
Jim Alstad, Anandi Hira, Mike Konrad, A Winsor Brown
Alstad@acm.org, A.Hira@usc.edu, MDK@sei.cmu.edu, AWBrown@usc.edu
University of Southern California and/or Software Engineering Institute

BCSSE COCOMO® Forum
November 9-10, 2022
Presentation Outline

- Motivation
- Causal Analysis in SW Cost

- Intro to Causal Inference
- Algorithms and Tool Used

- Datasets – COCOMO® II, COSYSMO 3.0

- Approaches and Results

- Conclusions and Questions
Motivation for this Line of Research

• Managers are frequently faced with issues of controlling project costs
  • My estimated cost is too high. What project aspects can I modify that would most likely reduce the cost?
  • I have some money to improve my organization’s performance. Changing which organizational aspects would be most likely to improve cost performance?
  • As an acquirer, I need to add a new stakeholder and remove flexibility in modifying requirements. Is that likely to have a significant influence on project cost?

• Causal Analysis is a modern technique that analyzes datasets to determine causal relationships among its variables

• The Goal of this Research: Identify factors of software and systems engineering costs that are direct causes
  • To help manage real projects
Motivation of Revisit

• Causal Learning is an active research area
• New algorithms have been developed and incorporated into Tetrad since our previous analysis [1]
  • New search method (BOSS) to better find causal relationships
  • New validation method (Markov Checker) for causal search results
History of Causal Analyses for Effort

Boehm – COCOMO® Models [2]
- In-depth behavioral analyses for effort drivers
- Including COSYSMO models

Unified Code Count Maintenance [4]
- Software maintenance and upgrade data
- Project data has limited scope
  - Similar projects, from a single environment

Evidence-Based SW Engineering [3]
- Suggests running Experiments to identify causal relationships:
  - Cause precedes effect
  - Cause covaries with effect
  - Alternative explanations are implausible

Our difference: 2 calibration datasets (observational data) with varying values of cost drivers, application types, and project types

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We Employ Causal Search [5] as the Basis of Our Research

Causal Learning

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

- Causal Inference
  - Algorithms to identify and quantify causal effects
Causal Search Algorithm Results

Result is a “causal graph”, with each box representing a variable and each edge representing a causal relationship.

Here are the different possible types of edge:

- $X_1 \rightarrow X_2$ \hspace{1cm} $X_1$ directly causes $X_2$

- $X_1 \rightarrow X_2$ \hspace{1cm} $X_1$ directly causes $X_2$ or $X_2$ directly causes $X_1$

- No directly causal relationship between $X_1$ and $X_2$
Tetrad Tool

• Implements causal search and inference algorithms
• Maintained by Carnegie Mellon University (CMU) and University of Pittsburgh
• For information, tutorials and tools:
  • https://sites.google.com/view/tetradcausal
  • https://www.ccd.pitt.edu

• Our 2020-2021 [1] results come from Tetrad versions 6.5.4 and 6.7.0
• Our 2022 results come from a pre-release version of Tetrad 7.1.3 that implements the BOSS algorithm [8]
New Causal Algorithms

**BOSS**

- Score-based search algorithm based on permutations
- Adaptation and optimization of the Greedy Relaxations of Sparsest Permutation (GRaSP) algorithm in [8]
- In testing, near-perfect adjacency and orientation of graph edges

**Markov Checker**

- The Causal Markov Condition (CMC) is “all graph-implied conditional independences (CIs) hold in the dataset”
- Many causal algorithms assume CMC
- The new Markov Checker algorithm (MC) tests for CMC
- MC reports what % of CIs implied by the graph hold in the dataset
- 1.0% is the expected rate of CIs failing due to chance; an actual rate near this suggests that the CMC holds, so the causal algorithm results can be trusted
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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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Direct Causes of Effort Found in 2021 Analysis [1]  
(FGES Algorithm with Bootstrapping and Weak Signal Analysis #4)

**COCOMO® II - Effort**
- 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)

**COCOMO® II - Schedule**
- Size (SLOC)
- Platform Experience (PLEX)
- Schedule Constraint (SCED)
- Effort (LogPM)

**COSYSMO 3.0 - Effort**
- Size
- Level of Service Requirements (LSVC)
COCOMO® II BOSS Results

Markov Check
• % dependent = 4.08%
• Reasonably close to the expected 1%
• Suggests strong agreement between graph and dataset
COYSYMO 3.0 BOSS Results

Markov Check
- % dependent = 9.52%
- Not as close to the expected 1%
- Suggests agreement between graph and dataset
Changes to the Direct Causes of Effort/Schedule

COCOMO® II - Effort
• Size (SLOC) (LogSize)
• 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)
• Programmer Capability (PCAP)
• Analyst Capability (ACAP)
• Computer Turnaround Time (TURN)

COCOMO® II - Schedule
• Size (SLOC) (LogSize)
• Platform Experience (PLEX)
• Schedule Constraint (SCED)
• Effort (LogPM)

COSYSMO 3.0 - Effort
• Size
• Level of Service Requirements (LSVC)

And 12 of the COCOMO® II factors influence Effort indirectly
And 3 of the COSYSMO 3.0 factors influence Effort indirectly
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Conclusion – Causal Search

• How do BOSS results compare to previous results [1]?
  • Our previous results used the algorithms WSA#4 (custom script outside of Tetrad), and FGES with bootstrapping. This time, we did no bootstrapping and used BOSS.
• COCOMO® II Results
  • Gives similar # of causes without the extra data analyst effort
  • Provided additional controls for project managers but fewer controls for organizations’ upper management or acquirers
• COSYSMO 3.0 Results
  • Discovered additional causes

• Does Markov Checker seem to provide useful info?
  • Idea and its implementation by Elias Bareinboim (Columbia), Joe Ramsey (CMU), and Mike
    • This presentation may be the first formal reporting of such a validity check anywhere in the literature.
  • Evaluated validity of causal structures obtained from causal search
  • Results: We think a reasonably low “% dependent” was returned on both COCOMO® and COSYSMO datasets
  • Initial evaluation of Markov Checker: seems useful but difficult to interpret “% dependent”
Future Work

- Compute new estimation “mini-models” based on our new searches
- Continue to check out new algorithms as they become available in Tetrad
Bibliography


