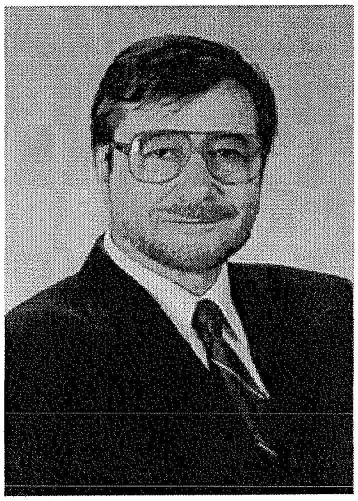
TECHNICAL REPORT
R-248
March 1997

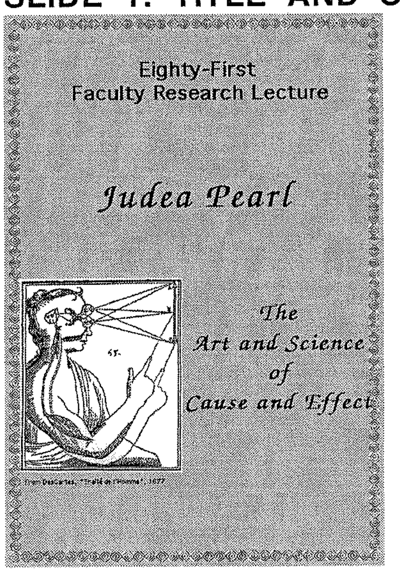
The Art and Science of Cause and Effect



JUDEA PEARL

Transcript of a lecture given
Thursday, October 29, 1996,
as part of the
UCLA 81st Faculty Research Lecture Series

SLIDE 1: TITLE AND OPENING



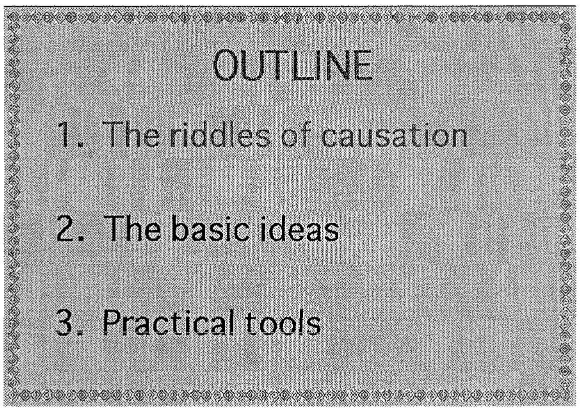
Thank you Chancellor Young, colleagues, and members of the Senate Selection Committee for inviting me to deliver the eighty-first lecture in the UCLA Faculty Research Lectureship Program. It is a great honor to be deemed worthy of this podium, and to be given the opportunity to share my research with such a diverse and distinguished audience.

The topic of this lecture is causality - namely, our awareness of what causes what in the world and why it matters. Though it is basic to human thought, Causality is a notion shrouded in mystery, controversy, and caution, because scientists and philosophers have had difficulties defining when one event TRULY CAUSES another.We all understand that the rooster's crow does not cause the sun to rise, but even this simple fact cannot easily be translated into a mathematical equation.

Today, I would like to share with you a set of ideas which I have found very useful in studying phenomena of this kind. These ideas have led to practical tools that I hope you will find useful on your next encounter with a cause and effect.

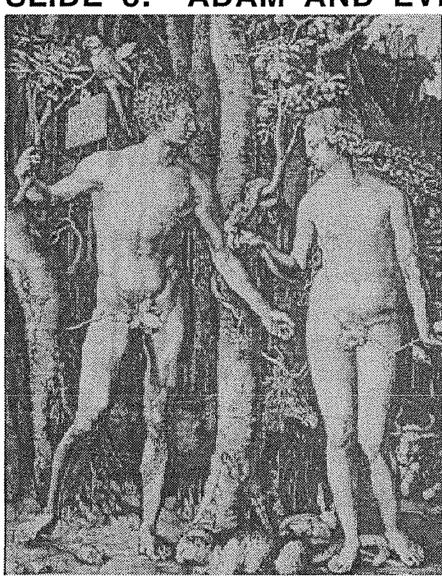
And it is hard to imagine anyone here who is NOT dealing with cause and effect. Whether you are evaluating the impact of bilingual education programs or running an experiment on how mice distinguish food from danger or speculating about why Julius Caesar crossed the Rubicon or diagnosing a patient or predicting who will win the 1996 presidential election, you are dealing with a tangled web of cause-effect considerations. The story that I am about to tell is aimed at helping researchers deal with the complexities of such considerations, and to clarify their meaning.

SLIDE 2: OUTLINE



This lecture is divided into three parts. I begin with a brief historical sketch of the difficulties that various disciplines have had with causation. Next I outline the ideas that reduce or eliminate several of these historical difficulties. Finally, in honor of my engineering background, I will show how these ideas lead to simple practical tools, which will be demonstrated in the areas of statistics and social science.

SLIDE 3: ADAM AND EVE (DURER)



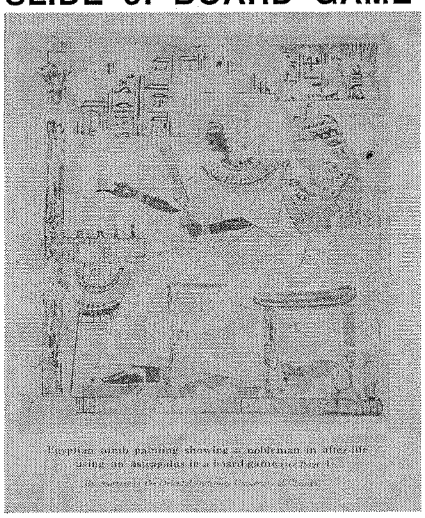
In the beginning, as far as we can tell, causality was not problematic. The urge to ask WHY and the capacity to find causal explanations came very early in human development. The bible, for example, tells us that just a few hours after tasting from the tree of knowledge, Adam is already an expert in causal arguments. When God asks: "Did you eat from that tree?" This is what Adam replies: "The woman whom you gave to be with me, She handed me the fruit from the tree; and I ate." Eve is just as skillful: "The serpent deceived me, and I ate."

The thing to notice about this story is that God did not ask for explanation, only for the facts: It was Adam who felt the need to explain -- the message is clear, causal explanation is a man-made concept. Another interesting point about the story: explanations are used exclusively for passing responsibilities. Indeed, for thousands of years explanations had no other function. Therefore, only Gods, people and animals could cause things to happen, not objects, events or physical processes.

SLIDE 4: THE FLIGHT OF LOT (DORE)

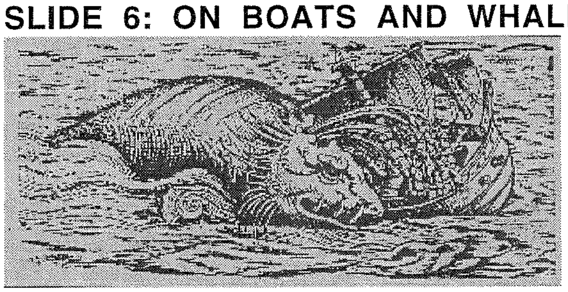
Natural events entered into causal explanations much later, because, in the ancient world, events were simply PREDETERMINED. Storms and earthquakes were CONTROLLED by the angry gods, and could not, in themselves, assume causal responsibility for the consequences.

SLIDE 5: BOARD GAME (EGYPTIAN TOMB)



Even an erratic and unpredictable event such as the roll of a die was not considered CHANCE event but rather a divine message demanding proper interpretation.

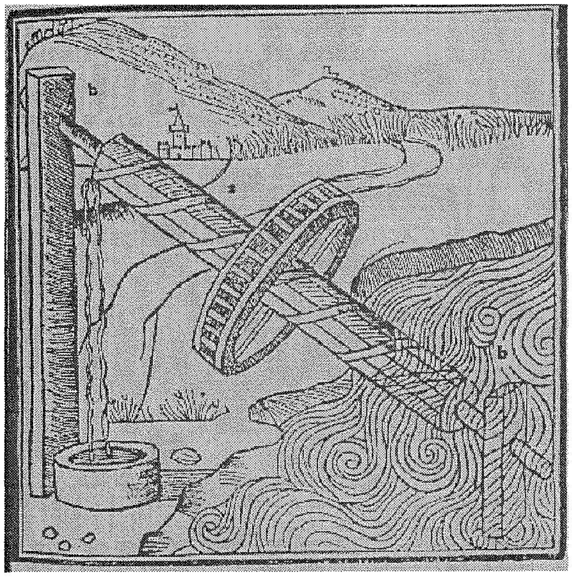
SLIDE 6: ON BOATS AND WHALES



One such message gave the prophet Jonah the scare of his life when he was identified as God's renegade and was thrown OVERBOARD. Quoting from the book of Jonah: "And the sailors said: `Come and let us cast lots to find out who is to blame for this ordeal. So they cast lots and the lot fell on Jonah." Obviously, on this luxury Phoenician cruiser, "casting Lots" were not used for recreation, but for communication - a one-way modem for processing messages of vital importance.

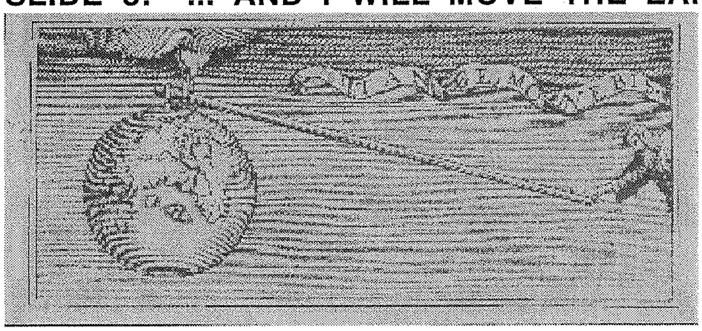
In summary, the agents of causal forces in the ancient world were either deities, who cause things to happen for a purpose, or human beings and animals, who possess free will, for which they are punished and rewarded.

SLIDE 7: ARCHIMEDES' SCREW PUMP (VITRUVIUS, 1511)



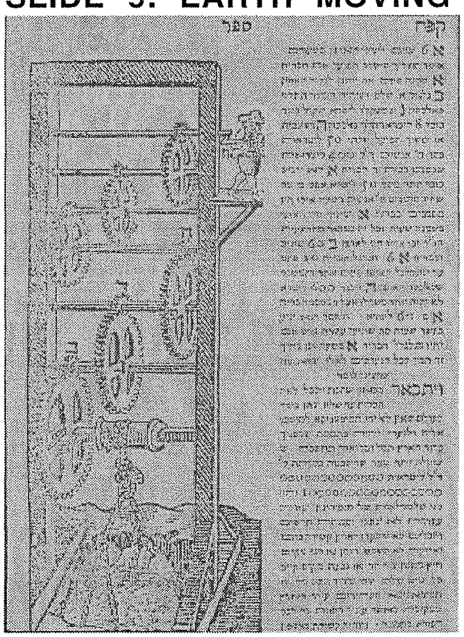
This notion of causation was naive, but clear and unproblematic. The problems began, as usual, with engineering; when machines had to be constructed to do useful jobs.

SLIDE 8: "... AND I WILL MOVE THE EARTH" (VAVIGNON, 1687)



As engineers grew ambitious, they decided that the earth, too, can be moved, but not with a single lever.

SLIDE 9: EARTH MOVING MACHINE (DELMEDIGO, 1629)

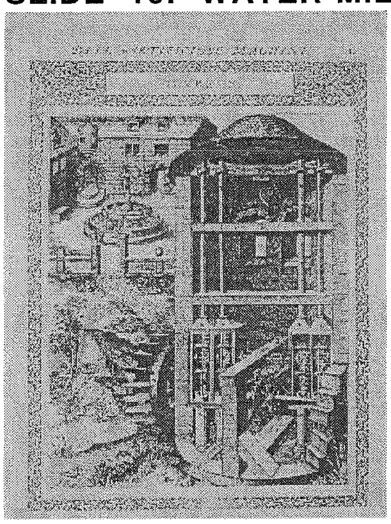


Systems consisting of many pulleys and wheels, one driving another, were needed for projects of such magnitude. And, once people started building multi-stage systems, an interesting thing happened to causality - PHYSICAL OBJECTS BEGAN ACQUIRING CAUSAL CHARACTER. When a system like that broke down, it was futile to blame God or the operator - instead, a broken rope or a rusty pulley were more useful explanations, simply because those could be replaced easily, and make the system work. At that point in history, Gods and humans ceased to be the sole agents of causal forces - lifeless objects and processes became partners in responsibility. A wheel turned and stopped BECAUSE the wheel proceeding it turned and stopped - the human operator became secondary.

Not surprisingly, these new agents of causation TOOK ON some of the characteristics of their predecessors - Gods and humans. Natural objects became not only carriers of credit and blame, but also carriers of force, will, and even purpose. Aristotle regarded explanation in terms of a PURPOSE to be the only complete and satisfactory explanation for why a thing is what it is. He even called it a "FINAL CAUSE", namely, the final aim of scientific inquiry.

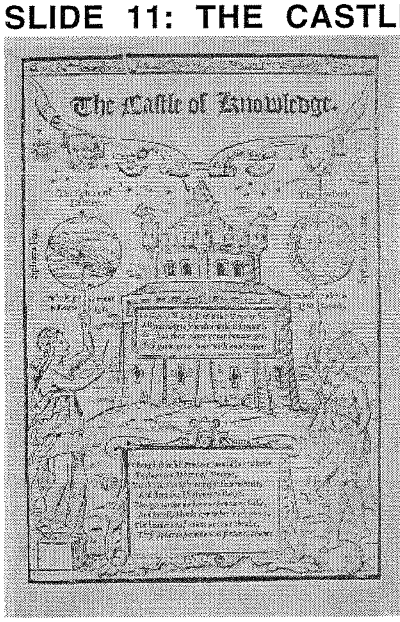
From that point on, causality served a dual role: CAUSES were the targets of credit and blame on one hand, and the carriers of physical flow of control on the other.

SLIDE 10: WATER-MILL



This duality survived in relative tranquillity until about the time of the Renaissance, when it encountered conceptual difficulties.

SLIDE 11: THE CASTLE OF KNOWLEDGE (RECORDES, 1575)

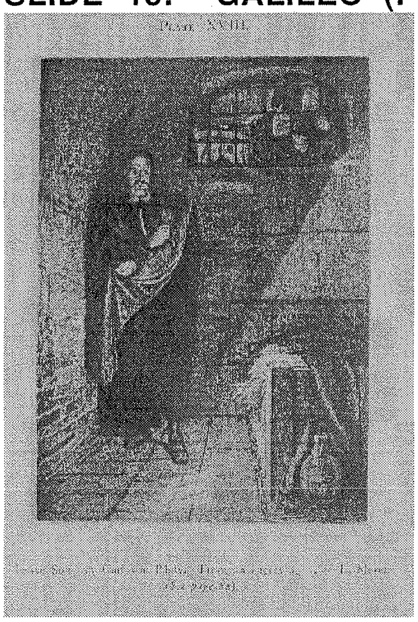


What happened can be seen on the title page of Recordes' book "The Castle of Knowledge," the first science book in English, published in 1575. The wheel of fortune is turned, not by the wisdom of God, but by the ignorance of man. And, as the role of God, the final cause, was taken over by human knowledge, the whole notion of causal explanation came under attack.

SLIDE 12: GALILEO (PORTRAIT, 1613)

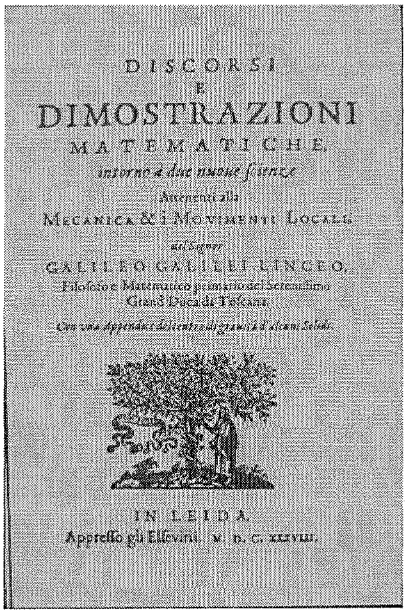
The erosion started with the work of Galileo.

SLIDE 13: GALILEO (PRISON SCENE)



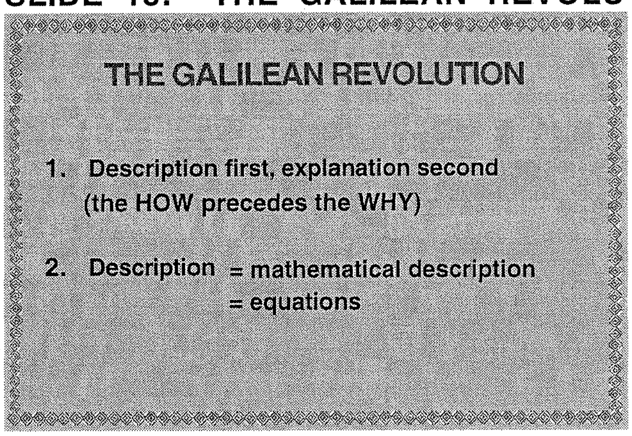
Most of us know Galileo as the man who was brought before by the inquisition and imprisoned for defending the heliocentric theory of the world. But while all that was going on, Galileo also managed to quietly engineer the most profound revolution that science has ever known.

SLIDE 14: TITLE PAGE OF DISCORSI



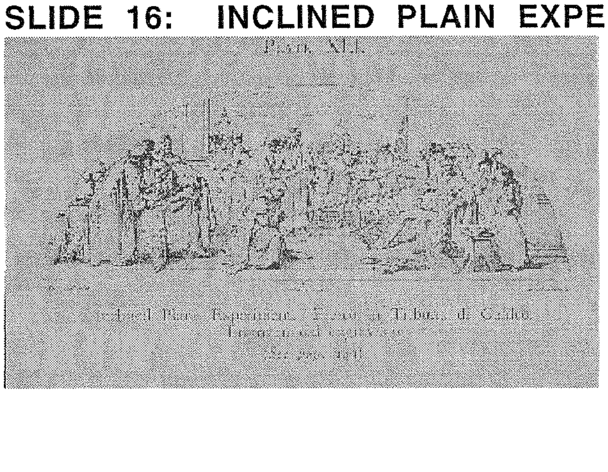
This revolution, expounded in his 1638 book "Discorsi" published in Leyden, far from Rome, consists of two Maxims:

SLIDE 15: THE GALILEAN REVOLUTION



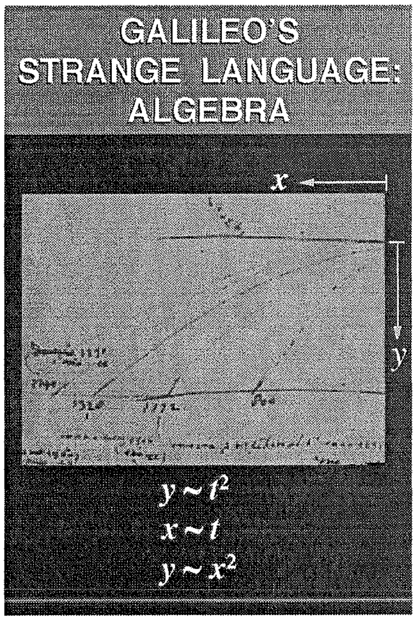
ONE, description first, explanation second-that is, the how precedes the why; and TWO, description is carried out in the language of mathematics; namely, equations. Ask not, said Galileo, whether an object falls because it is pulled from below or pushed from above.

SLIDE 16: INCLINED PLAIN EXPERIMENT



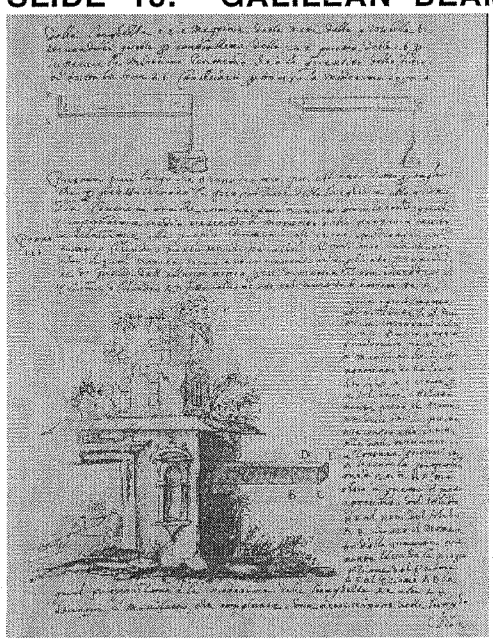
Ask how well you can predict the time it takes for the object to travel a certain distance, and how that time will vary from object to object, and as the angle of the track changes. Moreover, said Galileo, do not attempt to answer such questions in the qualitative and slippery nuances of human language; say it in the form of mathematical equations.

SLIDE 17: GALILEAN EQUATION $d = t^2$



It is hard for us to appreciate today how strange that idea sounded in 1638, barely 50 years after the introduction of algebraic notation by Vieta. To proclaim algebra the UNIVERSAL language of science, would sound today like proclaiming Esperanto the language of economics. Why would Nature agree to speak Algebra? of all languages? But you can't argue with success. The distance traveled by an object turned out indeed to be proportional to the square of the time; — a strange mathematical entity, time multiplied by time, resisting any straight geometrical interpretation.

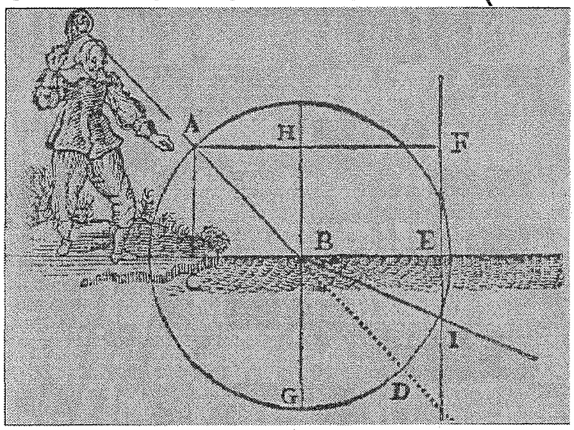
SLIDE 18: GALILEAN BEAM (MANUSCRIPT, DISCORSI, 1638)



Even more successful than predicting outcomes of experiments were the computational aspects of algebraic equations. They enabled engineers, for the first time in history, to ask "how to" questions, in addition to "what if" questions. In addition to asking: "What if we narrow the beam, will it carry the load?" They began to ask more difficult questions: "How to shape the beam so that it WILL carry the load?" This was made possible by the availability of methods for solving equations. The algebraic machinery does not descriminate among variables; instead of predicting behavior in terms of parameters, we can turn things around and solve for the parameters, in terms of the desired behavior.

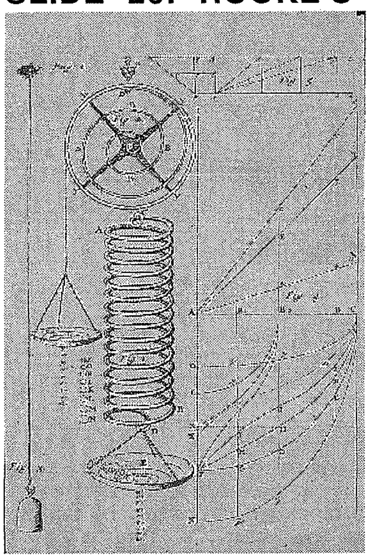
Let us concentrate now on Galileo's first maxim, "description first explanation second", because that idea was taken very seriously by the scientists, and changed the character of science from speculative to empirical.

SLIDE 19: SNELL'S LAW (DESCARTE'S DIOPTRICS, 1637)



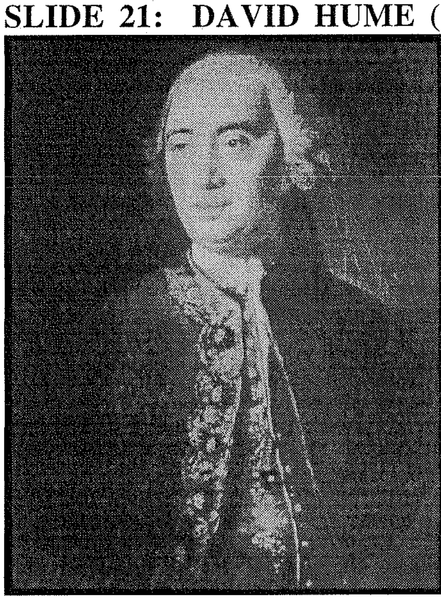
Physics became flooded with empirical laws that were extremely useful. Snell law, Hookes law, Ohm's law, and Joule's law are examples of purely empirical generalizations that were discovered and used much before they were explained by more fundamental principles.

SLIDE 20: HOOKE'S LAW (1678)



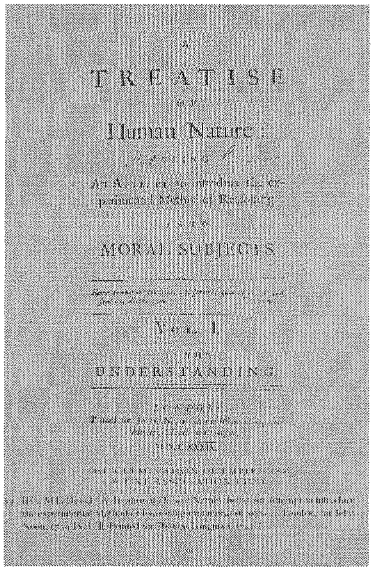
Philosophers, however, were reluctant to give up the idea of causal explanation, and continued to search for the origin and justification of those successful Galilean equations. For example, Descartes ascribed cause to ETERNAL TRUTH. Liebnitz made cause a SELF-EVIDENT LOGICAL LAW.

SLIDE 21: DAVID HUME (PORTRAIT)



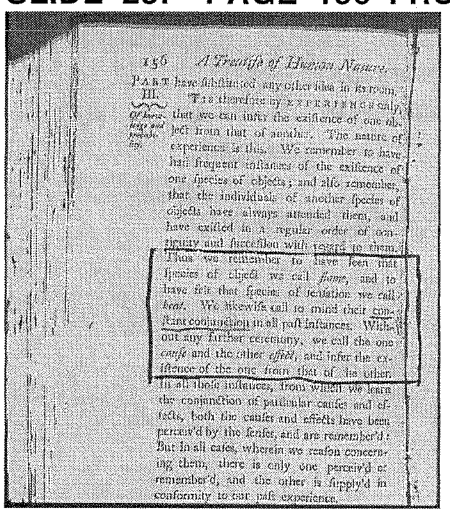
Finally, about one hundred years after Galileo, a Scottish philosopher by the name of David Hume carried Galileo's first maxim to an extreme.

SLIDE 22: TITLE PAGE OF HUME-"A TREATISE OF HUMAN NATURE"


A
TREATISE
OF
Human Nature:
An ATTEMPT to introduce the experimental Method of Reasoning
INTO
MORAL SUBJECTS
VOL. I.
OF THE
UNDERSTANDING.
MDCCXXXIX.

Hume argued convincingly that the WHY is not merely second to the HOW, but that the WHY is totally superfluous as it is subsumed by the HOW.

SLIDE 23: PAGE 156 FROM "A TREATISE OF HUMAN NATURE"


156 *A Treatiſe of Human Nature.*

PART III. Of know-ledge and probab. have ſubſtituted any other idea in its room.

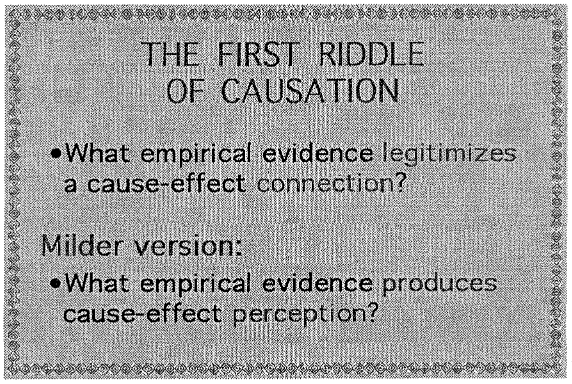
'Tis therefore by EXPERIENCE only, that we can infer the exiſtence of one object from that of another. The nature of experience is this. We remember to have had frequent inſtances of the exiſtence of one ſpecies of objects; and alſo remember, that the individuals of another ſpecies of objects have always attended them, and have exiſted in a regular order of contiguity and ſucceſſion with regard to them. Thus we remember to have ſeen that ſpecies of object we call *flame*, and to have felt that ſpecies of ſenſation we call *heat*. We likewiſe call to mind their conſtant conjunction in all paſt inſtances. Without any farther ceremony, we call the one *cauſe* and the other *effect*, and infer the exiſtence of the one from that of the other. In all thoſe inſtances, from which we learn the conjunction of particular cauſes and effects, both the cauſes and effects have been perceiv'd by the ſenſes, and are remember'd: But in all caſes, wherein we reaſon concerning them, there is only one perceiv'd or remember'd, and the other is ſupply'd in conformity to our paſt experience.

On page 156 of Hume's "Treatise of Human Nature", we find the paragraph that shook up causation so thoroughly that it has not recovered to this day. I always get a kick reading it: "Thus we remember to have seen that species of object we call *FLAME*, and to have felt that species of sensation we call *HEAT*. We likewise call to mind their constant conjunction in all past instances. Without any farther ceremony, we call the one *CAUSE* and the other *EFFECT*, and infer the existence of the one from that of the other."

Thus, causal connections according to Hume are product of observations. Causation is a learnable habit of the mind, almost as fictional as optical illusions and as transitory as Pavlov's conditioning. It is hard to believe that Hume was not aware of the difficulties inherent in his proposed recipe. He knew quite well that the rooster crow STANDS in constant conjunction to the sunrise, yet it does not CAUSE the sun to rise. He knew that the barometer reading STANDS in constant conjunction to the rain, but does not CAUSE the rain.

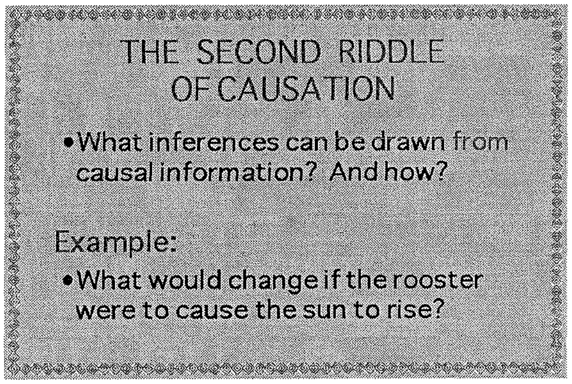
Today these difficulties fall under the rubric of SPURIOUS CORRELATIONS, namely "correlations that do not imply causation". Now, taking Hume's dictum that all knowledge comes from experience, that experience is encoded in the mind as correlation, and our observation that correlation does not imply causation, we are led into our first riddle of causation: How do people EVER acquire knowledge of CAUSATION?

SLIDE 24: THE FIRST RIDDLE OF CAUSATION



We saw in the rooster example that regularity of succession is not sufficient; what WOULD be sufficient? What patterns of experience would justify calling a connection "causal"? Moreover: What patterns of experience CONVINCES people that a connection is "causal"?

SLIDE 25: THE SECOND RIDDLE OF CAUSATION

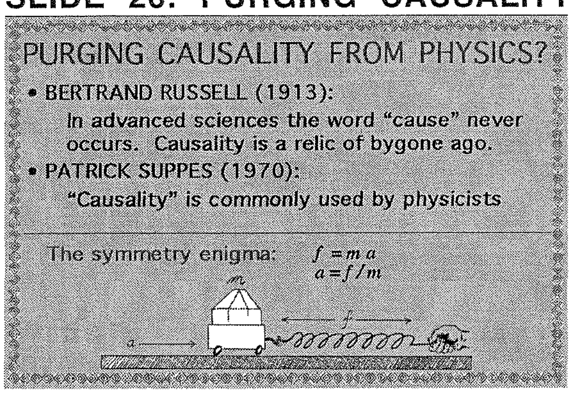


If the first riddle concerns the LEARNING of causal-connection, the second concerns its usage: What DIFFERENCE does it make if I told you that a certain connection is or is not causal:?

Continuing our example, what difference does it make if I told you that the rooster does cause the sun to rise? This may sound trivial. The obvious answer is that knowing what causes what makes a big difference in how we act. If the rooster's crow causes the sun to rise we could make the night shorter by waking up our rooster earlier and make him crow - say by telling him the latest rooster joke.

But this riddle is NOT as trivial as it seems. If causal information has an empirical meaning beyond regularity of succession, then that information should show up in the laws of physics. But it does not! The philosopher Bertrand Russell made this argument in 1913:

SLIDE 26: PURGING CAUSALITY FROM PHYSICS?



"All philosophers," says Russell, "imagine that causation is one of the fundamental axioms of science, yet oddly enough, in advanced sciences, the word 'cause' never occurs ... The law of causality, I believe, is a relic of bygone age, surviving, like the monarchy, only because it is erroneously supposed to do no harm ...", Another philosopher, Patrick Suppes, on the other hand, arguing for the importance of causality, noted that: "There is scarcely an issue of *PHYSICAL REVIEW* that does not contain at least one article using either `cause' or `causality' in its title."

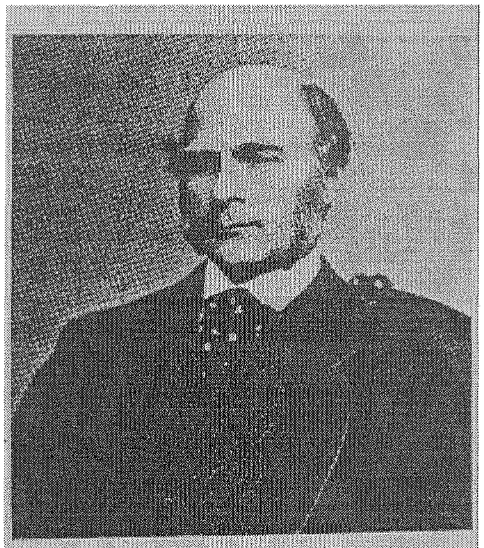
What we conclude from this exchange is that physicists talk, write, and think one way and formulate physics in another. Such bi-lingual activity would be forgiven if causality was used merely as a convenient communication device - a shorthand for expressing complex patterns of physical relationships that would otherwise take many equations to write. After all! Science is full of abbreviations: We use, "multiply x by 5", instead of "add x to itself 5 times"; we say: "density" instead of "the ratio of weight to volume". Why pick on causality?

"Because causality is different," Lord Russell would argue, "It could not possibly be an abbreviation, because the laws of physics are all symmetrical, going both ways, while causal relations are uni-directional, going from cause to effect." Take for instance Newton's law $f = ma$ .The rules of algebra permit us to write this law in a wild variety of syntactic forms, all meaning the same thing - that if we know any two of the three quantities, the third is determined. Yet, in ordinary discourse we say that force causes acceleration - not that acceleration causes force, and we feel very strongly about this distinction. Likewise, we say that the ratio f/a helps us DETERMINE the mass, not that it CAUSES the mass. Such distinctions are not supported by the equations of physics, and this leads us to ask whether the whole causal vocabulary is purely metaphysical. "surviving, like the monarchy...etc."

Fortunately, very few physicists paid attention to Russell's enigma. They continued to write equations in the office and talk cause-effect in the CAFETERIA, with astonishing success, they smashed the atom, invented the transistor, and the laser. The same is true for engineering. But in another arena the tension could not go unnoticed, because in that arena the demand for distinguishing causal from other relationships was very explicit. This arena is statistics.

The story begins with the discovery of correlation, about one hundred years ago.

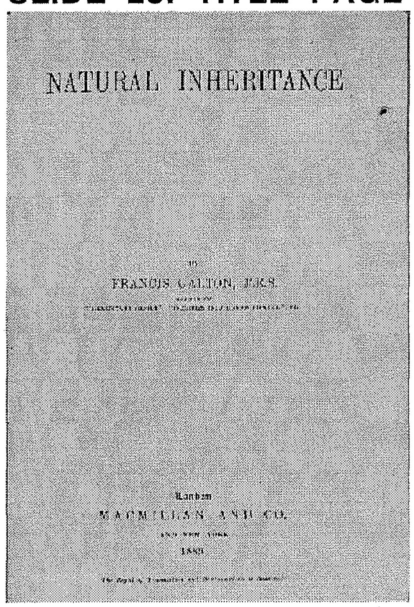
SLIDE 27: FRANCIS GALTON (PORTRAIT)



Francis Galton (1822–1911)

Francis Galton, inventor of fingerprinting and cousin of Charles Darwin, quite understandably set out to prove that talent and virtue run in families.

SLIDE 28: TITLE PAGE "NATURAL INHERITANCE"



NATURAL INHERITANCE

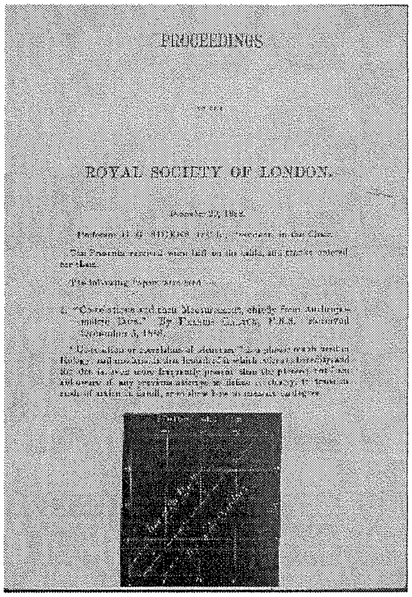
FRANCIS GALTON, F.R.S.

London

MACMILLAN AND CO.

These investigations, drove Galton to consider various ways of measuring how properties of one class of individuals or objects are related to those of another class.

SLIDE 29: GALTON'S PLOT OF CORRELATED DATA (1888)



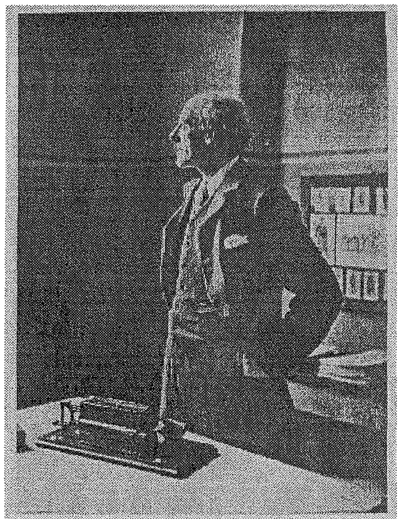
In 1888, he measured the length of a person's forearm and the size of that person's head and asked to what degree can one of these quantities predict the other. He stumbled upon the following discovery: If you plot one quantity against the other and scale the two axes properly, then the slope of the best-fit line has some nice mathematical properties: The slope is 1 only when one quantity can predict the other precisely; it is zero whenever the prediction is no better than a random guess and, most remarkably, the slope is the same no matter if you plot X against Y or Y against X. "It is easy to see," said Galton, "that co-relation must be the consequence of the variations of the two organs being partly due to common causes." Here we have, for the first time, an objective measure of how two variables are "related" to each other, based strictly on the data, clear of human judgment or opinion.

SLIDE 30: KARL PEARSON (PORTRAIT, 1890)

Karl Pearson (1857–1936), in 1890

Galton's discovery dazzled one of his students, Karl Pearson, now considered the founder of modern statistics. Pearson was 30 years old at the time, an accomplished physicist and philosopher about to turn lawyer, and this is how he describes, 45 years later, his initial reaction to Galton's discovery:

SLIDE 31: KARL PEARSON (1934)

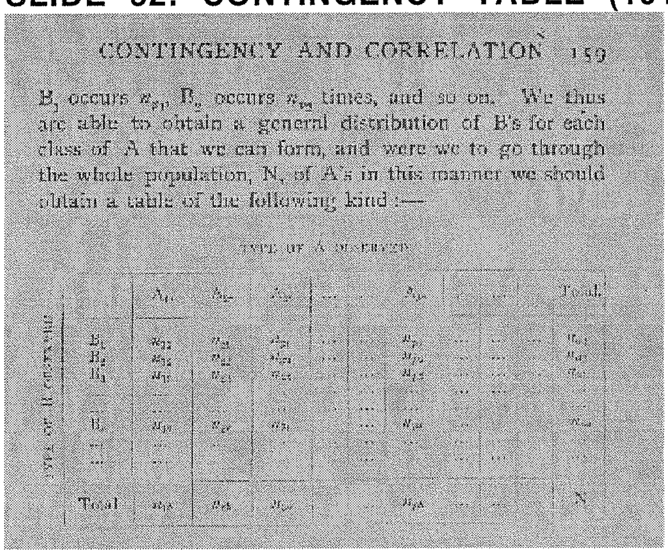


KARL PEARSON, 1934

"I felt like a buccaneer of Drake's days — ... I interpreted that sentence of Galton to mean that there was a category broader than causation, namely correlation, of which causation was only the limit, and that this new conception of correlation brought psychology, anthropology, medicine, and sociology in large parts into the field of mathematical treatment."

Now, Pearson has been described as a person "with the kind of drive and determination that took Hannibal over the Alps and Marco Polo to China." When Pearson felt like a buccaneer, you can be sure he gets his bounty.

SLIDE 32: CONTINGENCY TABLE (1911)



CONTINGENCY AND CORRELATION 159

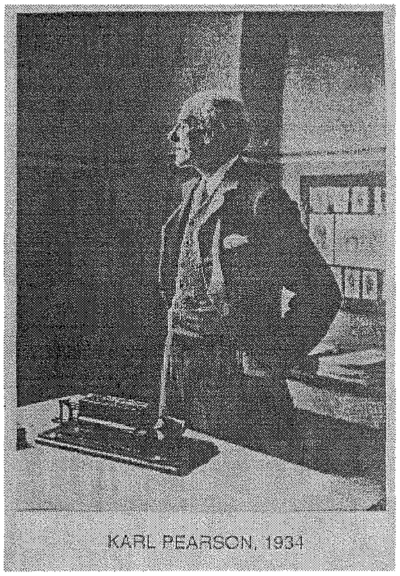
B_1 occurs n_{p1}, B_2 occurs n_{p2} times, and so on. We thus are able to obtain a general distribution of B's for each class of A that we can form, and were we to go through the whole population, N, of A's in this manner we should obtain a table of the following kind :—

TYPE OF A OBSERVED

	A_1	A_2	A_3	...	A_p	...	Total
B_1	[illegible]	[illegible]	[illegible]	...	[illegible]	...	[illegible]
B_2	[illegible]	[illegible]	[illegible]	...	[illegible]	...	[illegible]
B_3	[illegible]	[illegible]	[illegible]	...	[illegible]	...	[illegible]
...	...	...	...	...	...	...	...
B_q	[illegible]	[illegible]	[illegible]	...	[illegible]	...	[illegible]
...	...	...	...	...	...	...	...
Total	[illegible]	[illegible]	[illegible]		[illegible]	...	N

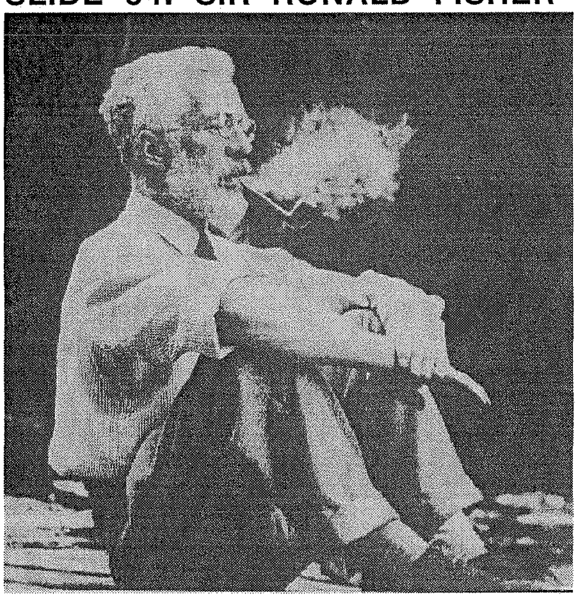
1911 saw the publication of the third edition of his book "The Grammar of Science". It contained a new chapter titled "Contingency and correlation - the insufficiency of causation," and this is what Pearson says in that chapter: "Beyond such discarded fundamentals as 'matter' and 'force' lies still another fetish amidst the inscrutable arcana of modern science, namely, the category of cause and effect."

SLIDE 33: KARL PEARSON (1934)



Thus, Pearson categorically denies the need for an independent concept of causal relation beyond correlation. He held this view throughout his life and, accordingly, did not mention causation in ANY of his technical papers. His crusade against animistic concepts such as "will" and "force" was so fierce and his rejection of determinism so absolute that he EXTERMINATED causation from statistics before it had a chance to take root.

SLIDE 34: SIR RONALD FISHER

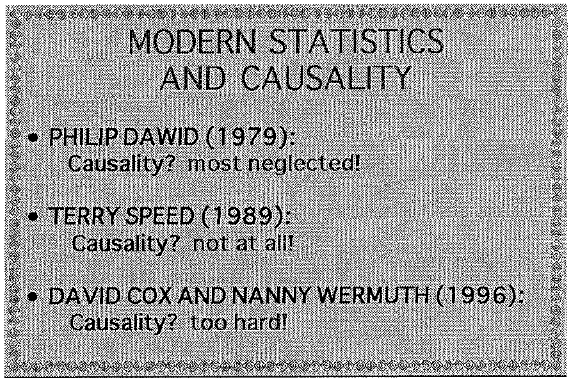


It took another 25 years and another strong-willed person, Sir Ronald Fisher, for statisticians to formulate the randomized experiment — the only scientifically proven method of testing causal relations from data, and which is, to this day, the one and only causal concept permitted in mainstream statistics.

And that is roughly where things stand today... If we count the number of doctoral theses, research papers, or textbooks pages written on causation, we get the impression that Pearson still rules statistics. The "Encyclopedia of Statistical Science" devotes 12 pages to correlation but only 2 pages to causation, and spends one of those pages demonstrating that "correlation does not imply causation."

Let us hear what modern statisticians say about causality

SLIDE 35: MODERN STATISTICS AND CAUSALITY



Philip Dawid , the current editor of Biometrika-the journal founded by Pearson - admits: "causal inference is one of the most important, most subtle, and most neglected of all the problems of statistics". Terry Speed, former president of the Biometric Society (whom you might remember as an expert witness at the O.J. Simpson murder trial), declares: "considerations of causality should be treated as they have always been treated in statistics: preferably not at all, (but if necessary, then with very great care.)" Sir David Cox and Nanny Wermuth, in a book published just a few months ago, apologize as follows: "We did not in this book use the words CAUSAL or CAUSALITY.... Our reason for caution is that it is rare that firm conclusions about causality can be drawn from one study."

This position of caution and avoidance has paralyzed many fields that look to statistics for guidance, especially economics and social science. A leading social scientist stated in 1987: "It would be very healthy if more researchers abandon thinking of and using terms such as cause and effect." Can this state of affairs be the work of just one person? even a buccaneer like Pearson? I doubt it.

But how else can we explain why statistics, the field that has given the world such powerful concepts as the testing of hypothesis and the design of experiment would give up so early on causation?

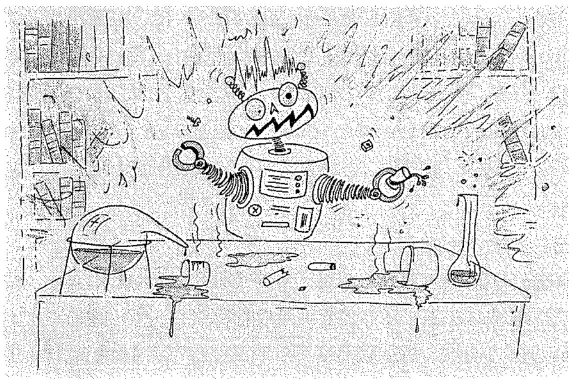
One obvious explanation is, of course, that causation is much harder to measure than correlation. Correlations can be estimated directly in a single uncontrolled study, while causal conclusions require controlled experiments.

But this is too simplistic; statisticians are not easily deterred by difficulties and children manage to learn cause effect relations WITHOUT running controlled experiments. The answer, I believe lies deeper, and it has to do with the official language of statistics, namely the language of probability. This may come as a surprise to some of you but the word "CAUSE" is not in the vocabulary of probability theory; we cannot express in the language of probabilities the sentence, "MUD DOES NOT CAUSE RAIN" - all we can say is that the two are mutually correlated, or dependent - meaning if we find one, we can expect the other. Naturally, if we lack a language to express a certain concept explicitly, we can't expect to develop scientific activity around that concept. Scientific development requires that knowledge be transferred reliably from one study to another and, as Galileo has shown 350 years ago, such transference requires the precision and computational benefits of a formal language.

I will soon come back to discuss the importance of language and notation, but first, I wish to conclude this historical survey with a tale from another field in which causation has had its share of difficulty. This time it is computer science - the science of symbols - a field that is relatively new, yet it has placed a tremendous emphasis on language and notation and, therefore, may offer a useful perspective on the problem.

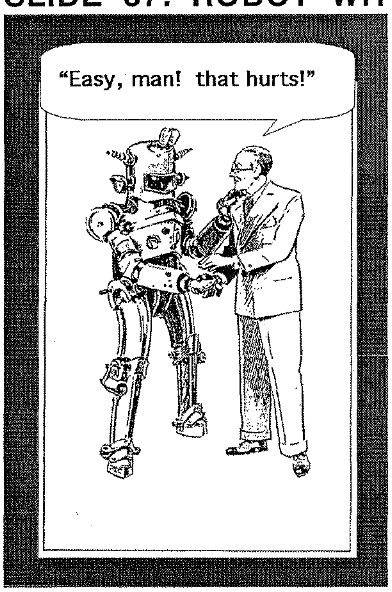
When researchers began to encode causal relationships using computers, the two riddles of causation were awakened with renewed vigor.

SLIDE 36: ROBOT IN LAB



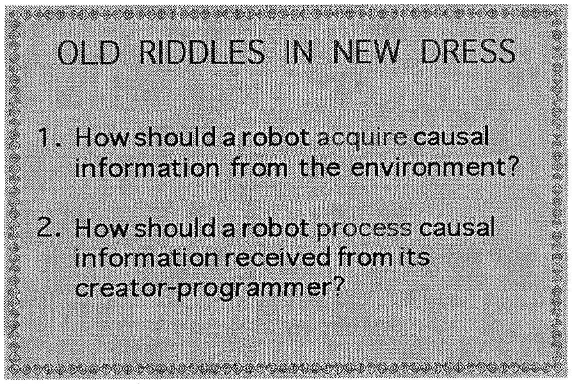
Put yourself in the shoes of this robot who is trying to make sense of what is going on in a kitchen or a laboratory. Conceptually, the robot's problems are the same as those faced by an economist seeking to model the National debt or an epidemiologist attempting to understand the spread of a disease. Our robot, economist, and epidemiologist all need to track down cause-effect relations from the environment, using limited actions and noisy observations. This puts them right at Hume's first riddle of causation: HOW?

SLIDE 37: ROBOT WITH MENTOR



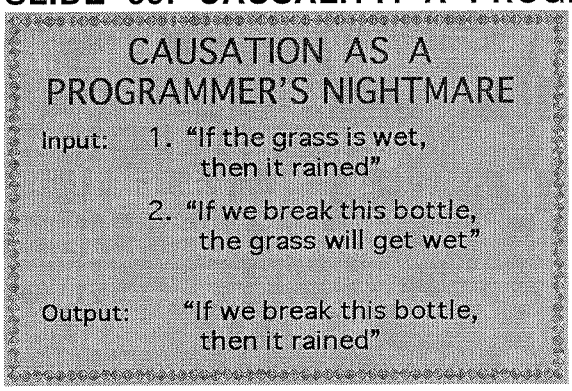
The second riddle of causation also plays a role in the robot's world. Assume we wish to take a shortcut and teach our robot all we know about cause and effect in this room. How should the robot organize and make use of this information? Thus, the two philosophical riddles of causation are now translated into concrete and practical questions:

SLIDE 38: OLD RIDDLES IN NEW DRESS



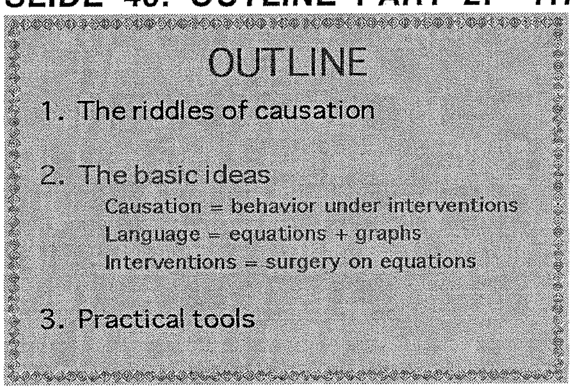
How should a robot acquire causal information through interaction with its environment? How should a robot process causal information received from its creator-programmer? Again, the second riddle is not as trivial as it might seem. Lord Russell's warning that causal relations and physical equations are incompatible now surfaces as an apparent flaw in logic.

SLIDE 39: CAUSALITY: A PROGRAMMER'S NIGHTMARE



For example, when given the information, "If the grass is wet, then it rained" and "If we break this bottle, the grass will get wet," the computer will conclude "If we break this bottle, then it rained." The swiftness and specificity with which such programming bugs surface, have made Artificial-Intelligence programs an ideal laboratory for studying the fine print of causation.

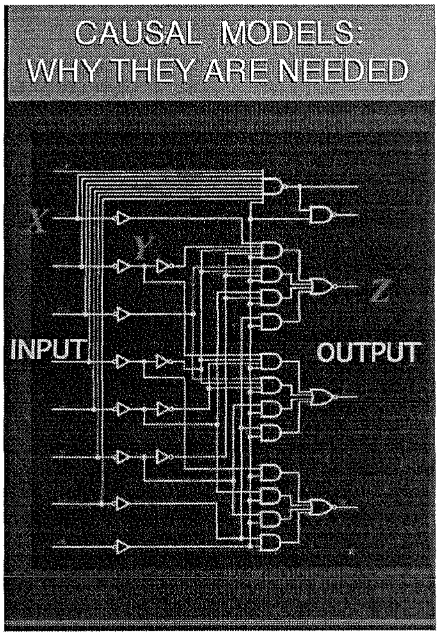
SLIDE 40: OUTLINE PART 2: THE BASIC IDEAS



This brings us to the second part of the lecture: how the second riddle of causation can be solved by combining equations with graphs, and how this solution makes the first riddle less formidable. The overriding ideas in this solution are: FIRST: treating causation as a summary of behavior under interventions and SECOND: using equations and graphs as a mathematical language within which causal thoughts can be represented and manipulated. And to put the two together, we need a THIRD concept: Treating interventions a s a surgery over equations.

Let us start with an area that uses causation extensively and never had any trouble with it: Engineering.

SLIDE 41: CIRCUIT DIAGRAM



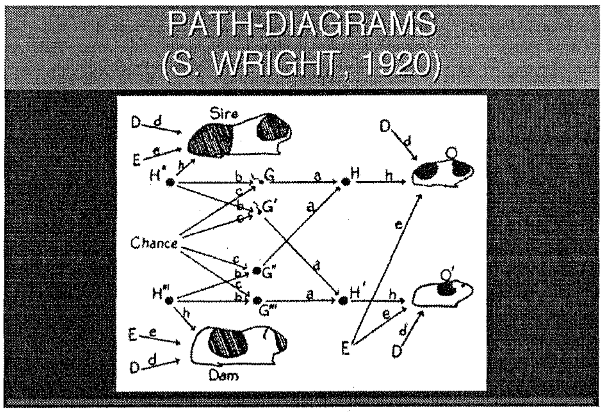
Here is an engineering drawing of a circuit diagram that shows cause-effect relations among the signals in the circuit. The circuit consists of AND gates and OR gates, each performing some logical function between input and output. Let us examine this diagram closely, since its simplicity and familiarity are very deceiving. This diagram is, in fact, one of the greatest marvels of science. It is capable of conveying more information than millions of algebraic equations or probability functions or logical expressions". What makes this diagram so much more powerful is the ability to predict not merely how the circuit behaves under normal conditions, but also how the circuit will behave under millions of ABNORMAL conditions. For example, given this circuit diagram, we can easily tell what the output will be if some input changes from 0 to 1. This is normal and can easily be expressed by a simple input-output equation. Now comes the abnormal part. We can also tell what the output will be when we set Y to 0 (zero), or tie it to X, or change this AND gate to an OR gate, or when we perform any of the millions combinations of these operations.

The designer of this circuit did not anticipate or even consider such weird interventions, yet, miraculously, we can predict their consequences. How? Where does this representational power come from?

It comes from what early economists called AUTONOMY, namely, the gates in these diagram represent independent mechanisms - it is easy to change one without changing the other. The diagram takes advantage of this independence and describes the normal functioning of the circuit USING PRECISELY THOSE BUILDING BLOCKS THAT WILL REMAIN UNALTERED UNDER INTERVENTION.

My colleagues from Boelter Hall are surely wondering why I stand here before you blathering about an engineering triviality as if it were the 8th wonder of the world. I have three reasons for doing this. First, I will try to show that there is a lot of unexploited wisdom in practices that engineers take for granted.

SLIDE 42: PATH DIAGRAMS

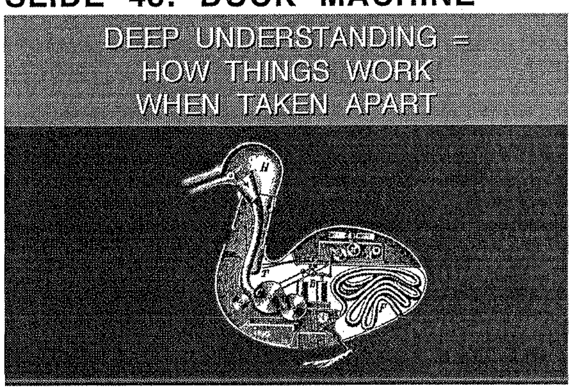


Second, I am trying to remind economists and social scientists of the benefits of this diagrammatic method. They have been using a similar method on and off for over 75 years, called structural equations modeling and path-diagrams, but in recent years have allowed algebraic convenience to suppress the diagrammatic representation, together with its benefits.

Finally, these diagrams capture in my opinion, the very essence of causation - the ability to predict the consequences of abnormal eventualities and new manipulations. In this diagram, for example, it is possible to predict what coat pattern the litter guinea-pig is likely to have, if we change environmental factors, shown here by as input (E) in green, or even genetic factors, shown in red as intermediate nodes between parents and offsprings (H). Such predictions cannot be made on the basis of algebraic or correlational analysis.

Viewing causality this way explains why scientists pursue causal explanations with such zeal, and why attaining a causal model is accompanied with a sense of gaining "deep understanding" and "being in control."

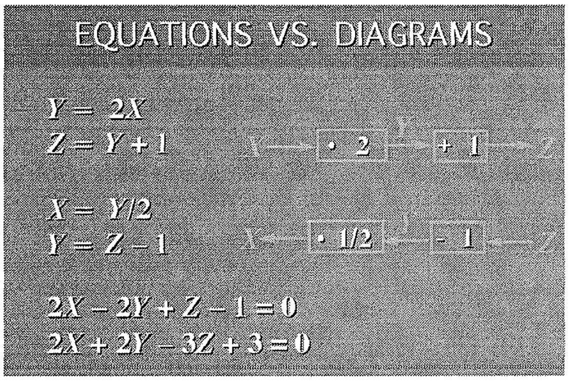
SLIDE 43: DUCK MACHINE



DEEP UNDERSTANDING means knowing, not merely how things behaved yesterday, but also how things will behave under new hypothetical circumstances, control being one such circumstance.

Interestingly, when we have such understanding we feel "in control" even when if we have no practical way of controlling things. For example, we have no practical way to control celestial motion, and still the theory of gravitation gives us a feeling of understanding and control, because it provides a blueprint for hypothetical control. We can predict the effect on tidal waves of unexpected new events, say, the moon being hit by a meteor or the gravitational constant suddenly diminishing by a factor of 2 and, just as important, the gravitational theory gives us the assurance that ordinary manipulation of earthly things will NOT control tidal waves. It is not surprising that causal models are viewed as the litmus test distinguishing deliberate reasoning from reactive or instinctive response. Birds and monkeys may possibly be trained to perform complex tasks such as fixing a broken wire, but that requires trial-and-error training. Deliberate reasoners, on the other hand, can anticipate the consequences of new manipulations WITHOUT EVER TRYING those manipulations.

SLIDE 44: EQUATIONS VS. DIAGRAMS



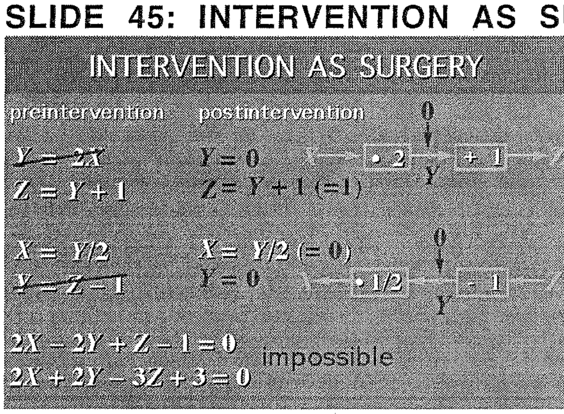
Let us magnify a portion of the circuit diagram so that we can understand why the diagram can predict outcomes that equations can not. Let us also switch from logical gates to linear equations (to make everyone here more comfortable), and assume we are dealing with a system containing just two components: a multiplier and an adder. The MULTIPLIER takes the input and multiplies it by a factor of 2; the ADDER takes its input and adds a 1 to it. The equations describing these two components are given here on the left.

But are these equations EQUIVALENT to the diagram on the right? Obviously not! If they were, then let us switch the variables around, and the resulting two equations should be equivalent to the circuit shown below. But these two circuits are different.

The top one tells us that if we physically manipulate Y it will affect Z, while the bottom one shows that manipulating Y will affect X and will have no effect on Z. Moreover, performing some additional algebraic operations on our equations, we can obtain two new equations, shown at the bottom, which point to no structure AT ALL; they simply represent two constraints on three variables, without telling us how they influence each other.

Let us examine more closely the mental process by which we determine the effect of physically manipulating Y, say setting Y to 0.

SLIDE 45: INTERVENTION AS SURGERY ON MECHANISM



Clearly, when we set Y to 0, the relation between X and Y is no longer given by the multiplier - a new mechanism now controls Y, in which X has no say. In the equational representation, this amounts to replacing the equation $Y=2X$ by a new equation, $Y=0$, and solving a new set of equations, which gives $Z=1$. If we perform this surgery on the lower pair of equations, representing to the lower model, we get of course a different solution. The second equation will need to be replaced, which will yield $X = 0$ and leave Z unconstrained.

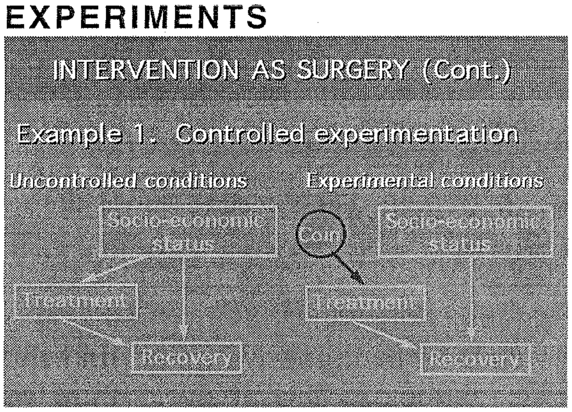
We now see how this model of intervention leads to a formal definition of causation: "Y is a cause of Z if we can change Z by manipulating Y, namely, if after surgically removing the equation for Y, the solution for Z will depend on the new value we substitute for Y". We also see how vital the diagram is in this process. THE DIAGRAM TELLS US WHICH EQUATION IS TO BE DELETED WHEN WE MANIPULATE Y. That information is totally washed out when we transform the equations into algebraically equivalent form, as shown at the bottom of the screen - from this pair equations alone, it is impossible to predict the result of setting Y to 0, because we do not know what surgery to perform - there is no such thing as "the equation for Y".

IN SUMMARY, INTERVENTION AMOUNTS TO A SURGERY ON EQUATIONS, GUIDED BY A DIAGRAM, AND CAUSATION MEANS PREDICTING THE CONSEQUENCES OF SUCH A SURGERY.

This is a universal theme that goes beyond physical systems. In fact, the idea of modeling interventions by "wiping out" equations was first proposed by an ECONOMIST, Herman Wold in 1960, but his teachings have all but disappeared from the economics literature. History books attribute this mysterious disappearance to Wold's personality, but I tend to believe that the reason goes deeper: Early econometricians were very careful mathematicians; they fought hard to keep their algebra clean and formal, and could not agree to have it contaminated by gimmicks such as diagrams. And as we see on the screen the surgery operation makes no mathematical sense without the diagram, as it is sensitive to the way we write the equations.

Before expounding on the properties of this new mathematical operation, let me demonstrate how useful it is for clarifying concepts in statistics and economics.

SLIDE 46: INTERVENTION AS SURGERY - CONTROLLED EXPERIMENTS

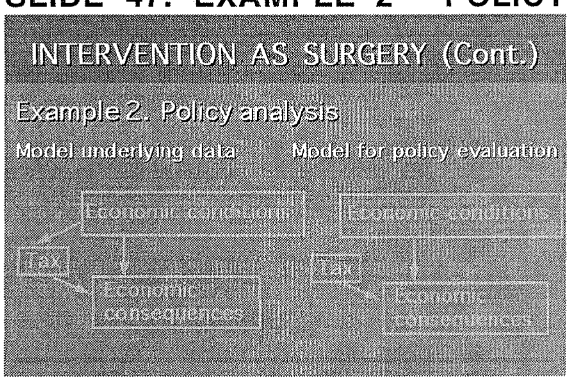


Why do we prefer controlled experiment over uncontrolled studies? Assume we wish to study the effect of some drug treatment on recovery of patients suffering from a given disorder. The mechanism governing the behavior of each patient is similar in structure to the circuit diagram we saw earlier: Recovery is a function of both the treatment and other factors, such as socio-economic conditions, life-style, diet, age etc. only one such factor is shown here. Under uncontrolled conditions, the choice of treatment is up to the patients, and may depend on the patients socio-economic background. This creates a problem, because we can't tell if changes in recovery rates are due to treatment or to those background factors. What we wish to do is compare patients of same backgrounds and that is precisely what Fisher's RANDOMIZED EXPERIMENT accomplishes. How?

It actually consists of two parts, randomization and INTERVENTION. Intervention means that we change the natural behavior of the individual: we separate subjects into two groups, called treatment and control, and we convince the subjects to obey the experimental policy. We assign treatment to some patients who, under normal circumstances, will not seek treatment, and we give placebo to patients who otherwise would receive treatment. That, in our new vocabulary, means SURGERY - we are severing one functional link and replacing it by another. Fisher's great insight was that connecting the new link to a random coin flip, GUARANTEES that the link we wish to break, is actually broken. The reason is, that a random coin is assumed unaffected by anything we can measure on a macroscopic level, including, of course, a patient socio-economic background.

This picture provides a meaningful and formal rationale for the universally accepted procedure of randomized trials. In contrast, our next example uses the surgery idea to point out inadequacies in widely accepted procedures.

SLIDE 47: EXAMPLE 2 - POLICY ANALYSIS



The example involves a Government official trying to evaluate the economic consequences of some policy, say taxation. A deliberate decision to raise or lower taxes is a surgery on the model of the economy because it modifies the conditions prevailing while the model was built. Economic models are built on the basis of data taken over some period of time, and during this period of time, taxes were lowered and raised in response to some economic conditions or political pressure. However, when we EVALUATE a policy, we wish to compare alternative policies under the SAME economic conditions, namely we wish to sever this link that, in the past, has tied policies to those conditions.

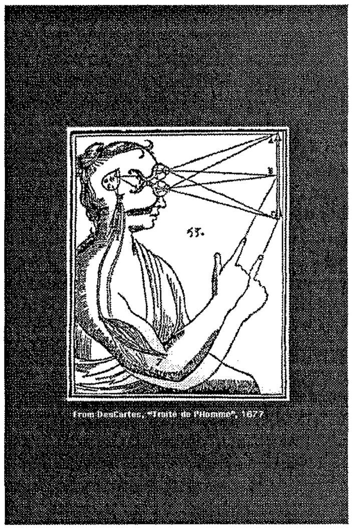
In this set-up, it is impossible of course to connect our policy to a coin and run a controlled experiment; we do not have the time for that, and we might ruin the economy before the experiment is over. Nevertheless the analysis that we

SHOULD CONDUCT is to infer the behavior of this mutilated model from data governed by a non-mutilated model.

I said, SHOULD CONDUCT, because you will not find such analysis in any economics textbook. As I mentioned earlier, the surgery idea of Herman Wold, was stamped out of the economics literature in the 1970's and all discussions on policy analysis that I could find, assume that the mutilated model prevails throughout. The fact that taxation is under government control at the time of evaluation is assumed to be sufficient for treating taxation an exogenous variable throughout when, in fact, taxation is an endogenous variable during the model-building phase, and turns exogenous only when evaluated. Of course, I am not claiming that reinstating the surgery model would enable the government to balance its budget overnight, but it is certainly something worth trying.

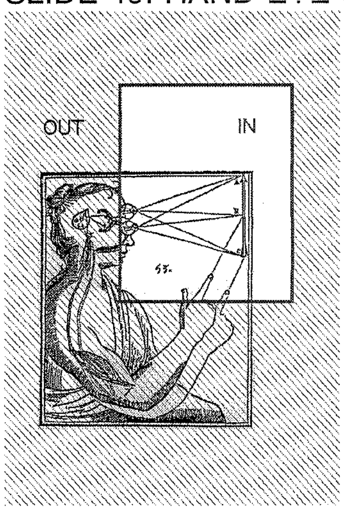
Let us examine now how the surgery interpretation resolves Russell's enigma: concerning the clash between the directionality of causal relations and the symmetry of physical equations. The equations of physics are indeed symmetrical, but when we compare the phrases "A CAUSES B" vs. "B CAUSES A" we are not talking about a single set of equations. Rather, we are comparing two world models, represented by two different sets of equations; one in which the equation for A is surgically removed, the other where the equation for B is removed. Russell would probably stop us at this point and ask: "How can you talk about TWO world models, when in fact there is only one world model, given by all the equations of physics put together?" The answer is: YES. If you wish to include the entire universe in the model, causality disappears because interventions disappear - the manipulator and the manipulated loose their distinction. However, scientists rarely consider the entirety of the universe as an object of investigation. In most cases the scientist carves a piece from the universe and proclaims that piece: IN namely, the FOCUS of investigation. The rest of the universe is then considered OUT or BACKGROUND, and is summarized by what we call BOUNDARY CONDITIONS. This choice of INs and OUTs creates asymmetry in the way we look at things, and it is this asymmetry that permits us to talk about "outside intervention", hence, causality and cause-effect directionality.

SLIDE 48: HAND-EYE SYSTEM (DESCARTES, L'HOMME)



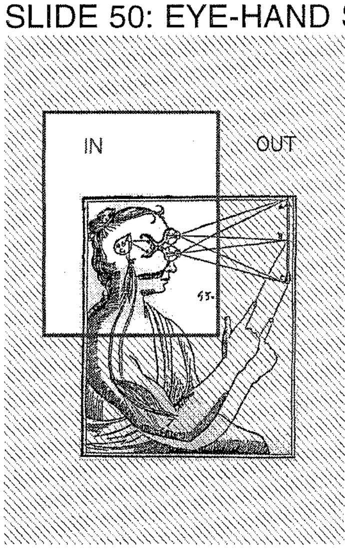
This can be illustrated quite nicely using Descartes classical drawing. As a whole, this hand-eye system knows nothing about causation. It is merely a messy plasma of particles and photons trying their very best to obey Schroedinger's Equation, which is symmetric.

SLIDE 49: HAND-EYE SECTION



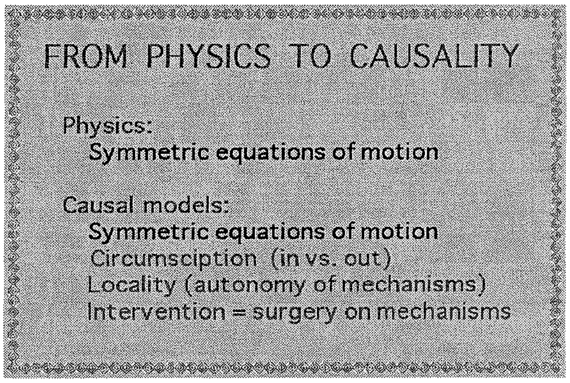
However, carve a chunk from it, say the object part, and we can talk about the motion of the hand CAUSING this light ray to change angle.

SLIDE 50: EYE-HAND SECTION



Carve it another way, focusing on the brain part, and, lo and behold, it is now the light ray that causes the hand to move - precisely the opposite direction. The lesson is that it is the way we carve up the universe that determines the directionality we associate with cause and effect. Such carving is tacitly assumed in every scientific investigation. In artificial intelligence it was called circumscription, by J. McCarthy. In economics, circumscription amount to deciding which variables are deemed endogenous and which ones exogenous, IN the model or EXTERNAL to the model.

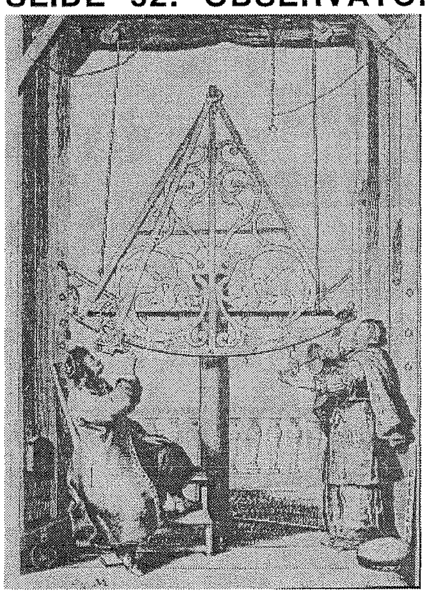
SLIDE 51: FROM PHYSICS TO CAUSALITY



Let us summarize the essential differences between equational and causal models. Both use a set of symmetric equations to describe normal conditions. The causal model, however, contains three additional ingredients: a distinction between the IN and the OUT. An assumption that each equation corresponds to an independent mechanism, hence, it must be preserved as a separate mathematical sentence. Interventions are interpreted as surgeries over those mechanism. This brings us closer to realizing the dream of making causality a friendly part of physics. But one ingredient is missing: THE ALGEBRA.

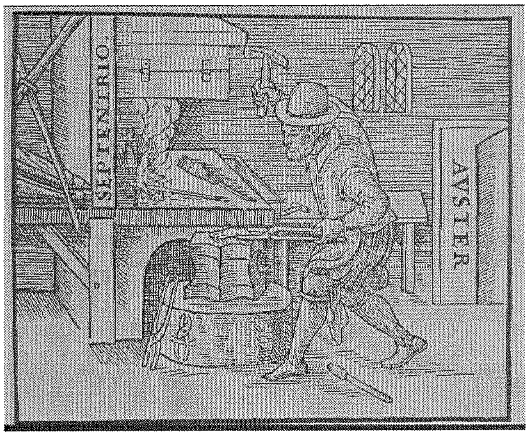
We discussed earlier how important the computational facility of algebra was to scientists and engineers in the Galilean era. Can we expect such algebraic facility to serve causality as well? Let me rephrase it differently: Scientific activity, as we know it, consists of two basic components:

SLIDE 52: OBSERVATORY (HEVELIUS, 1673)



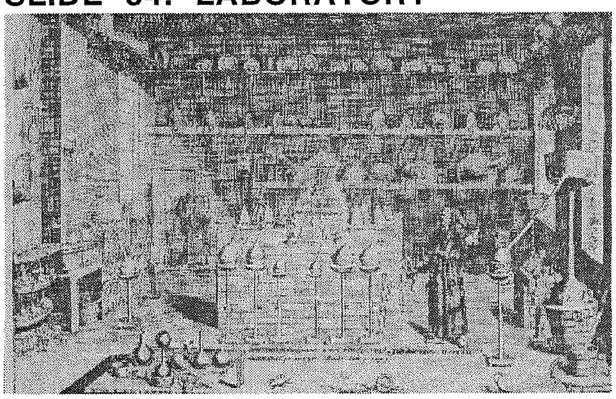
Observations

SLIDE 53: HAMMERING A MAGNET (GILBERT, DE MAGNET, 1600)



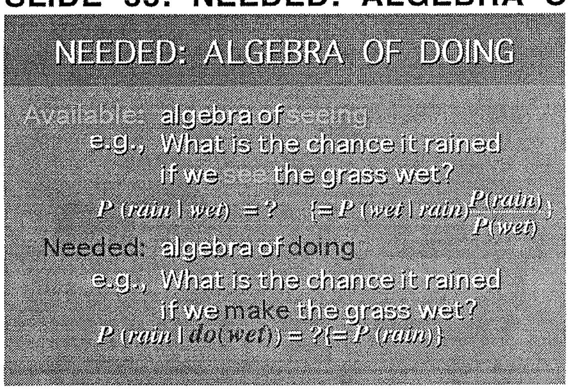
and interventions.

SLIDE 54: LABORATORY



The combination of the two is what we call a LABORATORY, a place where we control some of the conditions and observe others. It so happened that standard algebras have served the observational component very well, but, thus far, have not benefited the interventional component. This is true for the algebra of equations, Boolean algebra, and probability calculus, all are geared to serve observational sentences, but not interventional sentences.

SLIDE 55: NEEDED: ALGEBRA OF DOING



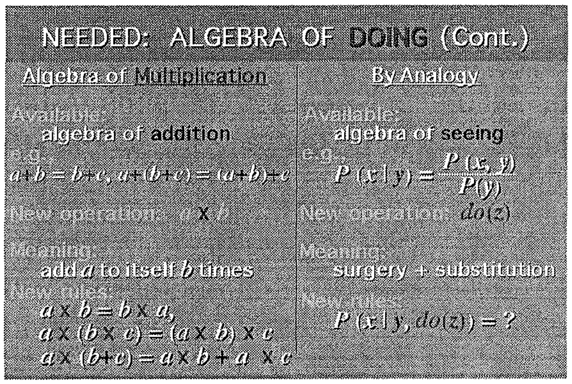
Take for example, probability theory. If we wish to find the chance it rained, given that we see the grass wet, we can express our question in a formal sentence written like that: $P(rain|wet)$ to be read: Probability~Of~Rain~Given~Wet. The vertical bar stands for the phrase: "given that we see". Not only can we express this question in a formal sentence but we can also use the machinery of probability theory and transform the sentence into other expressions. In our example, the sentence on the left can be transformed to the one on the right, if we find it more convenient or informative.

But suppose we ask a different question: "What is the chance it rained if we MAKE the grass wet?" We cannot even express our query in the syntax of probability, because the vertical bar is already taken to mean "given that I see".

We can invent a new symbol "DO", and each time we see a DO after the bar we read it "GIVEN THAT WE DO" - but this does not help us compute the answer to our question, because the rules of probability do not apply to this new reading. We know intuitively what the answer should be: $P(rain)$, because making the grass wet does not change the chance of rain. But can this intuitive answer, and others like it, be derived mechanically? so as to comfort our thoughts when intuition fails?

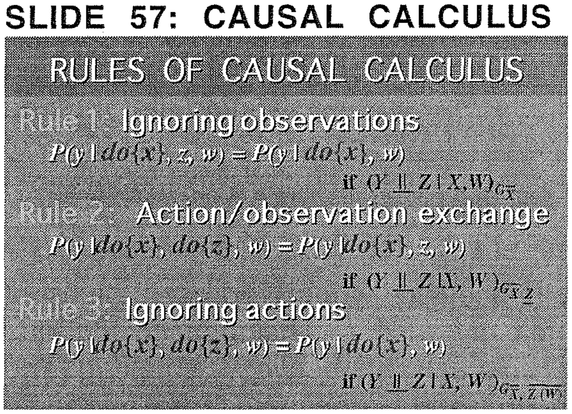
The answer is YES, and it takes a new algebra: First, we assign a symbol to the new operator "given that I do". Second, we find the rules for manipulating sentences containing this new symbol. We do that by a process analogous to the way mathematicians found the rules of standard algebra.

SLIDE 56: NEEDED: ALGEBRA OF DOING (CONT)



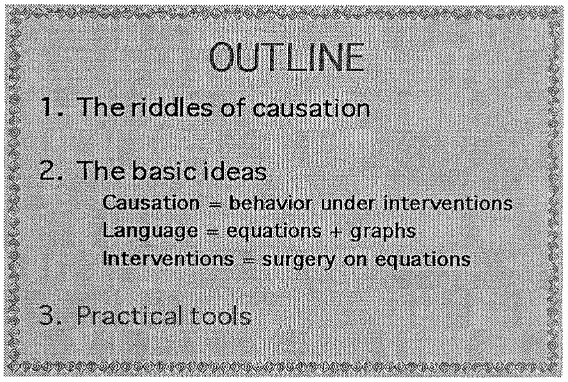
Imagine that you are a mathematician in the 16th century, you are now an expert in the algebra of ADDITION, and you feel an urgent need to introduce a new operator: MULTIPLICATION, because you are tired of adding a number to itself all day long. First thing you do is assign the new operator a symbol: MULTIPLY. Then you go down to the meaning of the operator, from which you can deduce its rules of transformations. For example: the commutative law of multiplication can be deduced that way, the associative law, and so on,.... we now learn all this in high school. In exactly the same fashion, we can deduce the rules that govern our new symbol: $do(x)$. We have an algebra for seeing, namely, probability theory. We have a new operator, with a brand new red outfit and a very clear meaning, given to us by the surgery procedure. The door is open for deduction and the result is give in the next slide.

SLIDE 57: CAUSAL CALCULUS



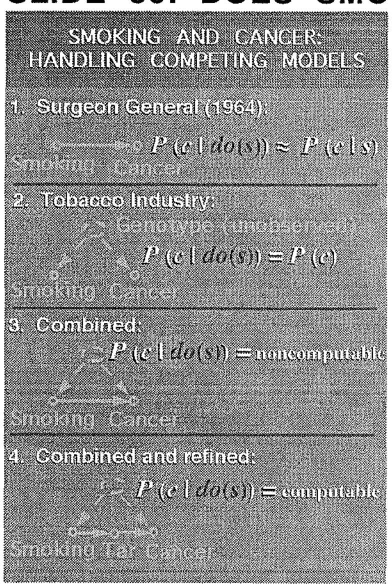
Please do not get alarmed, I do not expect you to read these equations right now, but I think you can still get the flavor of this new calculus. It consist of 3 rules that permit us to transform expressions involving actions and observations, into other expressions of this type. The first allows us to ignore an irrelevant observation, the third to ignore an irrelevant action, the second allows us to exchange an action with an observation of the same fact. What are those green symbols on the right? These are the green lights which the diagram gives us, whenever the transformation is legal. We will see them in action on our next example.

SLIDE 58: OUTLINE PART-3: PRACTICAL TOOLS



Things brings us to part-3 of the lecture, where I will demonstrate how the ideas presented thus far can be used to solve new problems of practical importance.

SLIDE 59: DOES SMOKING CAUSE CANCER



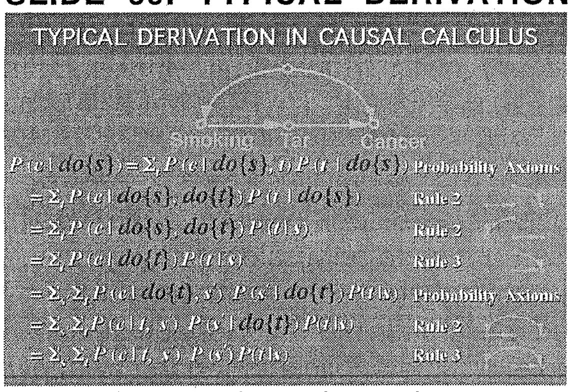
Consider the century old debate concerning the effect of smoking on lung cancer. In 1964, the Surgeon General issued a report linking cigarette smoking to death, cancer and most particularly, lung cancer. The report was based on non-experimental studies, in which a strong correlation was found between smoking and lung cancer, and the claim was that the correlation found is causal, namely: If we ban smoking, the rate of cancer cases will be roughly the same as the one we find today among non-smokers in the population.

These studies came under severe attacks from the tobacco industry, backed by some very prominent statisticians, among them Sir Ronald Fisher. The claim was that the observed correlations can also be explained by a model in which there is no causal connection between smoking and lung cancer. Instead, an unobserved genotype might exist which simultaneously causes cancer and produces an inborn craving for nicotine. Formally, this claim would be written in our notation as: $P(cancer \mid do(smoke)) = P(cancer)$ stating that making the population smoke or stop smoking would have no effect on the rate of cancer cases. Controlled experiment could decide between the two models, but these are impossible, and now also illegal to conduct.

This is all history. Now we enter a hypothetical era where representatives of both sides decide to meet and iron out their differences. The tobacco industry concedes that there might be some weak causal link between smoking and cancer and representatives of the health group concede that there might be some weak links to genetic factors. Accordingly, they draw this combined model, and the question boils down to assessing, from the data, the strengths of the various links. They submit the query to a statistician and the answer comes back immediately: IMPOSSIBLE. Meaning: there is no way to estimate the strength from the data, because any data whatsoever can perfectly fit either one of these two extreme models. So they give up, and decide to continue the political battle as usual.

Before parting, a suggestion comes up: perhaps we can resolve our differences, if we measure some auxiliary factors, For example, since the causal link model is based on the understanding that smoking affects lung cancer through the accumulation of tar deposits in the lungs, perhaps we can measure the amount of tar deposits in the lungs of sampled individuals, and this might provide the necessary information for quantifying the links? Both sides agree that this is a reasonable suggestion, so they submit a new query to the statistician: Can we find the effect of smoking on cancer assuming that an intermediate measurement of tar deposits is available??? The statistician comes back with good news: IT IS COMPUTABLE and, moreover, the solution is given in close mathematical form. HOW?

SLIDE 60: TYPICAL DERIVATION IN CAUSAL CALCULUS

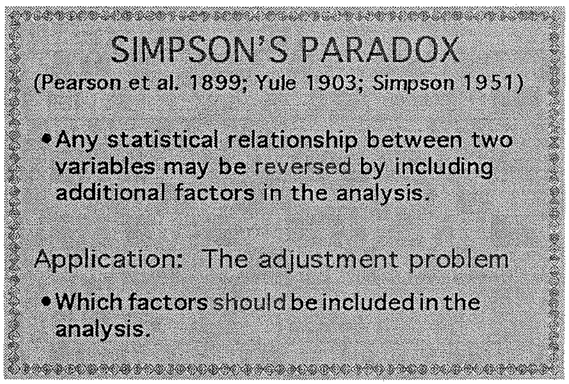


The statistician receives the problem, and treats it as a problem in High School ALGEBRA: We need to compute *P*(*cancer*) under hypothetical action, from non-experimental data, namely, from expressions involving NO ACTIONS. Or: we need to eliminate the "do" symbol from the initial expression. The elimination proceeds like ordinary solution of algebraic equation - in each stage, a new rule is applied, licensed by some subgraph of the diagram, until eventually leading to a formula involving only WHITE SYMBOLS, meaning expression computable from non-experimental data.

You are probably wondering whether this derivation solves the smoking-cancer debate. The answer is NO. Even if we could get the data on tar deposits, the model above is quite simplistic, as it is based on certain assumptions which both parties might not agree to. For instance, that there is no direct link between smoking and lung cancer, immediated by tar deposits. The model would need to be refined then, and we might end up with a graph containing 20 variables or more. There is no need to panic when someone tells us: "you did not take this or that factor into account". On the contrary, the graph welcomes such new ideas, because it is so easy to add factors and measurements into the model. Simple tests are now available that permit an investigator to merely glance at the graph and decide if we can compute the effect of one variable on another.

Our next example illustrates how a long-standing problem is solved by purely graphical means - proven by the new algebra. The problem is called THE ADJUSTMENT PROBLEM or "the covariate selection problem" and represents the practical side of Simpson's paradox.

SLIDE 61: SIMPSON'S PARADOX

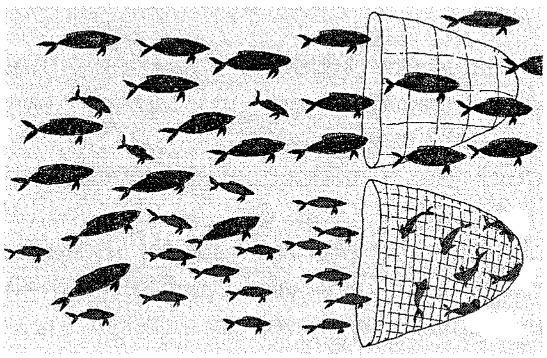


Simpson's paradox, first noticed by Karl Pearson in 1899, concerns the disturbing observation that every statistical relationship between two variables may be REVERSED by including additional factors in the analysis. For example, you might run a study and find that students who smoke get higher grades, however, if you adjust for AGE, the opposite is true, in every AGE GROUP namely, smoking predicts lower grades. If you further adjust for PARENT INCOME, you find that smoking predicts higher grades again, in every AGE-INCOME group, and so on.

Equally disturbing is the fact that no one has been able to tell us which factors SHOULD be included in the analysis. Such factors can now be identified by simple graphical means.

The classical case demonstrating Simpson's paradox took place in 1975, when UC Berkeley was investigated for sex bias in graduate admission. In this study, overall data showed a higher rate of admission among male applicants, but, broken down by departments, data showed a slight bias in favor of admitting female applicants. The explanation is simple: female applicants tended to apply to more competitive departments than males, and in these departments, the rate of admission was low for both males and females.

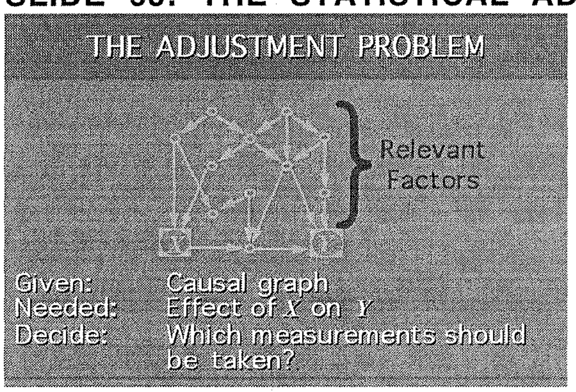
SLIDE 62: FISHNET



To illustrate this point, imagine a fishing boat with two different nets, a large mesh and a small net. A school of fish swim towards the boat and seek to pass it. The female fish try for the small-mesh challenge, while the male fish try for the easy route. The males go through and only females are caught. Judging by the final catch, preference toward female is clearly evident. However, if analyzed separately, each individual net would surely trap males more easily than females.

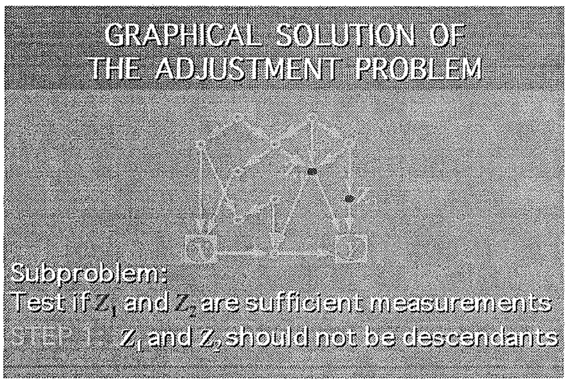
Another example involves a controversy called "reverse regression", which occupied the social science literature in the 1970's. Should we, in salary discrimination cases, compare salaries of equally qualified men and women, or, instead, compare qualifications of equally paid men and women? Remarkably, the two choices led to opposite conclusions. It turned out that men earned a higher salary than equally qualified women, and SIMULTANEOUSLY, men were more qualified than equally paid women. The moral is that all conclusions are extremely sensitive to which variables we choose to hold constant when we are comparing, and that is why the adjustment problem is so critical in the analysis of observational studies.

SLIDE 63: THE STATISTICAL ADJUSTMENT PROBLEM



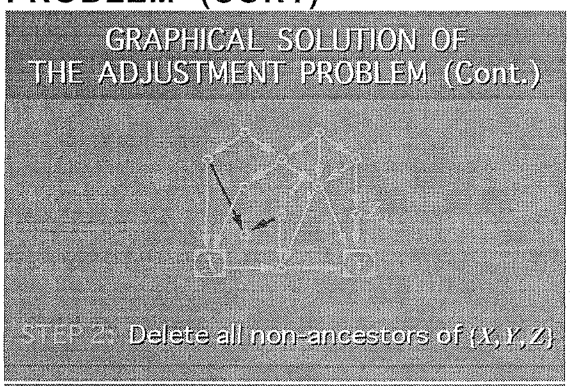
Consider an observational study where we wish to find the effect of Y on Y, for example, treatment on response. We can think of many factors that are relevant to the problem; some are affected by the treatment, some are affecting the treatment and some are affecting both treatment and response. Some of these factors may be unmeasurable, such as genetic t rait or life style, others are measurable, such as gender, age, and salary level. Our problem is to select a subset of these factors for measurement and adjustment, namely, that if we compare subjects under the same value of those measurements and average, we get the right result.

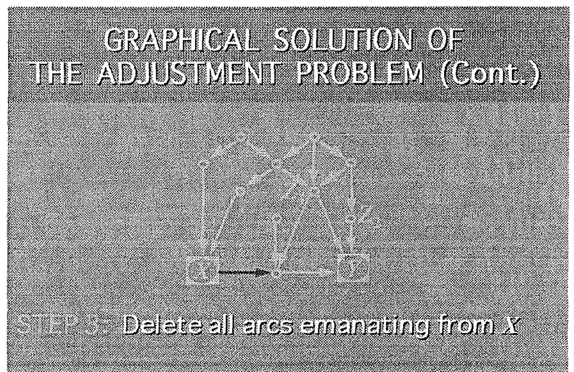
SLIDE 64: GRAPHICAL SOLUTION OF THE ADJUSTMENT PROBLEM

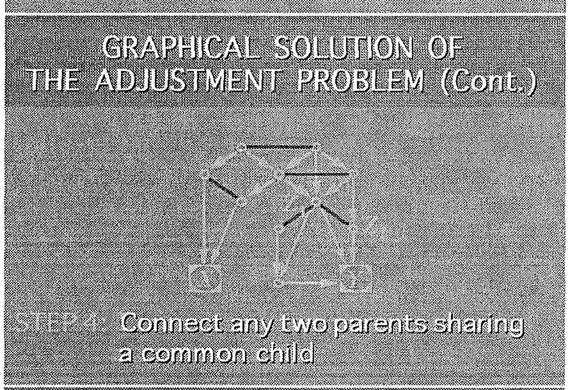


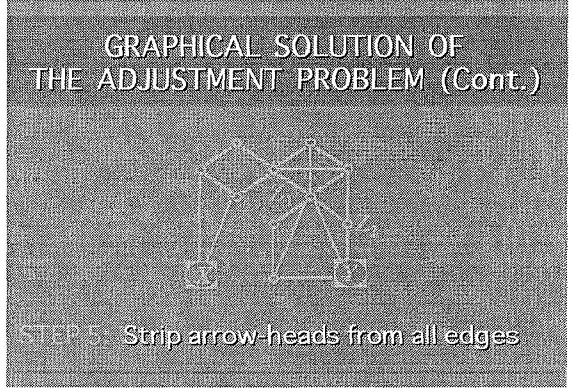
Let us follow together the steps that would be required to test if two candidate measurements, Z_1 and Z_2, would be sufficient. The steps are rather simple, and can be performed manually, even on large graphs. However, to give you the feel of their mechanizability, I will go through them rather quickly. Here we go.

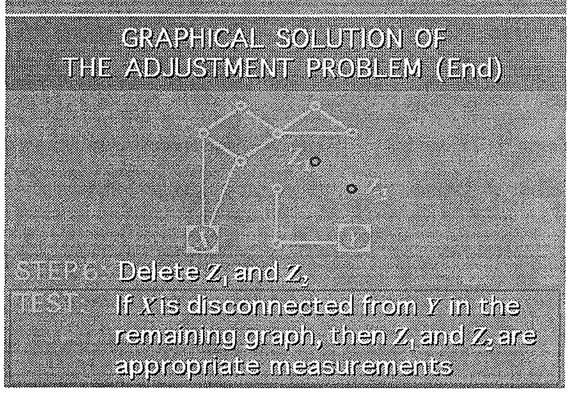
SLIDES 65-69: GRAPHICAL SOLUTION OF THE ADJUSTMENT PROBLEM (CONT)











At the end of these manipulations, we end up with the answer to our question: "IF X is disconnected from, Y then Z_1 and Z_2 are appropriate measurements."

ENDING STATEMENT

I now wish to summarize briefly the central message of this lecture. It is true that testing for cause and effect is difficult. Discovering causes of effects is even more difficult. But causality is not MYSTICAL OR METAPHYSICAL. It can be understood in terms of simple processes, and it can be expressed in a friendly mathematical language, ready for computer analysis.

SLIDE 70: ABACUS

Fig. 155 Little Johnny and his "calculating machine."

What I have presented to you today is a sort of pocket calculator, an ABACUS, to help us investigate certain problems of cause and effect with mathematical precision. This does not solve all the problems of causality, but the power of SYMBOLS and mathematics should not be underestimated.

SLIDE 71: A CONTEST BETWEEN THE OLD AND THE NEW ARITHMETIC

Many scientific discoveries have been delayed over the centuries for the lack of a mathematical language that can amplify ideas and let scientists communicate results. And I am convinced that many discoveries have been delayed in our century for lack of a mathematical language that can handle causation. For example, I am sure that Karl Pearson could have thought up the idea of RANDOMIZED EXPERIMENT in 1901, if he had allowed causal diagrams into his mathematics.

But the really challenging problems are still ahead: We still do not have a causal understanding of POVERTY and CANCER and INTOLERANCE, and only the accumulation of data and the insight of great minds will eventually lead to such understanding. The data is all over the place, the insight is yours, and now an abacus is at your disposal too. I hope the combination amplifies each of these components. Thank you.

Remarks: technical details can be found in

J. Pearl, "Causal diagrams for experimental research," (with discussion), *Biometrika*, 82(4), 669-710, December 1995,

J. Pearl, "Structural and probabilistic causality," In D.R. Shanks, K.J. Holyoak, and D.L. Medin (Eds.), *The Psychology of Learning and Motivation*, Vol. 34 Academic Press, San Diego, CA, 393-435, 1996.

J. Pearl, "The new challenge: From a century of statistics to an age of causation," *Computing Science and Statistics*, 29(2), 415--423, 1997.

Hard copies of these and other related publications can be obtained from

Prof. Judea Pearl
UCLA Computer Science Department
4532 Boelter Hall
Los Angeles, CA 90095-1596

or downloaded (postscript file) through http://Bayes.cs.ucla.edu/jp_home.html.