Causal Inference and Invariance

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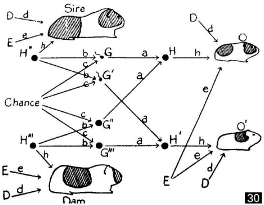
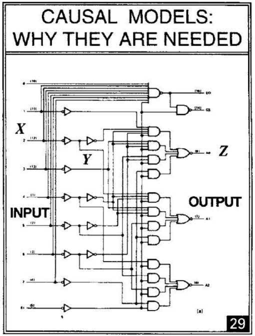
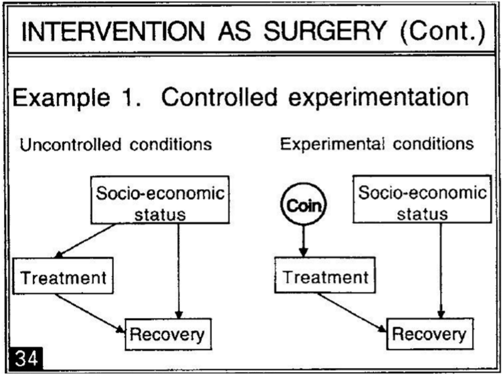
(Part 1/2)

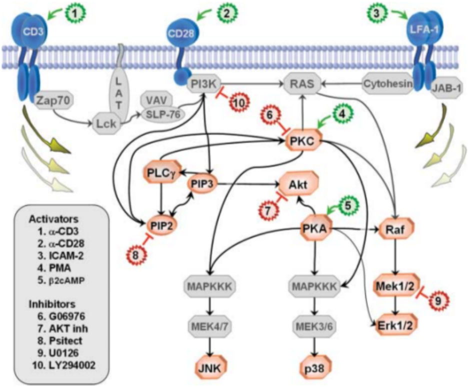
Understanding nature = cause and effect





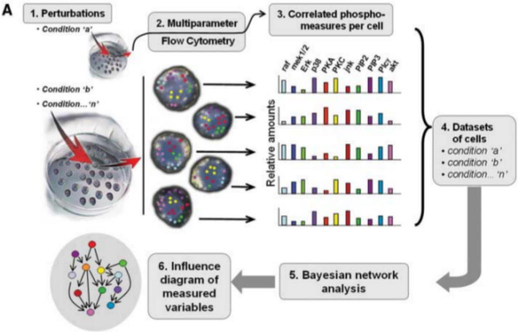


A hot application: systems biology



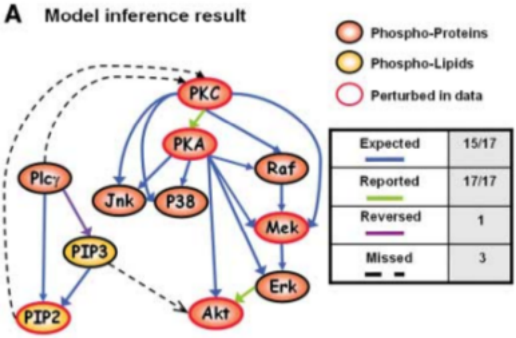
- In biology: causal relationships due to *chemical interactions*.
- Experimenters *intervene* by injecting *activators* and *inhibitors*.

Protein signalling data



- Flow cytometry data from Sachs et al.*Science*, 2005.
- 1 observational data set + 9 interventions (selective activation/inhibition).

Putative causal model



- Causal inference applied to observational + interventional data.
- Recovered most of the known interactions.

Where does statistics fit into this?

Not just statistics: numerous fields are interested in causal inference.

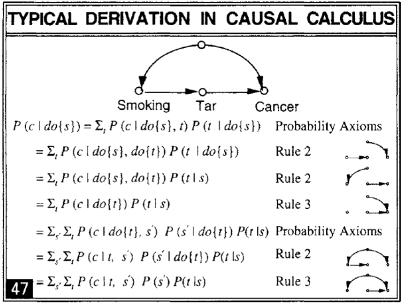
- *Philosophy.* Starting from Aristotle and still being debated today. What is causality? How do we learn about cause and effect?
- *Computer science.* Can we build an artificial intelligence which reasons like humans? Motivation for Judea Pearl's work.
- *Social science.* What influences an individual's life choices? (Career, political participation, etc.) Can we discover *social mechanisms*?

Statistical applications focus on:

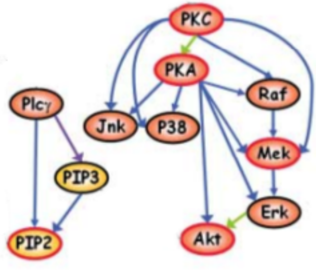
- *Estimating causal effects.* Can we predict a causal effect based on observational or experimental data? E.g. effect of a medical treatment based on clinical trial data? Motviation for potential outcomes approach developed by Rubin, etc.
- *Bayesian networks, structure learning.* Can we model multivariate relationships using a network structure? Networks *can be* given causal interpretation, but causal inference is not the only motivation. Motivation for graphical lasso.

Principles of Causal Inference

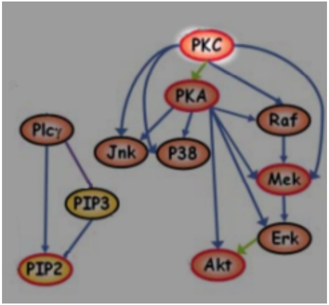
- These diverse applications of causal inference share a common set of useful principles.
- The *graphical approach* pioneered by Judea Pearl is the best approach for developing causal intuition.



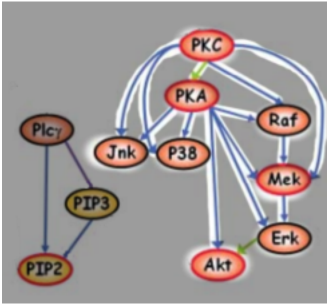
Graphs: nodes and vertices



- Each variable in the dataset is given a *node*.
- Arrows indicate which variables *cause* which other variables.
- Undirected or bidirected edges indicate that variables are associated, but neither causes the other.



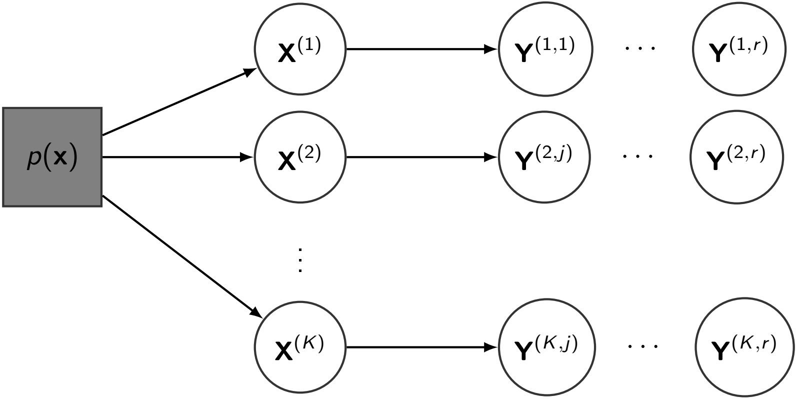
- The *observational distribution* is the joint distribution under the "natural" state of the system.
- One can consider *intervening* on one of the variables in the system. This changes the joint distribution of the system.



- However, not every variable will be affected by the intervention!
- By following the arrows, we determine the set of variables which are affected by the intervention.

Look! A diagram!

Don't put this in the final presentation.



Legend: $K = \{$ 2, 9, 99, 999 $\}$