Causal Analysis and Software and Systems Engineering

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Note: We use “Causal Inference” in our talk to mean “Causal Analysis”

• Introduction to the Theory of Causal Inference
  • Intro to Causal Inference
    • How direction of causality is determined
    • Aspects of Causal Inference: Causal Search, Causal Estimation
    • Tetrad Demo
    • Summary

• Application to 2 Datasets
  • Description of Datasets
  • Causal Search Results
  • Causal Estimation Results

• Conclusions
• How to get started with Causal Inference
• End Matter
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  • Backup slides
Causal Inference: Introduction to the Theory

Following slides adapted from Carnegie Mellon University (CMU)
Causal Model – An Example

Ice Cream Sales → Shark Attacks

Does high correlation imply causation?
Causal Model – An Example Cont.

Ice Cream Sales

Shark Attacks

Does high correlation imply causation?

So...to prevent shark attacks, we should limit the number of ice cream cones sold, right?
Causal Model – An Example Cont.

- **Hot Temperature**
  - Often, an excluded common cause results in a misinterpretation of correlation!

- **Ice Cream Sales**
  - Does high correlation imply causation?

- **Shark Attacks**
Causal Model – An Example Cont.

- **Hot Temperature**
  - Often, an excluded common cause results in a misinterpretation of correlation!
  - **Ice Cream Sales**
  - **Shark Attacks**
Heritage of Causal Inference

Modern Theory of Statistical Causal Models

- Graphical Models
- Intervention & Manipulation
- Potential Outcome Models
- Testable Constraints (e.g., Conditional Independence)
- Counterfactuals

This is Causal Inference
Heritage of Causal Inference (Cont.)

Causal Structure  Testable Statistical Predictions

Causal Graphs

\[ X \rightarrow Y \rightarrow Z \]

\[ X \perp\!
\perp Z \mid Y \]

e.g., Conditional Independence

Now we can go from Testable Statistical Predictions to Causal Structure
Definition of Conditional Independence

**Independence**
- $X \perp \perp Z$ means “$X$ and $Z$ are independent”
- Statistically, this means that $X$ and $Z$ are not correlated

**Conditional Independence**
- $X \perp \perp Z \mid Y$ means “Given any value of $Y$, $X$ and $Z$ are independent”
- Statistically, this means that, for each value of $Y$, $X$ and $Z$ are not correlated
  - If you take a subset of data for any single value of $Y$, $X$ and $Z$ are not correlated
Conditional Independence: Implication of being Causally Disconnected

Weak Causal Markov Assumption

\[ X, Z \text{ causally disconnected} \Rightarrow X \perp\!
\perp Z \]

\[ X, Z \text{ causally disconnected} \iff \text{No trek between } X \text{ and } Z, \text{ i.e.,} \]

i. \( X \) not a cause of \( Z \), and

ii. \( Z \) not a cause of \( X \), and

iii. There is no common cause \( Y \) of \( X \) and \( Z \)
Causal Graph Edge Adjacency: Variables Not Adjacent

Per the previous slide,

X and Z are not adjacent if they

are independent conditional on any subset of variables

that doesn’t include X and Z
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Causal Graph Edge Adjacency: Interaction of 3 (Sets of) Variables

• Chain: X -> Y -> Z
  • X and Z are conditionally independent given Y

• Fork: X <- Y -> Z
  • X and Z are independent conditional on Y
  • As long as there is no other path between X and Z

• Collider: X -> Y <- Z
  • X and Z are unconditionally independent, but dependent conditional on Y and any effects of Y
  • As long as there is only 1 path between X and Z
Causal Graph Edge Adjacency: Collider and Chain Examples

**Conditioning on Colliders**

*Induce* Association

- **Gas** [y,n]
- **Battery** [live, dead]
- **Car Starts** [y,n]

**Conditioning on Non-Colliders**

Screen-off Association

- **Exp** [y,n]
- **Symptoms** [yes, no]
- **Infection** [y,n]

### Graph Edges

- **Gas || Battery**
- **Exp || Symptoms**
- **Gas | Battery | Car starts = no**
- **Exp | Symptoms | Infection**
Causal Graph Edge Adjacency: Trying To Statistically Determine Orientation

Test: $X \perp \!\!\!\!\!\!\perp Z \mid S$, where $Y \in S$

In the collider case, have determined the orientation of 2 edges.

In the non-collider case, have not determined any orientation of edges.
Causal Graph Edge Adjacency: Conclusion

X₁ and X₂ are not adjacent

X₁ → X₂ (X₁ is a cause of X₂)

X₁ → X₂ or X₂ → X₁; orientation could not be determined.
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Causal Inference

Causal Search/Discovery
- Algorithms and domain knowledge on observational data

Causal Estimation
- Algorithms to quantify causal influence; structural equation modeling (SEM)
2 Types of Causal Search Algorithms

**Constraint-Based**
- Example: PC [4]
- Uses conditional independence to determine which causal relationships exist and their orientations

**Score-Based**
- Example: FGES [2]
- Uses a step-by-step search to pick the next edge that best captures the causal aspects of the data
Applying Constraints on the Algorithms

**Constraint-Based**
- Alpha (usually 0.1, 0.05, or 0.01)
- = Allowed level of confidence for causal relationship
- Larger value is more lenient

**Score-Based**
- Penalty Discount (usually 1)
- = Amount of penalty applied for cases where assumed graph does not match changes in data
- Smaller discount is more lenient
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Tetrad Demo

- Loading a dataset (Data)
- Running Causal Search algorithms (Algorithm)
- Running Bootstrap (part of Algorithm)
- Including Knowledge to improve results (Knowledge)
- Generating an Estimate (Estimator)
Tetrad

• Implements the causal search algorithms [3]
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Tool Chain for Simple Tetrad Session

2Tiers (Knowledge)
Tier 1: (all not in Tier 2)
Tier 2: LogEffort

C3_T_FGES_05 (Algorithm and parameters)
Choose Algorithm: FGES
Score: SEM BIC Score
Penalty Discount: 0.5

Applies algorithm, guided by parameters and Knowledge, to yield a causal graph.
Bootstrap Results: Edge Probability Table

- Randomly sample dataset multiple times
  - Results less sensitive to outliers

- Results in an **edge probability table (EPT)**
  - Percentage of times edge found, reflecting the fraction of data points that has this direct-causal relationship

- Filter by probability of no edge (PNE) to keep only reasonable edges
Causal Estimation

- **Causal estimation** involves parameterizing the relationships appearing in the causal search graph and then determining what values to assign to these parameters.
  - Enables making predictions about the values that variables will attain as a result of hypothesized events; i.e., allows making an estimating model.
  - Causal estimation, when applied to just a single variable and its direct causes works like ordinary linear regression: **coefficients** are assigned to each edge
  - A *one-unit* change in a direct cause, with all other variables held constant, results in a change in the child of **coefficient** units.
- The resulting model is then evaluated for **model fit**.
  - **Model fit statistics** include: Chi square (per degrees of freedom), Bayesian Information Criterion (BIC), Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA).
- More information can be found in [4, 5]
Causal Inference Summary

1. Allows analysts find causal relationships from observational data vs running experiments

2. Uses interactions among variables to determine causal relationships

3. Tetrad allows us to run these causal algorithms relatively easily and efficiently
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Datasets

**COCOMO® II Calibration Dataset**
- 16 organizations, various application types
- Variability in all 26 variables
- 161 projects
- See [6] for more details

**COSYSMO 3.0 Calibration Dataset**
- Covers various types of systems
  - > 2 orders of magnitude size variation
- Variability in all 18 variables
- 68 projects
- See [7] for more details

Each dataset is reasonably representative of projects of its type
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Our Methodology for Causal Search on Small Samples

• Problem: Search did not produce structures that were very informative
  • Using strict parameter settings, few edges were found
    • Frequently only one: Size $\rightarrow$ Effort
  • Using looser parameter settings, too many edges were found
    • Found additional plausible causes of Effort, but found non-plausible edges also
    • Such edges might be spurious (due to accidental correlations)—how would we know?
  • A consequence of having relatively few data points (projects)

• Solution: We invented an approach called weak-signal analysis (WSA), which consists of these steps, some based on the PNE (probability of no edge):

1. Inject **null variables**: For each original variable, add a “null variable” column, a copy of the original variable values randomly sorted.
2. Do causal search with **bootstrap**: determine for each edge terminating on a null variable (a “random edge”) its PNE
3. Set a **trim threshold** at the 10th percentile of random edge PNEs (i.e., 90% of random edges will have a higher PNE)
4. Discard all edges among original variables whose PNE > trim threshold. Also, discard all null variables and random edges.
Unsatisfactory Simple Tetrad Results Using COSYSMO 3.0 Dataset as an Example

Results of FGES Algorithm, with Penalty Discount = 0.5 (less strict): 24 edges, with 23 directed, & 2 direct causes of Effort

Results of FGES Algorithm, with Penalty Discount = 2.0 (more strict): 9 edges, with 1 directed, and 1 direct cause of Effort

Less strict simple search produces many spurious edges, while more strict simple search produces fewer useful results (direct causes of effort).
Direct Causes Using WSA of Software Engineering Effort
Intervening on These in a Project May Improve Outcomes

- Size (SLOC)
- Team Cohesion (TEAM)
- Platform Volatility (PVOL)
- Reliability (RELY)
- Storage Constraints (STOR)
- Time Constraints (TIME)
- Product Complexity (CPLX)
- Process Maturity (PMAT)
- Risk and Architecture Resolution (RESL)
Direct Causes Using WSA of Systems Engineering Effort
Intervening on These in a Project May Improve Outcomes

• Size
• Level of Service Requirements (LSVC)
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Using Tetrad to Derive “Mini-Models” to Produce Plausible Cost Estimates

We were guided by the existing COCOMO® II and COSYSMO 3.0 estimating models’ structure.

1. The structure of the estimating models does not directly conform to that needed by Tetrad. We therefore transformed the structure of each estimating equation:
   • We took the logarithm of the equation (Size -> LogSize, etc)
   • Cost drivers and scale factors are represented differently in the linear mini model.
   • Cost drivers are additive variables, which we directly included in the mini model.
   • Scale factors are multipliers of LogSize, we replaced each with the scale factor times LogSize.

2. We forced cost predictors to be independent of each other (with the Knowledge box in Tetrad).

3. We applied WSA to obtain a plausible causal graph. We discarded any variables that have no edges.

4. We used the Tetrad Estimation capability to obtain coefficients and intercepts on the resulting graph. The mini-model was obtained by extracting the mini-estimating equation from the resulting graph.

5. However, intercepts need further work (below).
Tool Chain for Applying WSA

Top 3 boxes: per previous Tool Chain (slide 23)

Outside Tetrad, perform WSA analysis (per slide 33) on the PNE table (slide 27): Analyze the distribution of random edge PNEs to determine the 10th-percentile (trim) threshold; all edges with lower probability are deleted. (Therefore only those edges among the original variables whose PNE < trim threshold are retained.) Also discard all null variables, and all variables without edges. Import the resulting graph back into a Tetrad DAG box.

The SEM PM (Parametric Model) and SEM Est (Estimator) boxes, together with the Data, produce a graph annotated with estimation results.
Resulting COSYSMO 3.0 Estimation

Model fit statistics (listed on slide 28) lead to the conclusion that:
This model fit is Poor-to-Fair.
How to Get a Mini-Model from that Tetrəd Estimation Model

• Reading off from the Tetrəd estimation model, a mini-model would be:
  \[ \text{LogEffort} = 1.0380 \times \text{LogSize} + 0.1325 \times \text{LSVC} + 4.2838 \]

• First attempt at Effort estimation:
  \[ \text{Effort} = \text{Size}^{1.0380} \times 1.357^{\text{LSVC}} \times 10^{4.2838} \]

• That, however, doesn’t work
  • The problem is that 4.2838 is the mean of the LogEffort values; however, raising 10 to that power does not yield the mean of the Effort values.

• One has to do a separate linear regression of LogEffort against LogSize and LSVC
  • That yields an exponent for 10 of 1.805, which gives this estimating equation:
    \[ \text{Effort} = 63.834 \times \text{Size}^{1.0380} \times 1.357^{\text{LSVC}} \]
Resulting COCOMO® II Estimation

Model fit statistics (listed on slide 28) lead to the conclusion that: This model fit is Fair-to-Good.
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Conclusion – Causal Search

• Straightforward use of causal discovery algorithms may result in little information about cost-causing factors
  • Relatively small datasets (# of cases) compared to # of variables
• Weak-Signal Approach (WSA) enhanced results
  • Identified additional causes of effort and duration, while minimizing spurious correlations
  • Established a principled approach (methodology) to determining what cutoff to use for trimming results of a bootstrapped search (based on null variables and EPT)
• We identify (on slides 35 & 36) specific direct causes, where action has been shown statistically to cause the cost or schedule
  • The data we used considered multiple application types and multiple organizations
  • We also investigated choice of Tetrad search algorithm and parameter values
Conclusion – Causal Estimation

• We developed a methodology (slide 33) for generating cost estimation mini-models based on datasets that deliver plausible results
  • Based mostly on features built in to Tetrad
  • Tetrad can deliver off-the-shelf models, if logarithms don’t need to be applied to data
• Observation
  • Modestly fitting with somewhat inferior predictions compared to original model
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How You Can Get Started with Causal Inference

• We encourage you to try Tetrad on your data
  • Find out what the most important (i.e., causal) factors are
  • If results are unsatisfactory, consider using WSA
• Applicable to an organizational project database of moderate or larger size
• Get Tetrad [3] and the Tetrad Manual [8]
• Obtain training in Causal Discovery and Tetrad [9, 10]
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Bibliography


3. Center for Causal Discovery (CCD), a partnership among data scientists from the University of Pittsburgh (Pitt), Carnegie Mellon University (CMU), and the Pittsburgh Supercomputing Center (PSC), Tetrad Software. https://www.ccd.pitt.edu/tools/


9. Center for Causal Discovery (CCD), Training in Causal Discovery from those who pioneered Tetrad: https://www.ccd.pitt.edu/video-tutorials/

10. SEI, Training in Causal Discovery from the SEI: contact Mike Konrad (also the source for WSA Python scripts): MDK@SEI.CMU.edu
Backup Slides
## Prediction Accuracy: Mini-Models vs Estimating Models

### COSYSMO 3.0 - Effort

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<th>Mini-Model</th>
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<td>Max MRE</td>
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### COCOMO® II - Effort

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<td>PRED(30)</td>
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