Extended Case Study of Causal Learning within Architecture Research (preliminary)

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Document Markings

This material is based upon work funded and supported by the Department of Defense under Contract No. FA8702-15-D-0002 with Carnegie Mellon University for the operation of the Software Engineering Institute, a federally funded research and development center.

DM18-1046

Goal of the Authors

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Goal is to motivate adoption of Causal Learning within software measurement!

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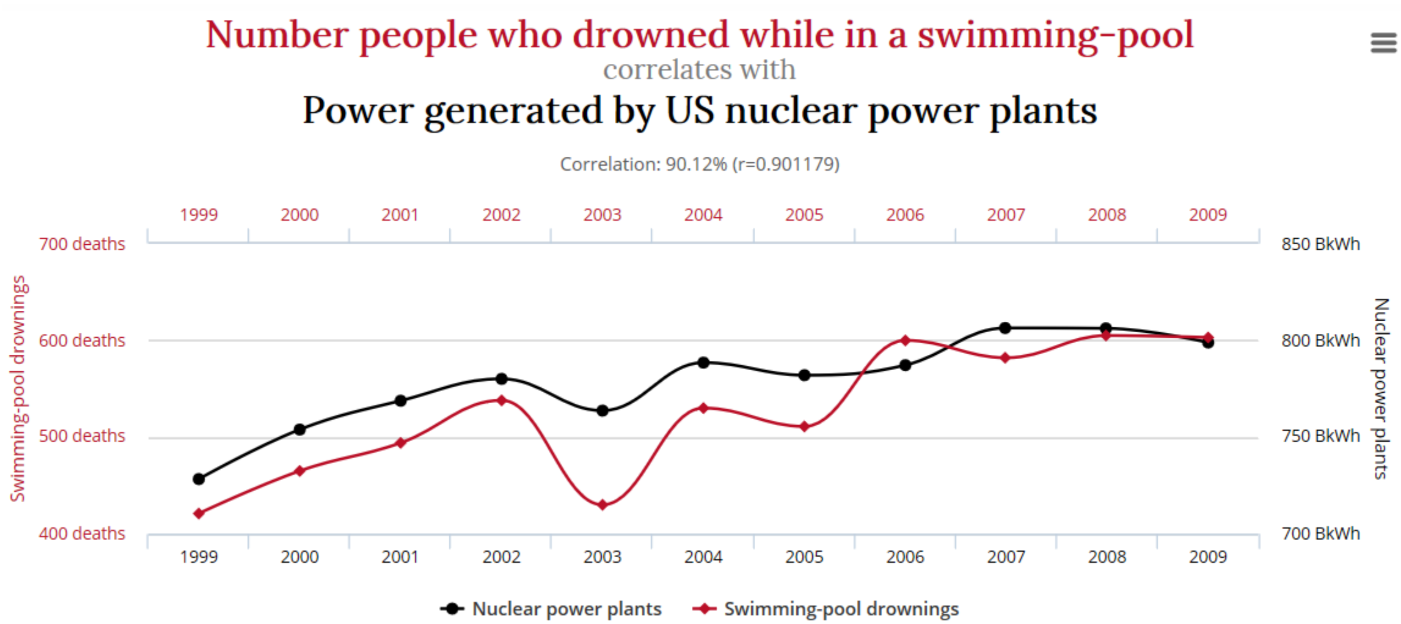
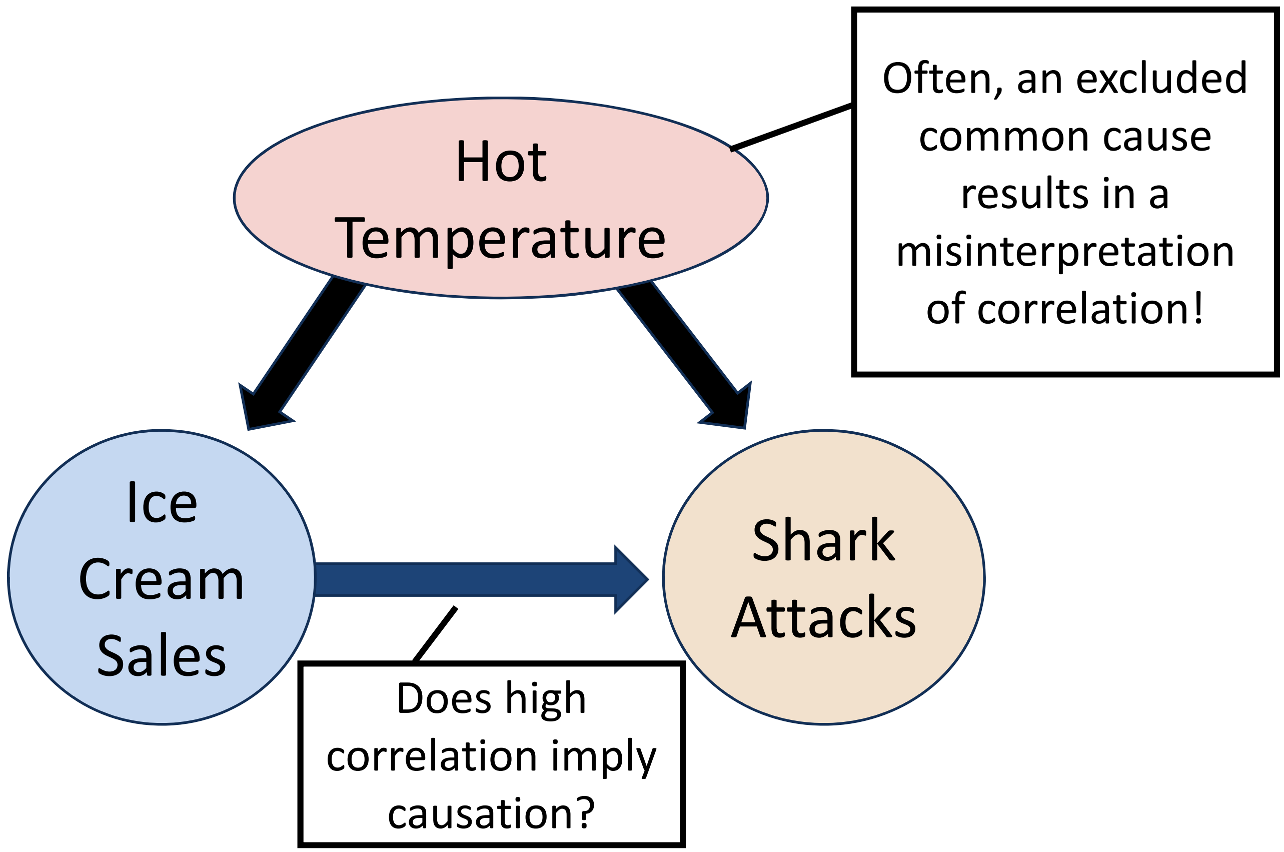
Why Do We Care about Causation?



http://www.tylervigen.com/spurious-correlations

More about Misinterpreting Correlation!



Regression Cannot be Trusted without a DAG!

Correlation, hence regression, may be fooled by spurious association!

Before jumping into regression, we need a Directed Acyclic Graph (DAG) representing our context

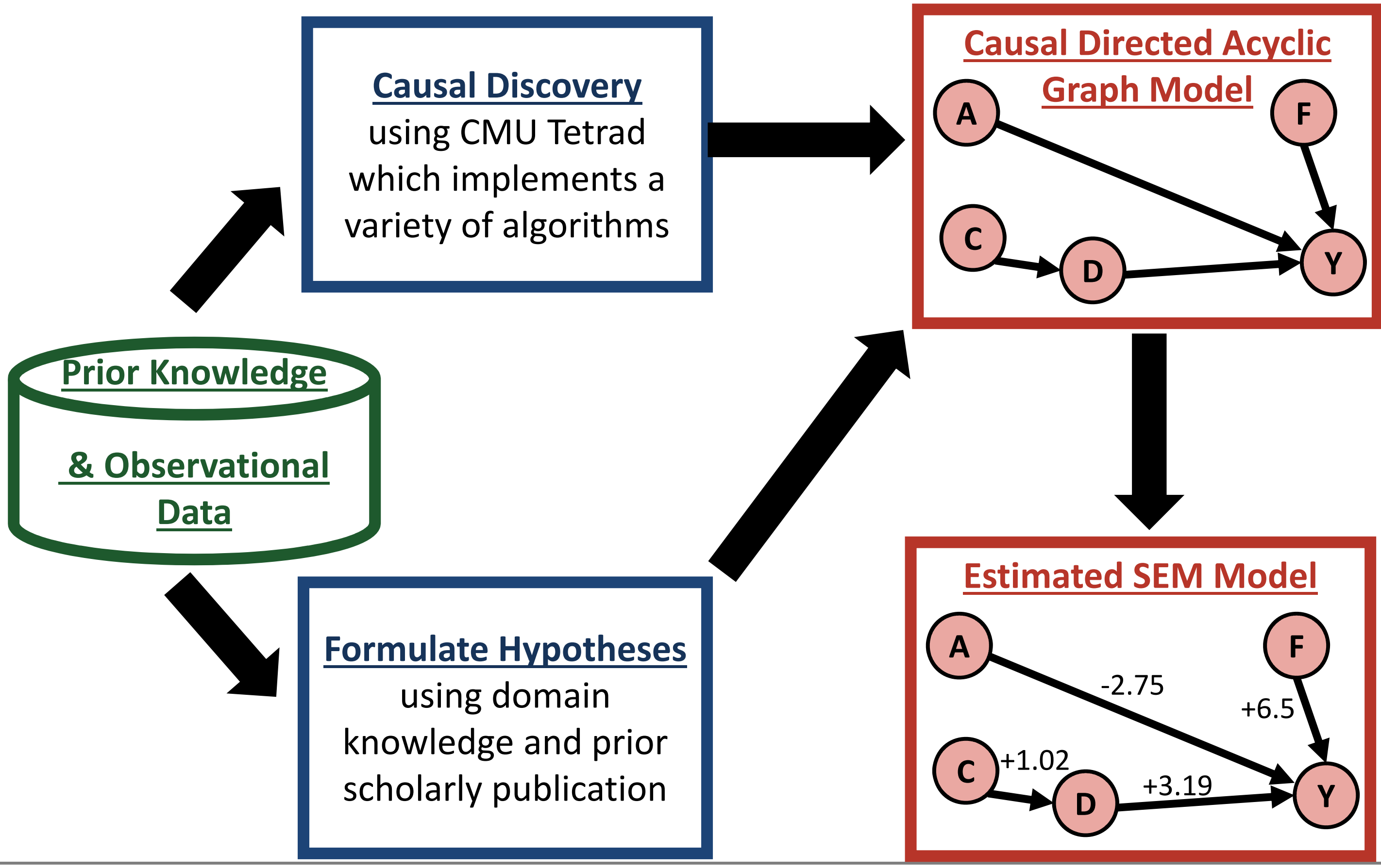
We then need to determine which paths are causal and which are spurious.

We then must block spurious correlation paths.

Lastly, we then conduct regression with the correct set of factors!

Remember, context of the DAG determines the suitability of the regression model!

The Causal Learning Landscape



Preliminary Architecture Research Causal Findings

Nine open source systems analyzed using static code analysis (> 9000 files)

Four architecture pattern violations studied for impact on quality

Each file had the following attributes measured:

- Age in Months
- Number of Developers touching each file
- Size in Lines of Code
- Number of times the file participated in a pattern violation of:
  - the cyclic dependency
  - Improper inheritance
  - Unstable interface
  - Lack of modularity
- Quality outcome of Number of Bugs associated with each file
- Bug churn associated with each file

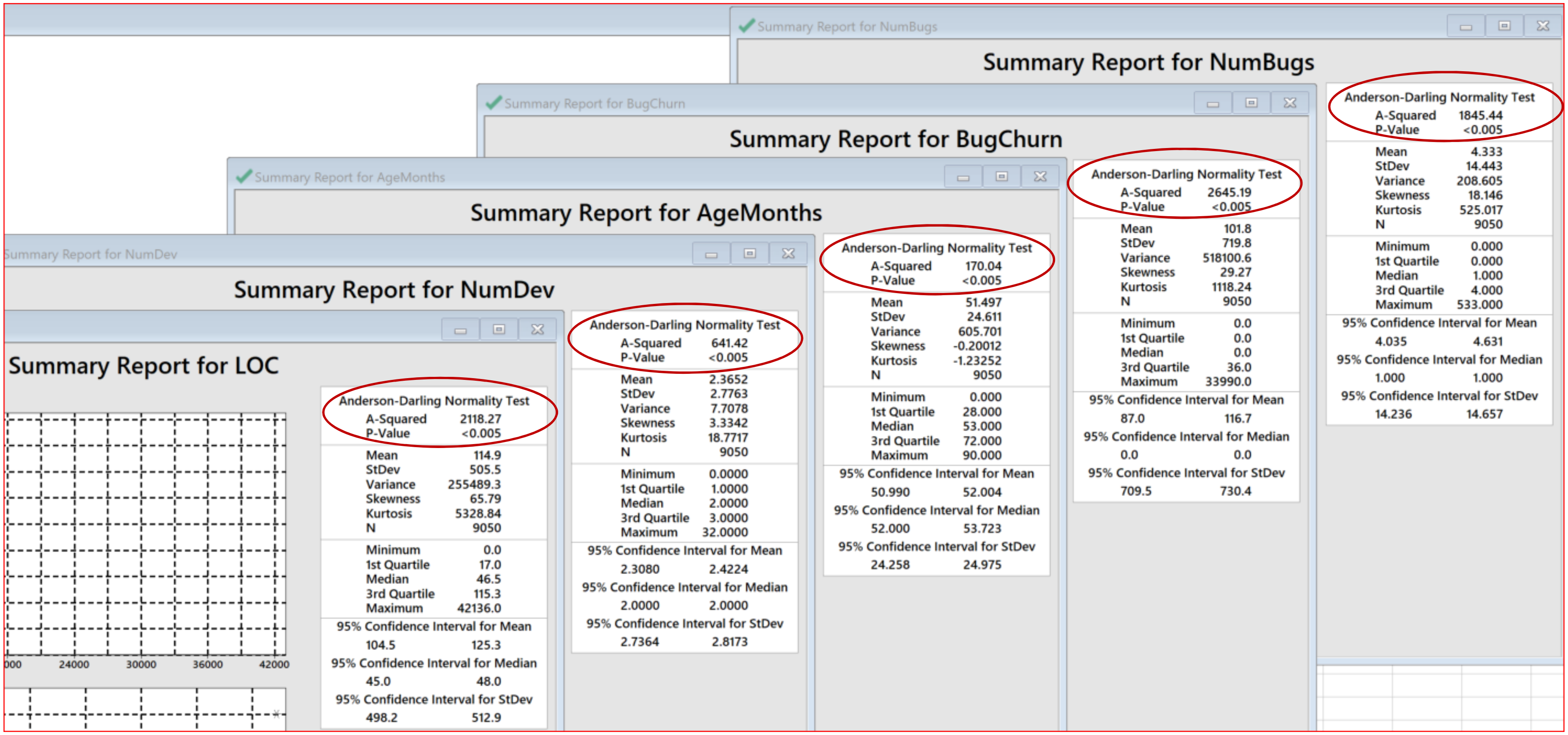
R. Mo, Y. Cai, R. Kazman and L. Xiao, "Hotspot Patterns: The Formal Definition and Automatic Detection of Architecture Smells," *2015 12th Working IEEE/IFIP Conference on Software Architecture*, Montreal, QC, 2015, pp. 51-60. doi: 10.1109/WICSA.2015.12

Correlation Matrix of All Factors

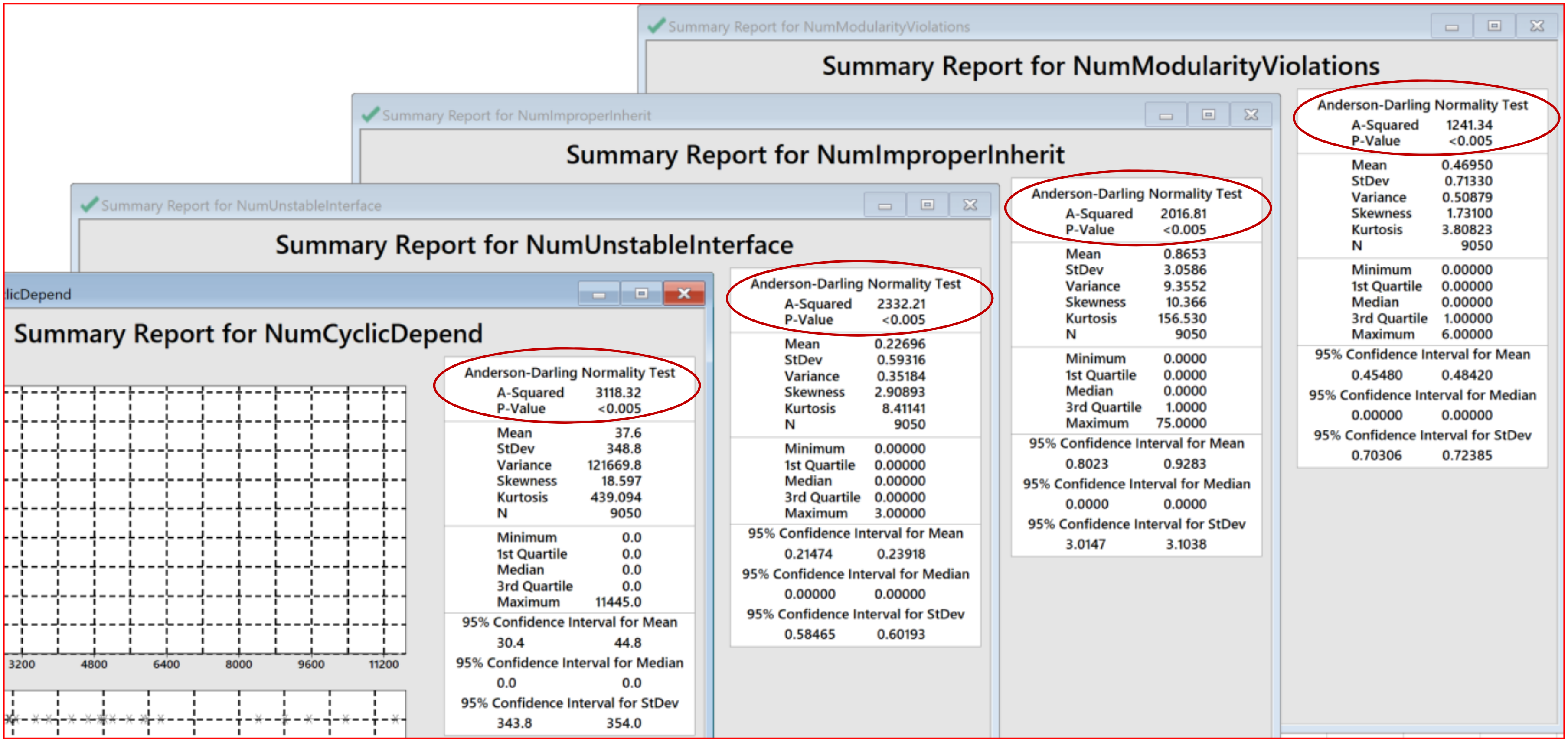
	AgeMonths	NumDev	NumCommits	LOC	NumBugs	NumChanges	BugChurn	ChangeChurn	NumCyclicDepend	NumModularityVio	NumUnstableInter
NumDev	0.1790										
	0.0000										
NumCommits	0.0930	0.6890									
	0.0000	0.0000									
LOC	0.0460	0.2640	0.2720								
	0.0000	0.0000	0.0000								
NumBugs	0.1160	0.6540	0.9330	0.2570							
	0.0000	0.0000	0.0000	0.0000							
NumChanges	0.0960	0.6880	0.9990	0.2720	0.9340						
	0.0000	0.0000	0.0000	0.0000	0.0000						
BugChurn	0.0380	0.3920	0.5810	0.7270	0.6390	0.5820					
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000					
ChangeChurn	0.0180	0.2980	0.4180	0.9400	0.4120	0.4180	0.8300				
	0.0880	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000				
NumCyclicDepend	0.0340	0.1520	0.2920	0.1000	0.2430	0.2900	0.1240	0.1080			
	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000			
NumModularityVio	0.0490	0.3270	0.2100	0.1070	0.1590	0.2100	0.0980	0.1000	0.0130		
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2140		
NumUnstableInter	0.0390	0.5400	0.4820	0.1580	0.3940	0.4810	0.2220	0.2000	0.1420	0.2670	
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	
NumImproperInher	0.1280	0.2060	0.2110	0.1040	0.1850	0.2120	0.1150	0.0740	0.1620	0.0020	0.1330
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.8540	0.0000

NumBugs, NumChanges, and NumCommits are highly correlated;
Will keep NumBugs only in the modeling;
Likewise, ChangeChurn and LOC highly correlated, so kept only LOC in the modeling

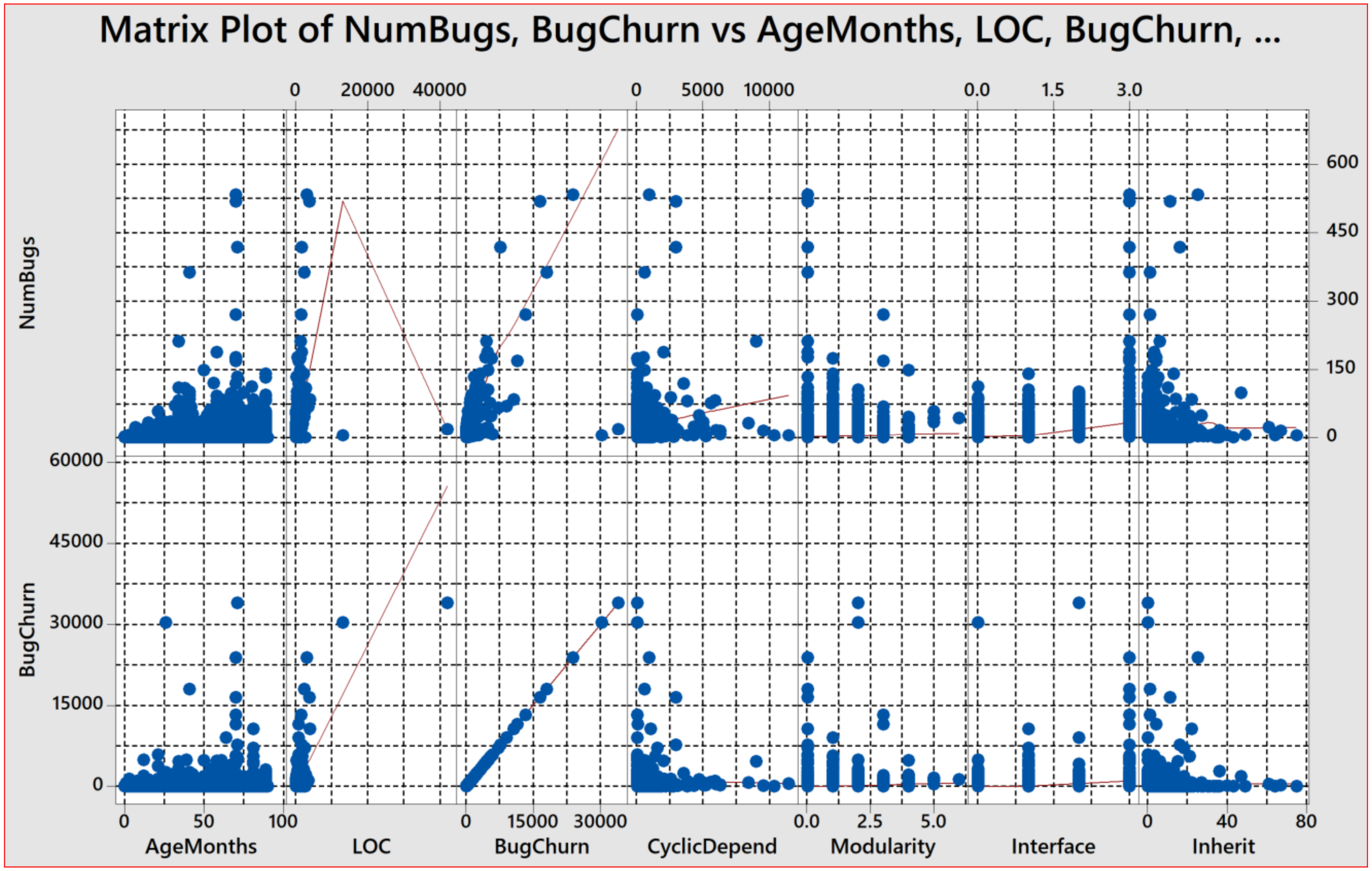
All Remaining Factors are Non-Normal - 01



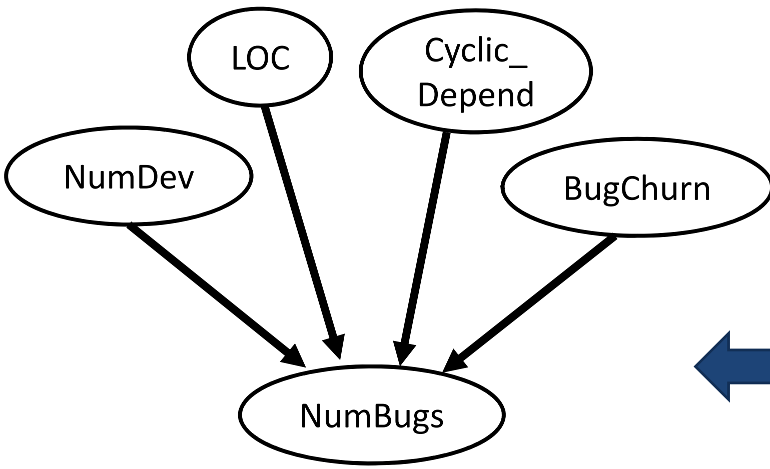
All Remaining Factors are Non-Normal - 02



Eyeballing Bivariate Relationships



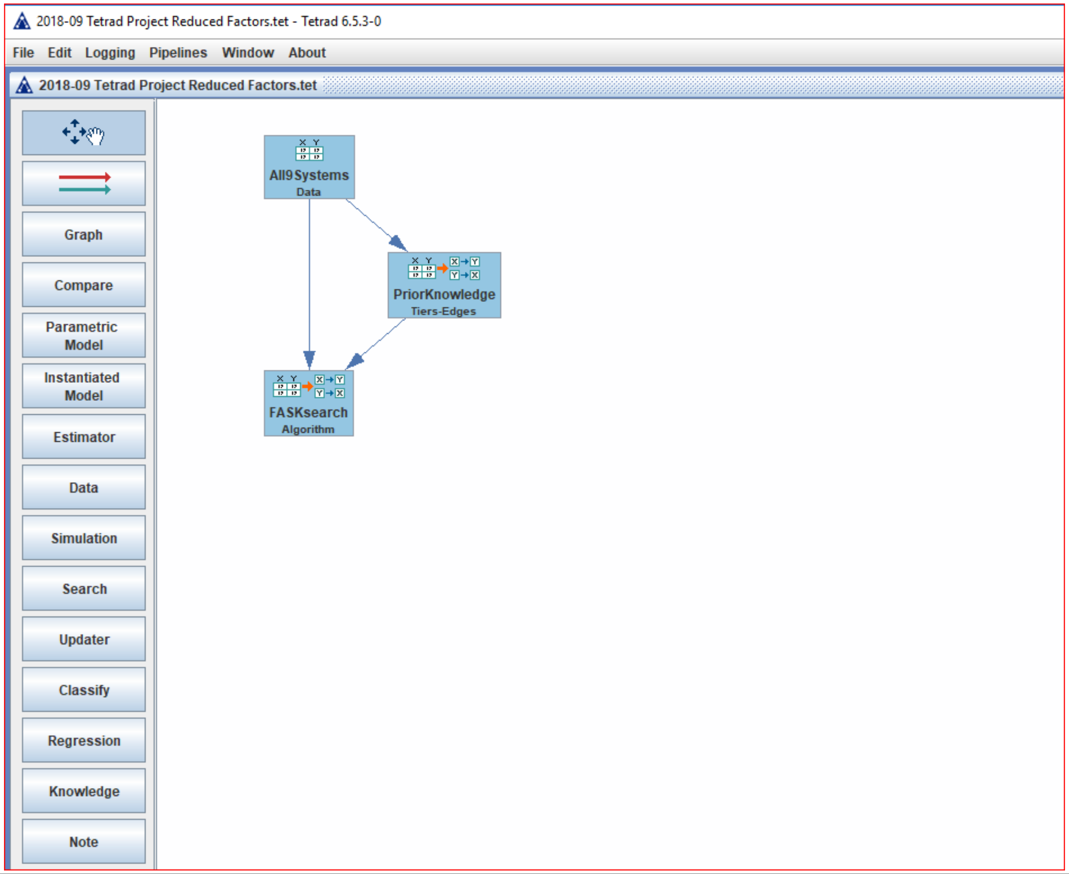
Best Subsets Regression



Response is NumBugs

Vars	R-Sq	R-Sq (adj)	R-Sq (pred)	Mallows Cp	S	AgeMonths	NumDev	LOC	BugChurn	CyclicDepend	Modularity	Interface	Inherit
1	42.8	42.8	42.1	8301.1	10.921		X						
1	40.9	40.9	27.7	8891.2	11.106				X				
2	60.1	60.1	50.8	3051.3	9.1201		X		X				
2	50.0	50.0	27.0	6132.0	10.216			X	X				
3	68.4	68.4	63.0	544.7	8.1199		X	X	X				
3	61.5	61.5	52.1	2647.3	8.9662		X		X	X			
4	69.9	69.9	64.7	101.9	7.9297		X	X	X	X			
4	68.6	68.6	63.2	480.3	8.0921		X	X	X			X	
5	70.0	70.0	64.8	59.3	7.9108		X	X	X	X		X	
5	70.0	69.9	64.8	77.0	7.9184		X	X	X	X			X
6	70.1	70.1	64.9	35.5	7.9000		X	X	X	X		X	X
6	70.1	70.1	64.9	42.5	7.9030		X	X	X	X	X	X	
7	70.2	70.1	65.0	21.6	7.8935		X	X	X	X	X	X	X
7	70.2	70.1	65.0	23.0	7.8941	X	X	X	X	X		X	X
8	70.2	70.2	65.0	9.0	7.8875	X	X	X	X	X	X	X	X

Conduct Causal Search using Tetrad



A View of the Data File Loaded into Tetrad

All9Systems (Data)

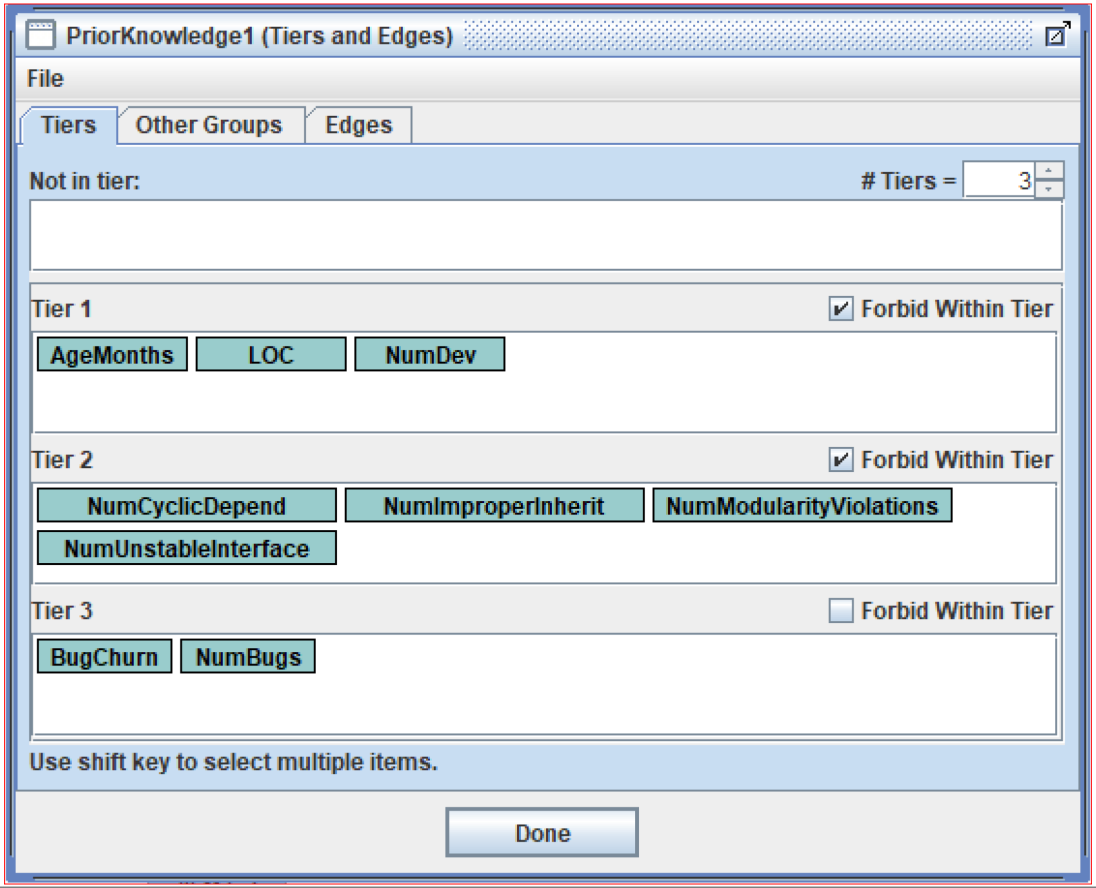
File Edit Tools

All 9 for Tetrad-v010.csv

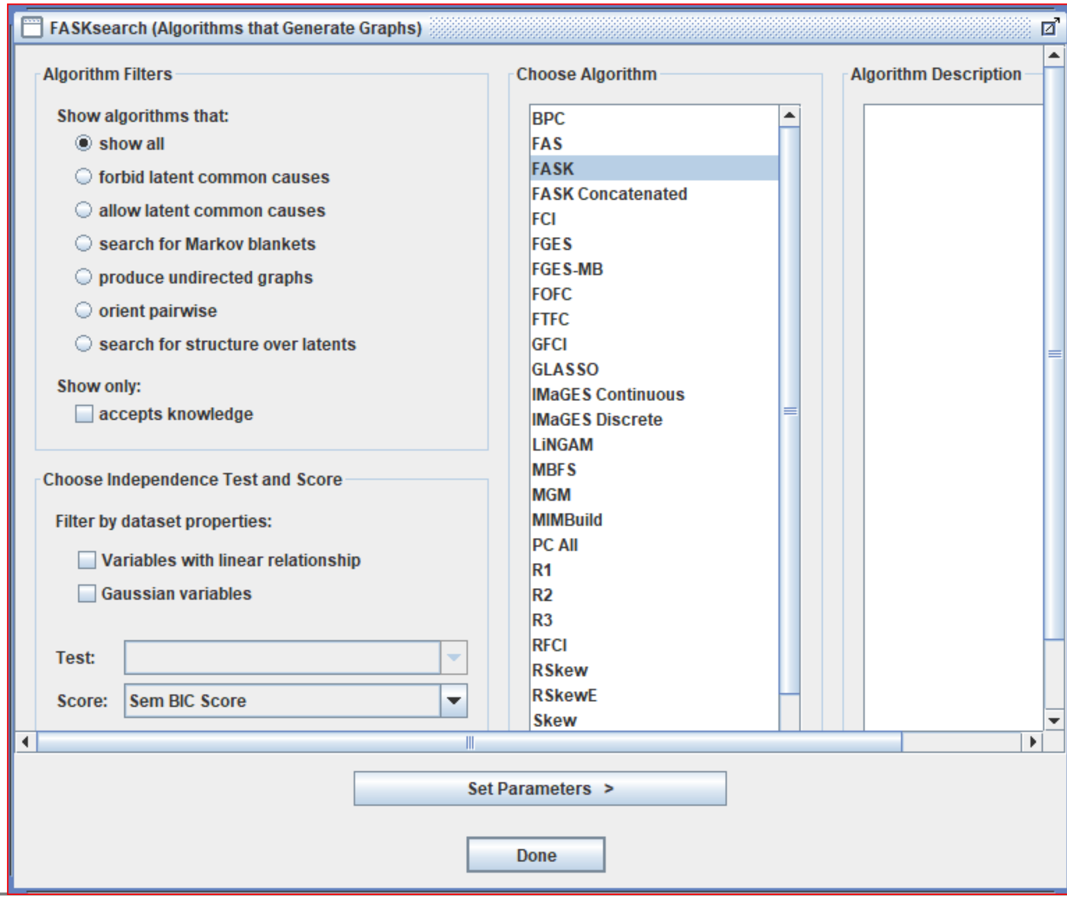
	C1	C2	C3	C4	C5	C6	C7	C8	C9
	AgeMonths	NumDev	LOC	NumBugs	BugChurn	NumCyclic...	NumModul...	NumUnsta...	NumImpro...
1	71.0000	8.0000	491.0000	18.0000	241.0000	8.0000	2.0000	3.0000	1.0000
2	35.0000	5.0000	270.0000	10.0000	329.0000	167.0000	1.0000	1.0000	4.0000
3	52.0000	2.0000	58.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
4	42.0000	1.0000	47.0000	2.0000	13.0000	0.0000	0.0000	0.0000	0.0000
5	49.0000	1.0000	10.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
6	36.0000	2.0000	103.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000
7	54.0000	2.0000	29.0000	2.0000	0.0000	0.0000	0.0000	0.0000	0.0000
8	75.0000	8.0000	163.0000	13.0000	134.0000	0.0000	1.0000	3.0000	0.0000
9	74.0000	2.0000	15.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000
10	57.0000	2.0000	26.0000	1.0000	16.0000	22.0000	0.0000	0.0000	0.0000
11	48.0000	4.0000	81.0000	2.0000	6.0000	0.0000	1.0000	0.0000	0.0000
12	39.0000	1.0000	30.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
13	49.0000	2.0000	46.0000	3.0000	36.0000	0.0000	0.0000	0.0000	0.0000
14	46.0000	3.0000	34.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000
15	75.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

Done

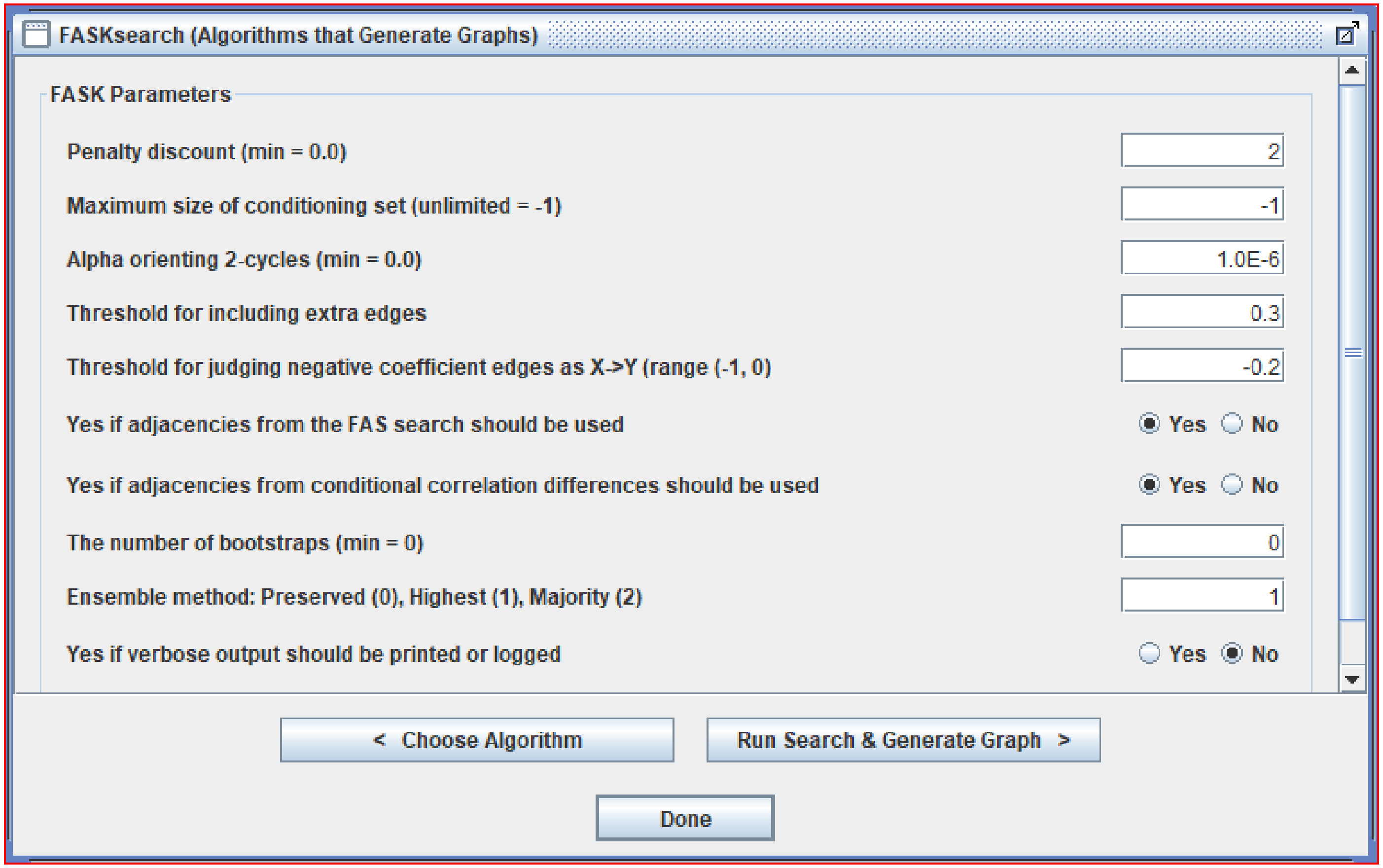
Prior Knowledge Entered into Tetrad



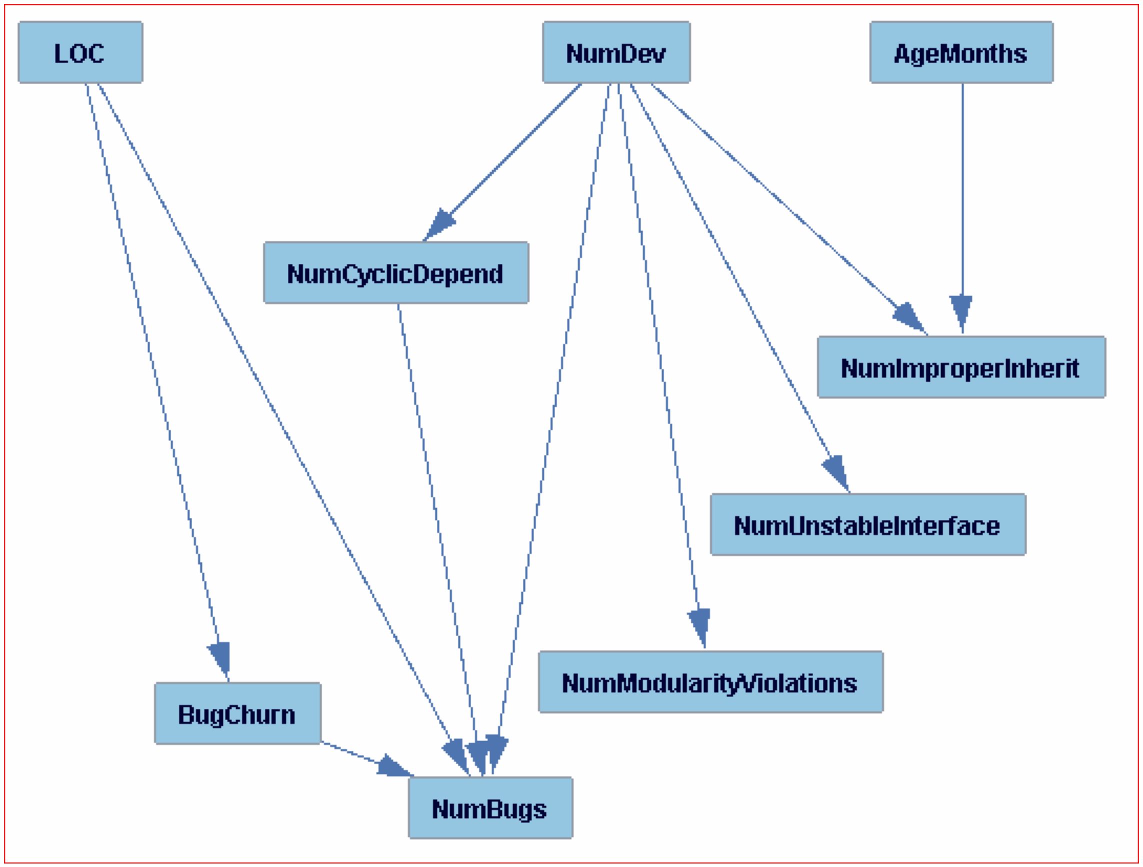
Using FASK Search with Associated Parameters



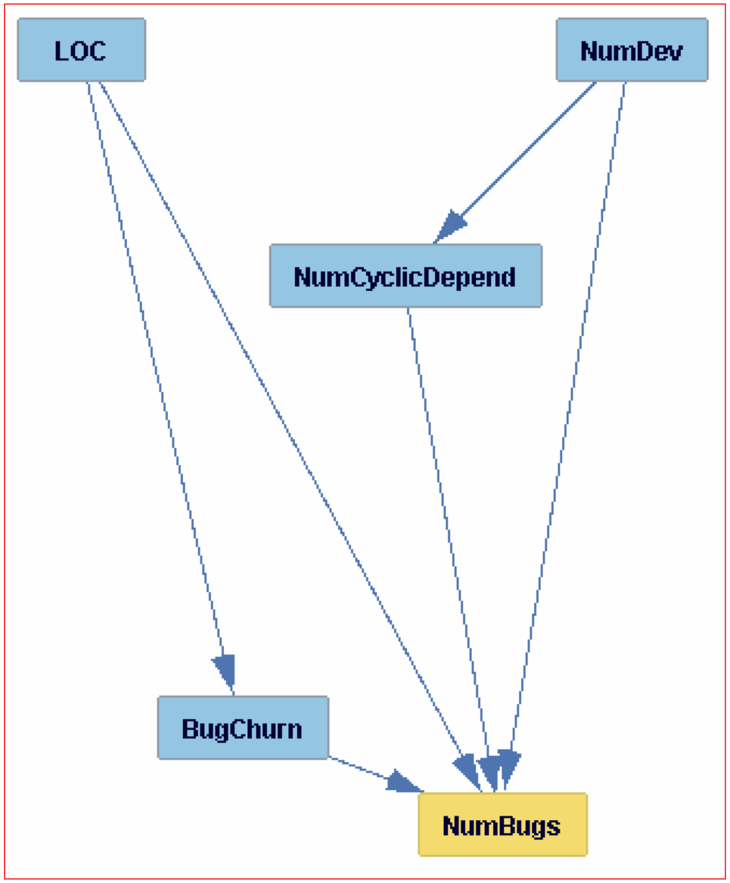
Additional FASK Search Parameter Settings



Causal Structure Graph Result



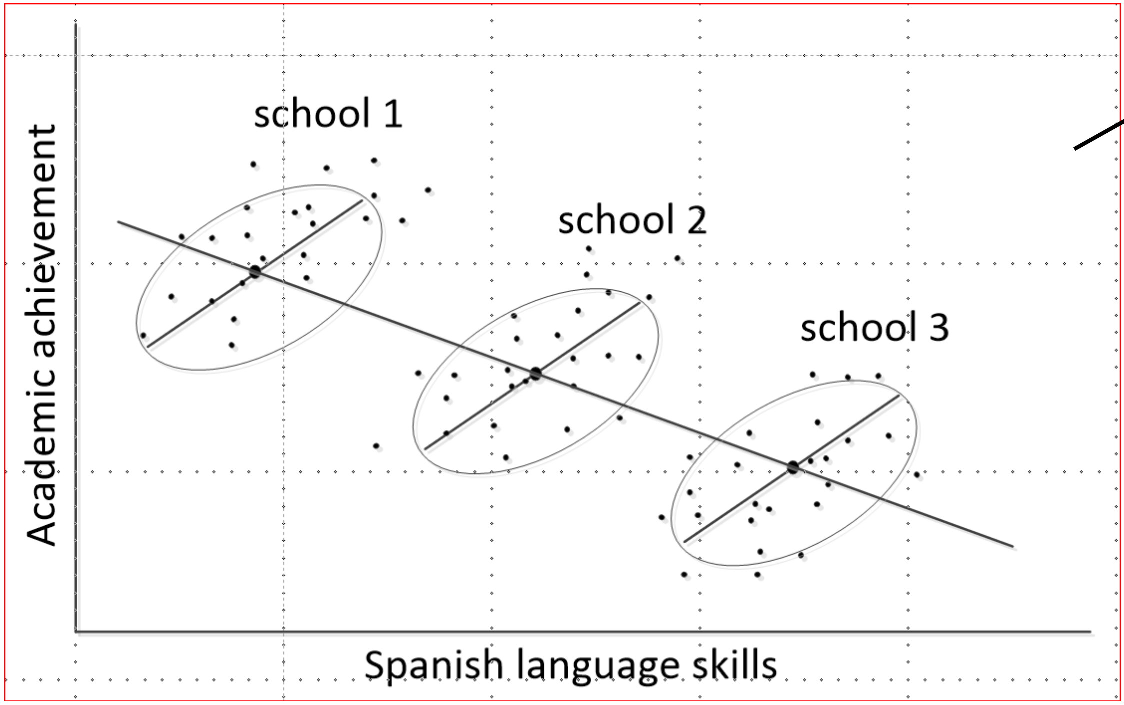
Markov Blanket of the NumBugs Factor



Motivation to Look at Multi-Level SEM Models (MSEM)

Within schools, students with better Spanish skills had higher academic achievement.

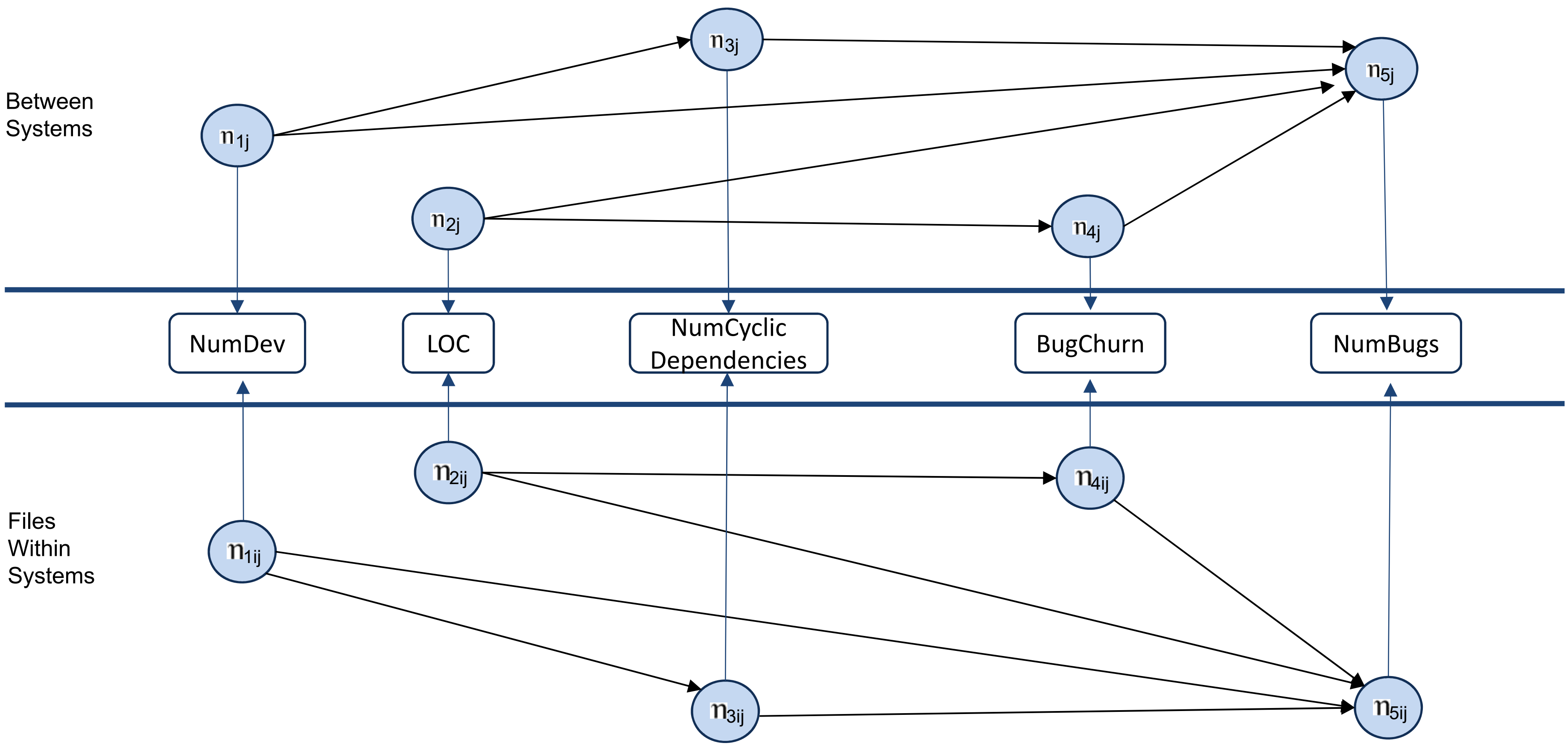
Yet, schools with highest proportion of Spanish speakers performed poorest.



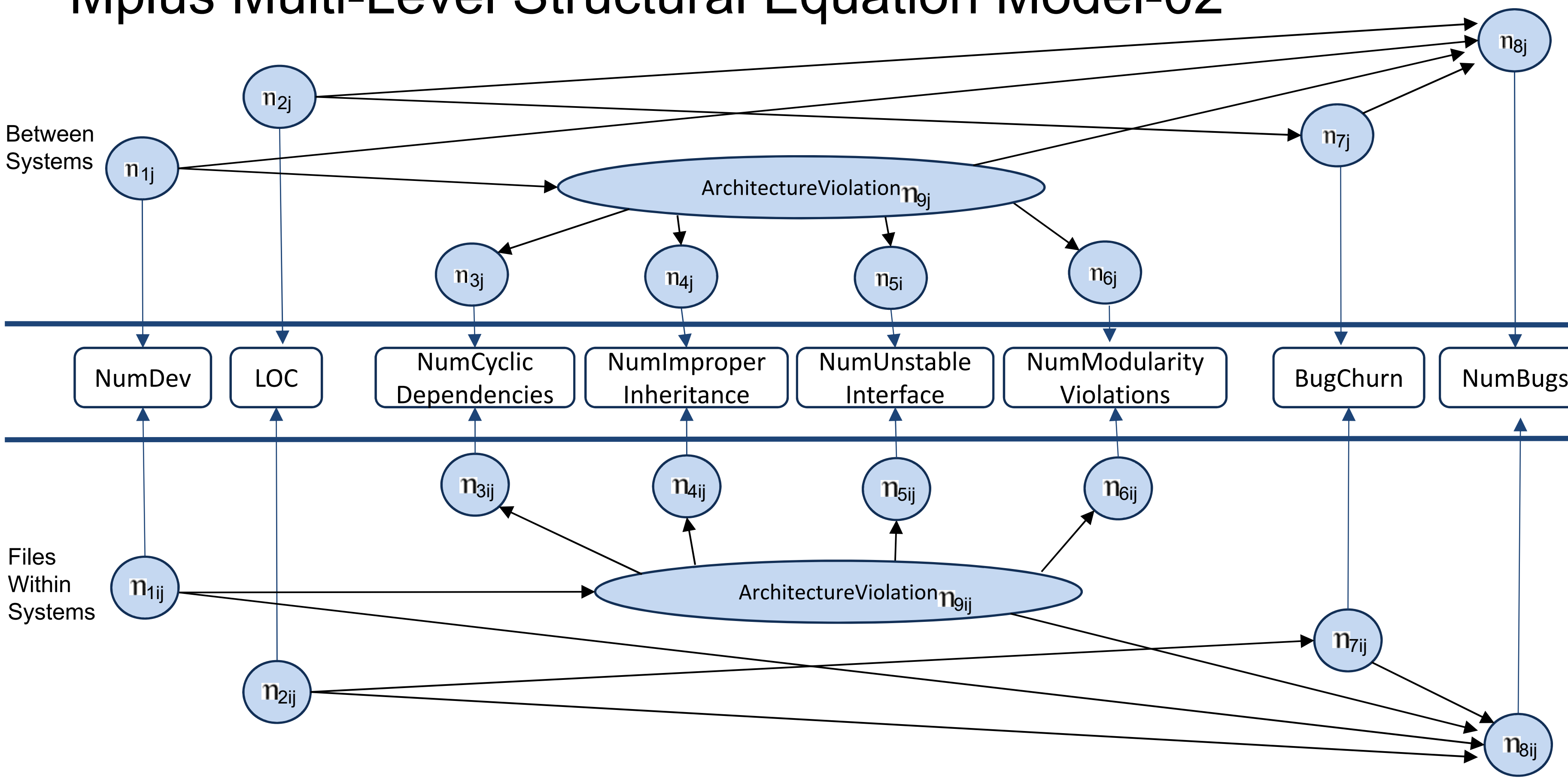
Also called Simpson's Paradox and the Ecological Fallacy

Kris Preacher, 2018

Mplus Multi-Level Structural Equation Model-01



Mplus Multi-Level Structural Equation Model-02



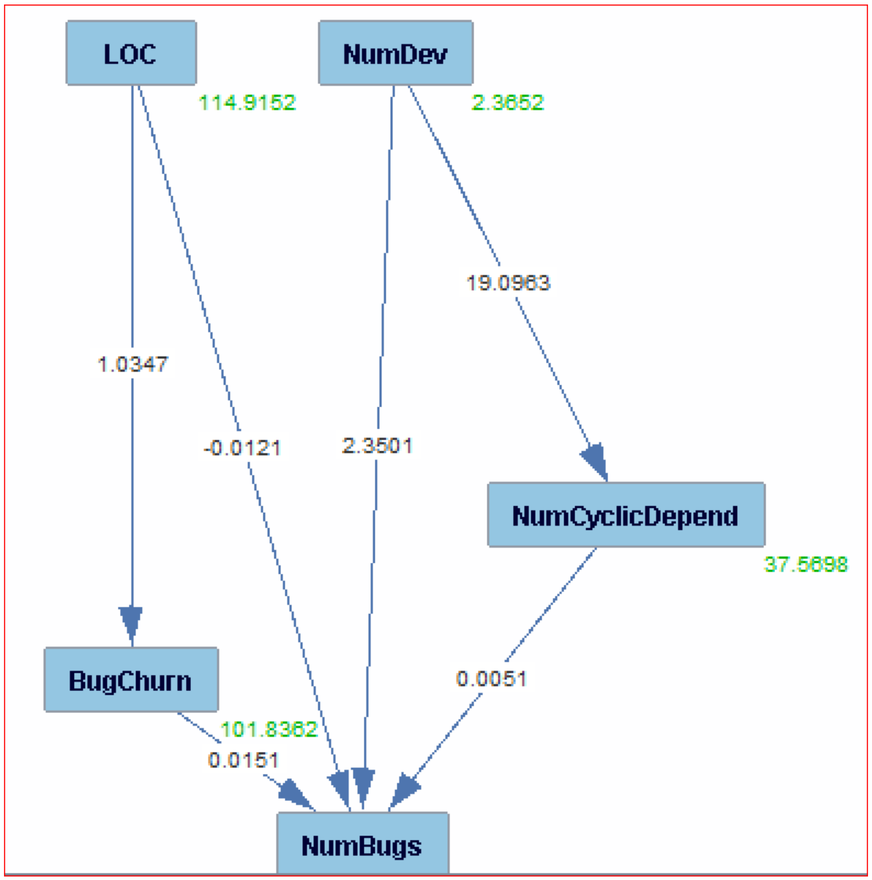
Mplus Code

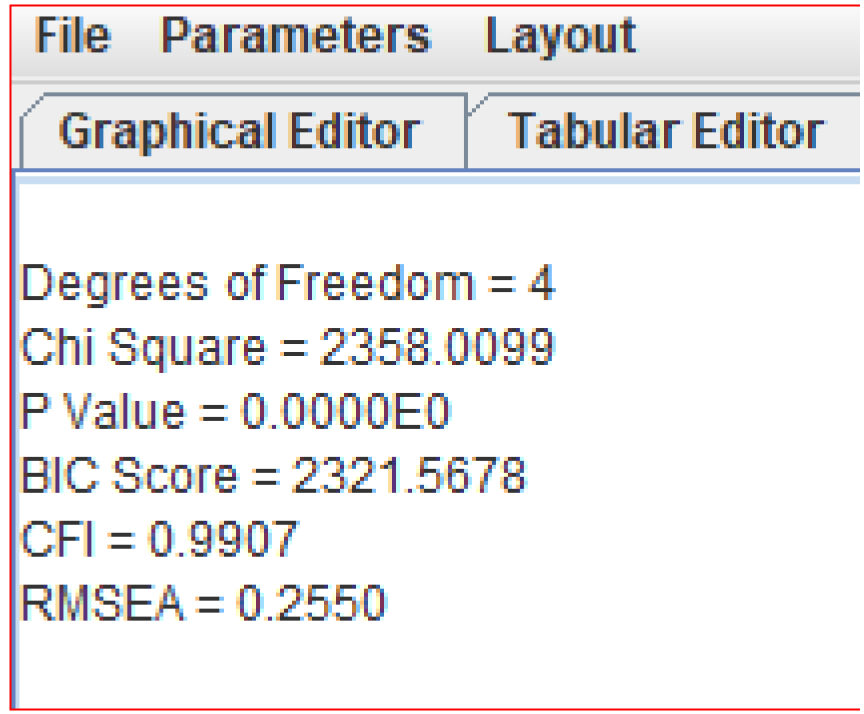
```
TITLE: Basic Model of NumBugs Markov Blanket;

DATA: FILE IS All9forMplus.csv;

VARIABLE: NAMES ARE AgeMos NumDev LOC Cycles Inherit Interfac Modular BugChurn NumBugs
System;

USEVARIABLES ARE NumDev LOC Cycles BugChurn NumBugs System;

CLUSTER IS System;

ANALYSIS: TYPE IS TWOLEVEL;

MODEL:

%BETWEEN%
NumBugs ON BugChurn LOC NumDev Cycles;
NumBugs; BugChurn; LOC; NumDev; Cycles;
[NumBugs]; [BugChurn]; [LOC]; [NumDev]; [Cycles];

%WITHIN%
NumBugs ON BugChurn LOC NumDev Cycles;

OUTPUT: SAMPSTAT STDYX;
```

Mplus MSEM Results

```
SUMMARY OF DATA

     Number of clusters                                  9

     Average cluster size     1005.556

     Estimated Intraclass Correlations for the Y Variables

                Intraclass              Intraclass              Intraclass
     Variable  Correlation   Variable  Correlation   Variable  Correlation

     NUMBUGS       0.052     NUMDEV        0.084     LOC           0.008
     CYCLES        0.039     BUGCHURN      0.026
```

Traditional SEM Results from Tetrad





Conclusions

1. We attempted MSEM modeling to be sensitive to the “between” and “within” variation components of all the factors
2. We also wanted to guard against Simpson’s paradox
3. The Mplus MSEM analysis, via the Intraclass Correlation measures, showed that in this data situation, we do not need to perform MSEM with two levels
4. We then conducted a single level, univariate SEM within Tetrad
5. We achieved regression coefficients that take into account the mediation effects occurring on the outcome, NumBugs
6. Traditional regression would have been ignorant of the above

Next Steps

Perform more causal searches

- Additional algorithms
- Sensitivity analysis of algorithm parameters
- Using bootstrapping to get confidence intervals on causal edges

Perform additional multilevel structural equation models:

- Investigate more factors associated with attributes of the open source system
- Evaluate whether a latent factor representing the “voice” of any architecture pattern might be helpful

Publish results:

- Comparison of different models
- Distinguish the causal influence of factors at both the file level and within a system

Convince others in the community to adopt Causal Learning and MSEM

Questions?

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