planetary orbits, the periodic table as a descriptor of all elements, equations describing area, volume, velocity, position, etc.)
- As soon as **uncertainty** comes in the picture it **shakes** the foundation of the deterministic science, because only **probabilistic statements** can be made in describing a phenomenon (e.g., roulette wheels, chaotic dynamic weather predictions, Geiger counter, earthquakes, etc.)
- **What is then science all about** – describing absolutely certain events and laws alone, or describing more general phenomena in terms of their behavior and chance of occurring? Or may be both!

*Slide 13 Stat 110A, UCLA, Ivo Dinov*

### Variation in sample percentages

Poll: Do you consider yourself overweight?

Target: True population percentage = 69%

10 Samples of 20 people

10 Samples of 500 people

Sample percentage

We are getting closer to The population mean, as  $n \rightarrow \infty$  is this a coincidence?

Comparing percentages from 10 different surveys each of 20 people with those from 10 surveys each of 500 people (all surveys from same population).

From Chance Encounters by C.J. Wild and G.A.F. Seber, © John Wiley & Sons, 2000.

*Slide 14 Stat 110A, UCLA, Ivo Dinov*

### Experiments vs. observational studies for comparing the effects of treatments

- In an Experiment
  - experimenter determines which units receive which treatments. (ideally using some form of random allocation)
- Observational study – useful when can't design a controlled randomized study
  - compare units that happen to have received each of the treatments
  - Ideal for describing relationships between different characteristics in a population.
  - often useful for identifying possible causes of effects, but cannot reliably establish causation.
- Only properly designed and executed experiments can reliably demonstrate causation.

*Slide 15 Stat 110A, UCLA, Ivo Dinov*

### The Subject of Statistics

- Statistics is concerned with the process of finding out about the world and how it operates - in the face of variation and uncertainty
- by collecting and analyzing, making sense (interpreting) of data.
- Data are measurements, facts and information about an object or a process that allows is to make inference about the object being observed.

*Slide 16 Stat 110A, UCLA, Ivo Dinov*

### The investigative process

The investigative process.

From Chance Encounters by C.J. Wild and G.A.F. Seber, © John Wiley & Sons, 2000.

*Slide 17 Stat 110A, UCLA, Ivo Dinov*

### Sources of non-sampling errors

- **Selection bias:** Arises when the population sampled is not exactly the population of interest.
- **Self-selection:** People themselves decide whether or not to be surveyed. Results akin to severe non-response.
- **Non-response bias:** Non-respondents often behave or think differently from respondents
  - low response rates can lead to **huge biases**.

*Slide 18 Stat 110A, UCLA, Ivo Dinov*

### Immigration Example

- Suppose that you want to set up a nationwide survey about **immigration issues**. Think as precisely as you can about the target population that you would be interested in.
  - Who would you want included?
  - Who would you want excluded?
  - Can you define some rules to characterize your target population?

Slide 19 Stat 110A, UCLA, Jon Dineen

### Immigration Example

- We could take all members of the population in the US at the time, who were entitled to vote in national elections. This may **exclude** the young, the illegal immigrants, those people in prisons and people legally committed to mental institutions. It would **include** any other permanent residents of the US, whether or not they were citizens, and citizens living overseas.
- You might want to be more, or less, restrictive. In practice, one would probably sample from something like the electoral
- districts [that subset of people who fit the eligibility criteria for voting and who have registered to do so].
- Should the goals of the study influence your survey design (in particular how conservative your selection is)?

Slide 20 Stat 110A, UCLA, Jon Dineen

### Poll Example

- A survey of High School principals taken after a widespread change in the public school system revealed that 20% of them were under stress-relief medication, and almost 50% had seen a doctor in the past 6 mo.s with stress complains. The survey was compiled from **250 questionnaires returned** out of **2500 sent out**. How **reliable** the results of this experiment are and why?

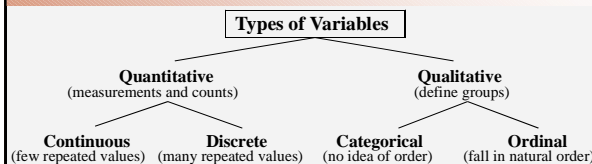
Slide 21 Stat 110A, UCLA, Jon Dineen

### Poll Example

- This is only a 10% response rate - the people who responded could be very **unrepresentative**. It could well be that the survey struck a responsive chord with stressed-out principals.

Slide 22 Stat 110A, UCLA, Jon Dineen

### Distinguishing between types of variable



Slide 23 Stat 110A, UCLA, Jon Dineen

### Experimental vs. Observation study

- A researcher wants to evaluate IQ levels are related to person's height. **100 people** are randomly selected and grouped into **5 bins**: [0:50), [50:100), [100:150), [150:200), [200:250] **cm** in height. The subjects undertook a IQ exam and the results are analyzed.
- Another researcher wants to assess the bleaching effects of **10 laundry detergents** on **3 different colors** (R,G,B). The laundry detergents are randomly selected and applied to 10 pieces of cloth. The discoloration is finally evaluated.

Slide 24 Stat 110A, UCLA, Jon Dineen

### Experimental vs. Observation study

- For each study, describe what *treatment* is being compared and what *response* is being measured to compare the treatments.
- Which of the studies would be described as *experiments* and which would be described as *observational* studies?
- For the studies that are *observational*, could an experiment have been carried out instead? If not, briefly explain why not.
- For the studies that are *experiments*, briefly discuss what *forms of blinding* would be possible to be used.
- In which of the studies has *blocking* been used? Briefly describe *what* was blocked and why it was blocked.

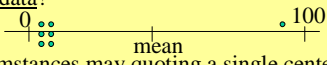
Slide 25 Stat 110A, UCLA, Ivo Dinov

### Experimental vs. Observation study

- What is the *treatment* and what is the *response*?
  1. *Treatment* is *height* (as a bin). *Response* is *IQ score*.
  2. *Treatment* is *laundry detergent*. *Response* is *discoloration*.
- *Experiment* or *observational* study?
  1. *Observational* – compare obs's (IQ) which happen to have the treatment (height).
  2. *Experimental* – experimenter controls which treatment is applied to which unit.
- For the *observational* studies, can we conduct an experiment?
  1. This *could not* be done as an experiment - it would require the experimenter to decide the (natural) height (treatment) of the subjects (units).
- For the *experiments*, is there *blinding*?
  2. The only form of blinding possible would be for the technicians measuring the cloth discoloration not to know which detergent was applied.
- Is there *blocking*?
  1. & 2. *No blocking*. Say, if there are two laundry machines with different cycles of operation and if we want to block we'll need to randomize which laundry does which cloth/detergent combinations, because differences in laundry cycles are a known source of variation.

Slide 26 Stat 110A, UCLA, Ivo Dinov

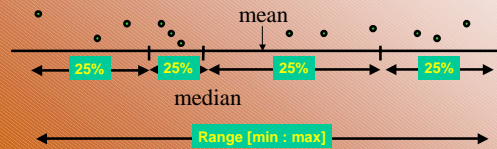
### Mean, Median, Mode, Quartiles, 5# summary

- The *sample mean* is the average of all numeric obs's.
  - The *sample median* is the obs. at the index  $(n+1)/2$  (note take avg of the 2 obs's in the middle for fractions like 23.5), of the observations ordered by size (small-to-large)?
  - The *sample median* usually preferred to the *sample mean* for *skewed data*?
- 
- Under what circumstances may quoting a *single center* (be it mean or median) not make sense? (multi-modal)
  - What can we say about the sample mean of a *qualitative variable*? (meaningless)

Slide 27 Stat 110A, UCLA, Ivo Dinov

### Quartiles

The first quartile ( $Q_1$ ) is the median of all the observations whose *position* is strictly below the position of the median, and the third quartile ( $Q_3$ ) is the median of those above.



Slide 28 Stat 110A, UCLA, Ivo Dinov

### Five number summary

The *five-number summary* = (Min,  $Q_1$ , Med,  $Q_3$ , Max)

Slide 29 Stat 110A, UCLA, Ivo Dinov

### Quantiles (vs. quartiles)

- The  $q^{\text{th}}$  *quantile* ( $100 \times q^{\text{th}}$  *percentile*) is a value, in the range of our data, so that proportion of at least  $q$  of the data lies at or below it and a proportion of at least  $(1-q)$  lies at or above it.
- E.x.,  $X = \{1, 2, 3, 4, 5, 6, 7, 8, 9, 10\}$ . The  $20^{\text{th}}$  percentile ( $0.2$  *quantile*) is the value **2**, since 20% of the data is below it and 80% above it. The  $70^{\text{th}}$  percentile is the value 7, etc.
- We could have also selected **2.5** and **7.5** for the  $20^{\text{th}}$  and  $70^{\text{th}}$  percentile, above. There is no agreement on the exact definitions of quantiles.

Slide 30 Stat 110A, UCLA, Ivo Dinov

### Measures of variability (deviation)

- **Mean Absolute Deviation (MAD)** –
 
$$MAD = \frac{1}{n-1} \sum_{i=1}^n |y_i - \bar{y}|$$
- **Variance** –
 
$$Var = s^2 = \frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2$$
- **Standard Deviation** –
 
$$SD = \sqrt{Var} = s = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2}$$

Slide 31 Stat 110A, UCLA, Ivo Dinov

### Measures of variability (deviation)

- **Example:**
- **Mean Absolute Deviation** –  $MAD = \frac{1}{n-1} \sum_{i=1}^n |y_i - \bar{y}|$
- **Variance** –  $Var = s^2 = \frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2$
- **Standard Deviation** –  $SD = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2}$

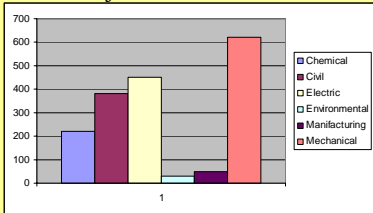
$X = \{1, 2, 3, 4\}$

	m=2.5		MAD=4/3=1.33
1	2	3	4
			Var=5/3=1.67
			SD=1.3

Slide 32 Stat 110A, UCLA, Ivo Dinov

### Bar Chart

- List all possible categories the data is classified in!
  - Represents the frequency of occurrence of the data in each category
- Example: Number of engineering students enrolled in different majors:



700
600
500
400
300
200
100
0

Slide 33 Stat 110A, UCLA, Ivo Dinov

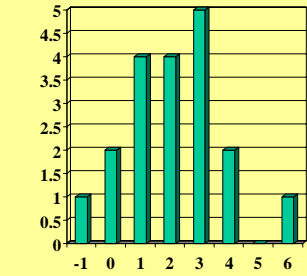
### Data Distribution

- A **data distribution** is a summary of the variation in a dataset. Data distribution is a list of all possible values (of the process/object) and their respective frequencies (e.g., how often is each possible value encountered, when we observe the object/process).
- E.g., {1, 2, 2, 3, -1, 0, 0, 1, 2, 3, 4, 3, 3, 1, 2, 1, 4, 6, 3}

Slide 34 Stat 110A, UCLA, Ivo Dinov

### Data Distribution

- E.g., {1, 2, 2, 3, -1, 0, 0, 1, 2, 3, 4, 3, 3, 1, 2, 1, 4, 6, 3}



Slide 35 Stat 110A, UCLA, Ivo Dinov

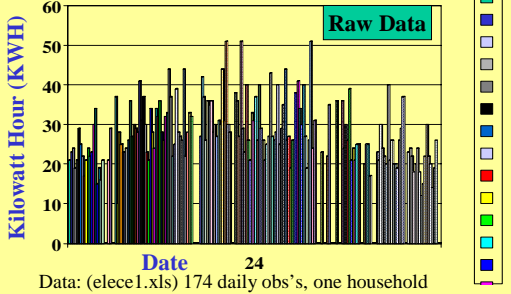
### Stationarity of Processes

- Does the variability of the data change significantly as more data is collected (say between different time points, different physical locations, etc.)?
- **Stationary process** is a data-generating mechanism for which the distribution of the resulting data does NOT change appreciably as more data is being observed.
- **Non-Stationary process** is a data-generating mechanism for which the distribution of the resulting data DOES change as more data is being observed.
- E.g., **Grades** (over time), **Air quality** (in different regions in the US), **Geiger counter** (time), Species Extinction (long-times). Other examples?

Slide 36 Stat 110A, UCLA, Ivo Dinov

### Stationary or Non-Stationary Process?

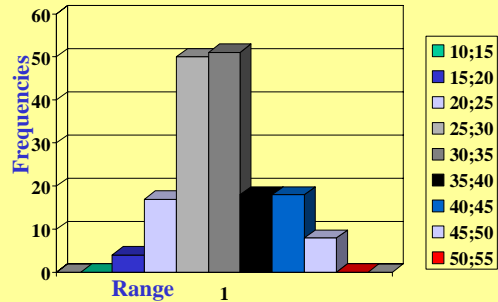
- **Histograms?** Do not work too well. Why?



Slide 37 Stat 110A, UCLA, Jon Dineen

### Stationary or Non-Stationary Process?

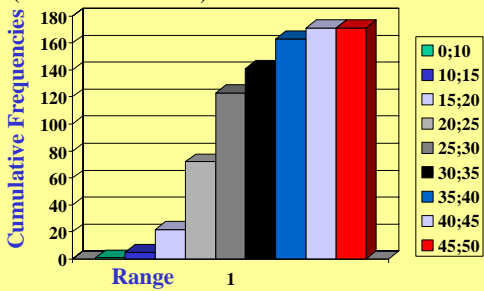
- **Histograms?** Do not work too well. Why?



Slide 38 Stat 110A, UCLA, Jon Dineen

### Stationary or Non-Stationary Process?

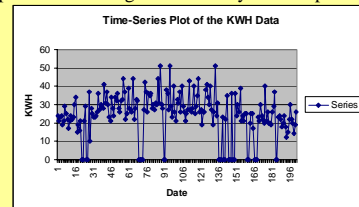
- **Histograms?** Do not work too well. Why? (Cumulative counts!)



Slide 39 Stat 110A, UCLA, Jon Dineen

### Stationary or Non-Stationary Process?

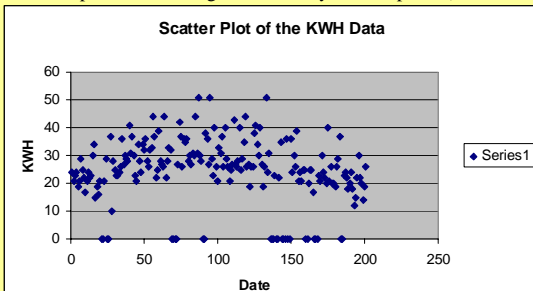
- **To assess stationarity:**
- **Rigorous assessment:** A stationary process has a **constant mean, variance, and autocorrelation** through time/place.
- **Visual assessment:** (Plot the data – observed vs. time/place – the parameter we argue stationarity with respect to).



Slide 40 Stat 110A, UCLA, Jon Dineen

### Stationary or Non-Stationary Process?

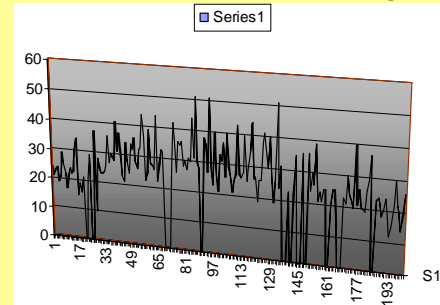
- **Visual assessment:** (Plot the data – observed vs. time/place, etc., – parameter we argue stationarity with respect to).



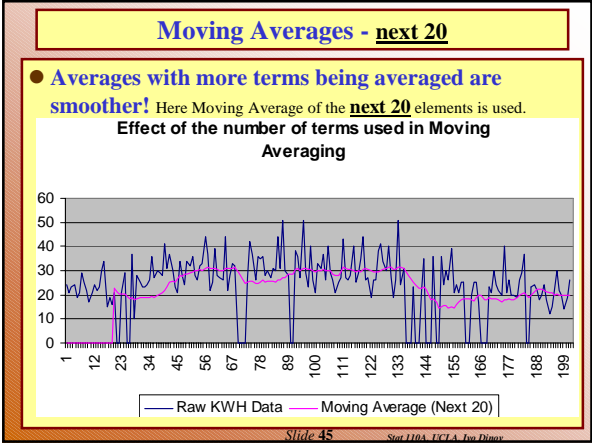
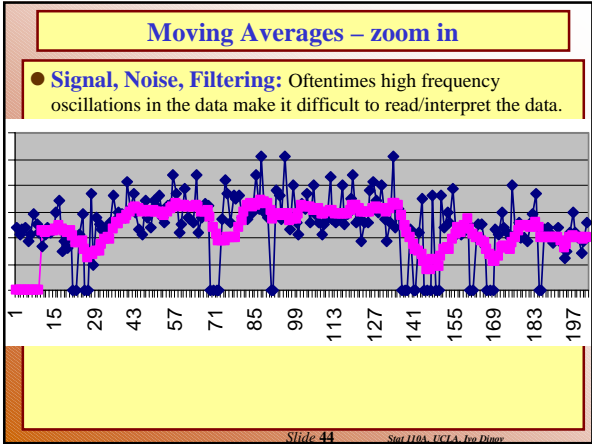
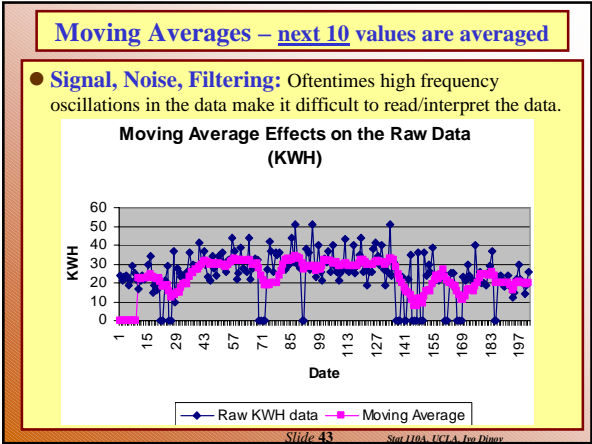
Slide 41 Stat 110A, UCLA, Jon Dineen

### Moving Averages

- **Signal, Noise, Filtering:** Oftentimes high frequency oscillations in the data make it difficult to read/interpret the data.



Slide 42 Stat 110A, UCLA, Jon Dineen



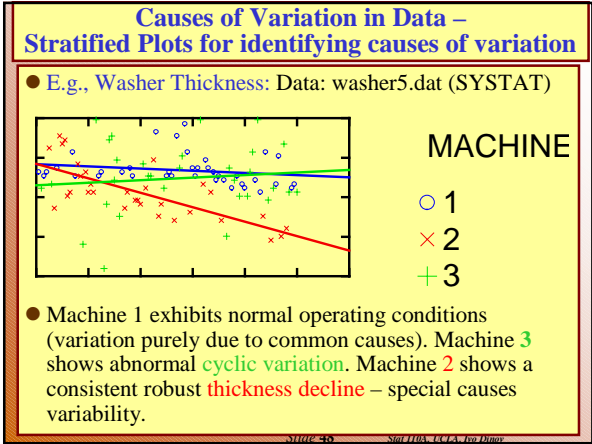
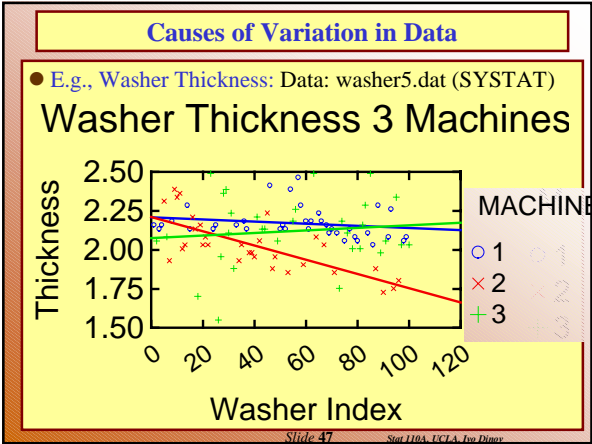
### Causes of Variation in Data

● **Cause of variation** is the reason/mechanism that introduces some of the observed variation in the data.

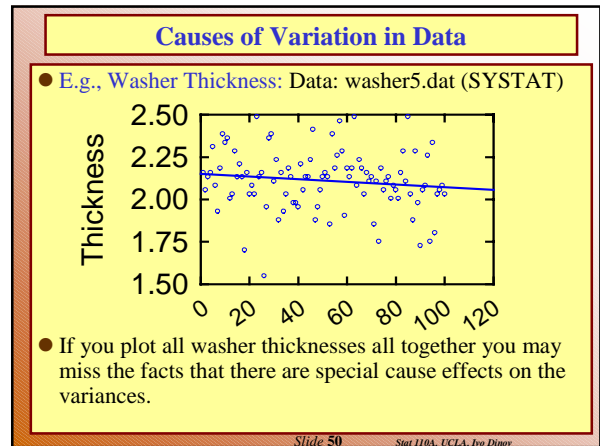
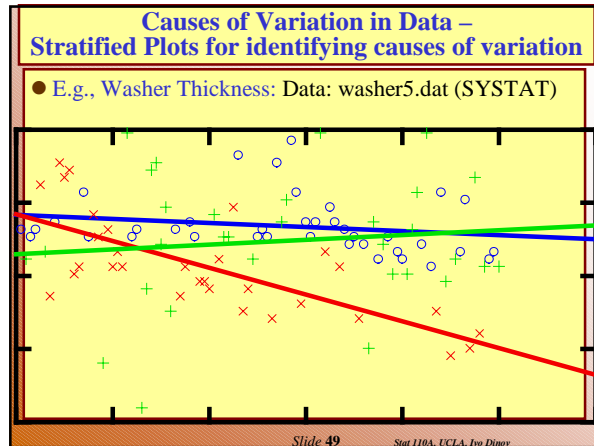
● **Kinds of causes of variation:**

- **Common cause** – the inherited fluctuations in a process, e.g., Geiger counter variances, random arrival time variances
- **Special causes** – periodically/cyclically arising variances, e.g., temp measures vary with season, wake-up times vary specially with day-of-week (weekends most people sleep longer), different machine settings/protocols (MRI imaging).

Slide 46 Stat 110A, UCLA, Jon Dineen







### Trimmed, Winsorized means and Resistancy

- A data-driven **parameter estimate** is said to be **resistant** if it does not greatly change in the presence of outliers.

- **K-times trimmed mean**  $\bar{y}_{tk} = \frac{1}{n - 2k} \sum_{i=k+1}^{n-k} y_{(i)}$

Order statistic

- **Winsorized k-times mean:**  $\bar{y}_{wk} = \frac{1}{n} \left[ (k+1)y_{(k+1)} + \sum_{i=k+2}^{n-k-1} y_{(i)} + (k+1)y_{(n-k)} \right]$

*Slide 51*     Stat 110A, UCLA, Joe Dineen

### Example - Trimmed, Winsorized means and Resistancy

- **K-times trimmed mean**  $\bar{y}_{tk} = \frac{1}{n - 2k} \sum_{i=k+1}^{n-k} y_{(i)}$
- **Winsorized k-times mean:**  $\bar{y}_{wk} = \frac{1}{n} \left[ (k+1)y_{(k+1)} + \sum_{i=k+2}^{n-k-1} y_{(i)} + (k+1)y_{(n-k)} \right]$
- **Data:**  $\{-11, 2, -1, 0, 1, 2, 0, -1, 15, 100\}$ ,  $n=10$ , **Sav  $k=2$**
- **Ordered statistics  $y_{(i)}$ :**  $\{-11, -1, -1, 0, 0, 1, 2, 2, 15, 100\}$

$$\bar{y} = \frac{1}{10} [-11 - 1 + \dots + 15 + 100] = 107/10 \sim 11$$

$$\bar{y}_{tk} = \frac{1}{10 - 4} (-1 + 0 + 0 + 1 + 2 + 2) = 4/6$$

$$\bar{y}_{wk} = \frac{1}{10} [3(-1) + (0 + 0 + 1 + 2) + 3 \times 2] = 3/5$$

*Slide 52*     Stat 110A, UCLA, Joe Dineen