Causal Models for Software Cost Prediction & Control (SCOPE)

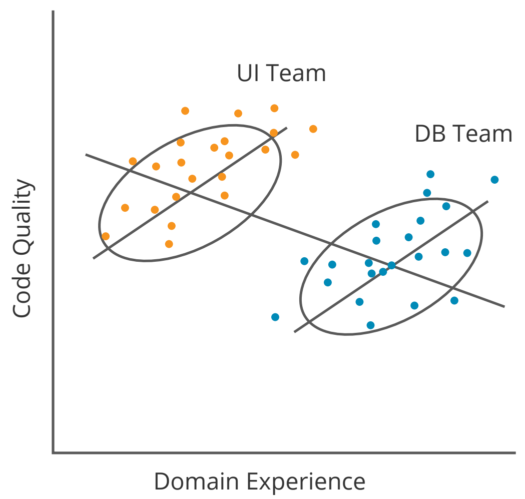
How can we control costs in software development and sustainment? We are collaborating with other researchers to apply causal learning to learn how.

DoD Problem

- DoD leadership needs to understand why software costs so much.
- DoD program offices need to know where to intervene to control software costs.

Why Causal Learning?

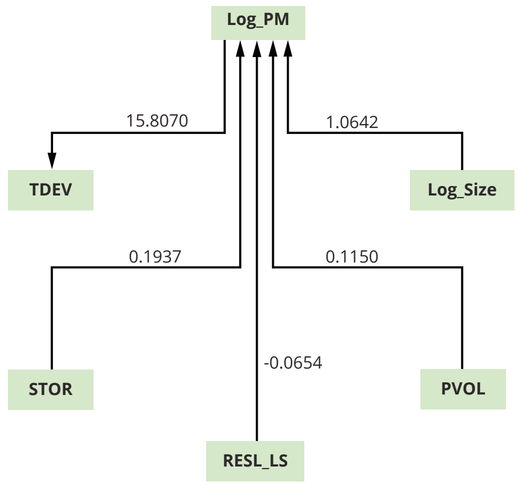
To reduce costs, the causes of an outcome (good or bad) need to be considered. Correlations are insufficient in part due to Simpson's Paradox. For example, in the figure below, if you did not segment your data by team (User Interface [UI] and Database [DB]), you might conclude that increasing domain experience reduces code quality (downward line); however, within each team, it's clear that the opposite is true (two upward lines). Causal learning identifies when factors such as team membership explain away (or mediate) correlations, and it works for much more complicated data sets too.



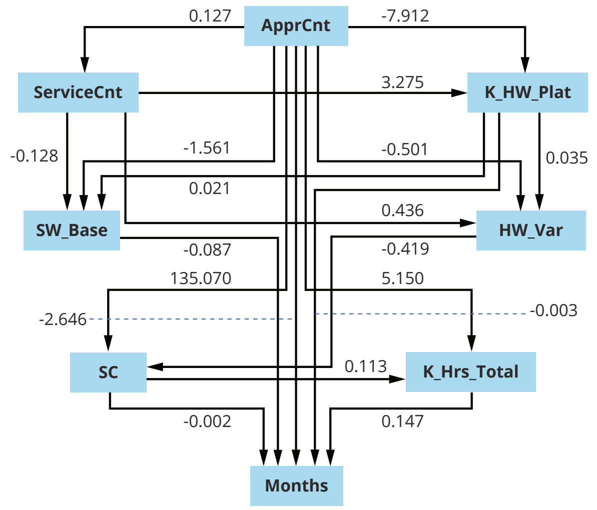
Simpson's Paradox as Applied to UI/DB Data

Causal learning reduces costs.

Recent Results



COCOMO® II Mini-Cost Estimation Model



Consensus Graph for U.S. Army Software Sustainment

COCOMO® II – Effort Drivers

Size (SLOC), Team Cohesion, Platform Volatility, Reliability, Storage Constraints, Time Constraints, Product Complexity, Process Maturity, Architecture/Risk Resolution (RESL)

COCOMO® II – Schedule Drivers

Size (SLOC), Platform Experience, Schedule Constraint, and Effort

COSYSMO 3.0 – Effort Drivers

Size and Level of Service Requirements

After identifying which of over 40 factors directly drive costs, we used Tetrad to generate mini cost-estimation models that fit well. (In the figure, RESL_LS is the product of RESL and Log_Size.)

A U.S. Army Sustainment data set was segmented into **(Superdomain, ACAT Level)** pairs resulting in five sets of data to search and estimate. Splitting addressed high fan-out for common causes, which can lead to structures typical of Simpson's Paradox. A consensus graph (see above) was built from the resulting five **searched and** fitted models.

For consensus estimation, the data from individual searches was pooled with previously excluded data because of missing values. The resulting 337 releases were used to estimate the consensus graph using Mplus with Bootstrap in estimation.

There was no cherry picking or re-do's—this model is a direct out-of-the-box estimation, achieving good model fit on the first try.

Acknowledgments

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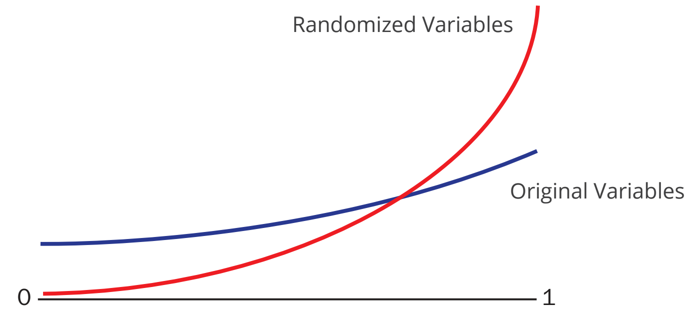
Our Solution

Our approach to causal inference is **principled** (i.e., no cherry picking) and **robust** (to outliers). This approach is **especially useful** for small samples—when the number of cases is < 5-10 times the number of variables.

1. Inject **null variables** by appending an independently randomized copy of each original variable.
2. Search (FGES or PC with default settings) with Bootstrap to determine each edge's **Probability of No Edge (PNE)** across the search.
3. Set a **threshold (10th percentile)** among the edges involving a null variable. (Of edges involving a null variable, 90% have a PNE exceeding that threshold.) Then drop the null variables but apply this same threshold to determine which edges to keep among the original variables.



Probability of No Edge

Summary

Causal models offer better insight for program control than models based on correlation. Knowing which factors drive which program outcomes is essential to sustain the warfighter by providing high-quality, secure software in a timely and affordable manner.

For More Information

For more information, including causal analyses of other data sets, see our SCOPE Project website.

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