Synthesis of Causal Discovery and Machine Learning – Questions Posed

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Agenda

SEI SCOPE Research Focus

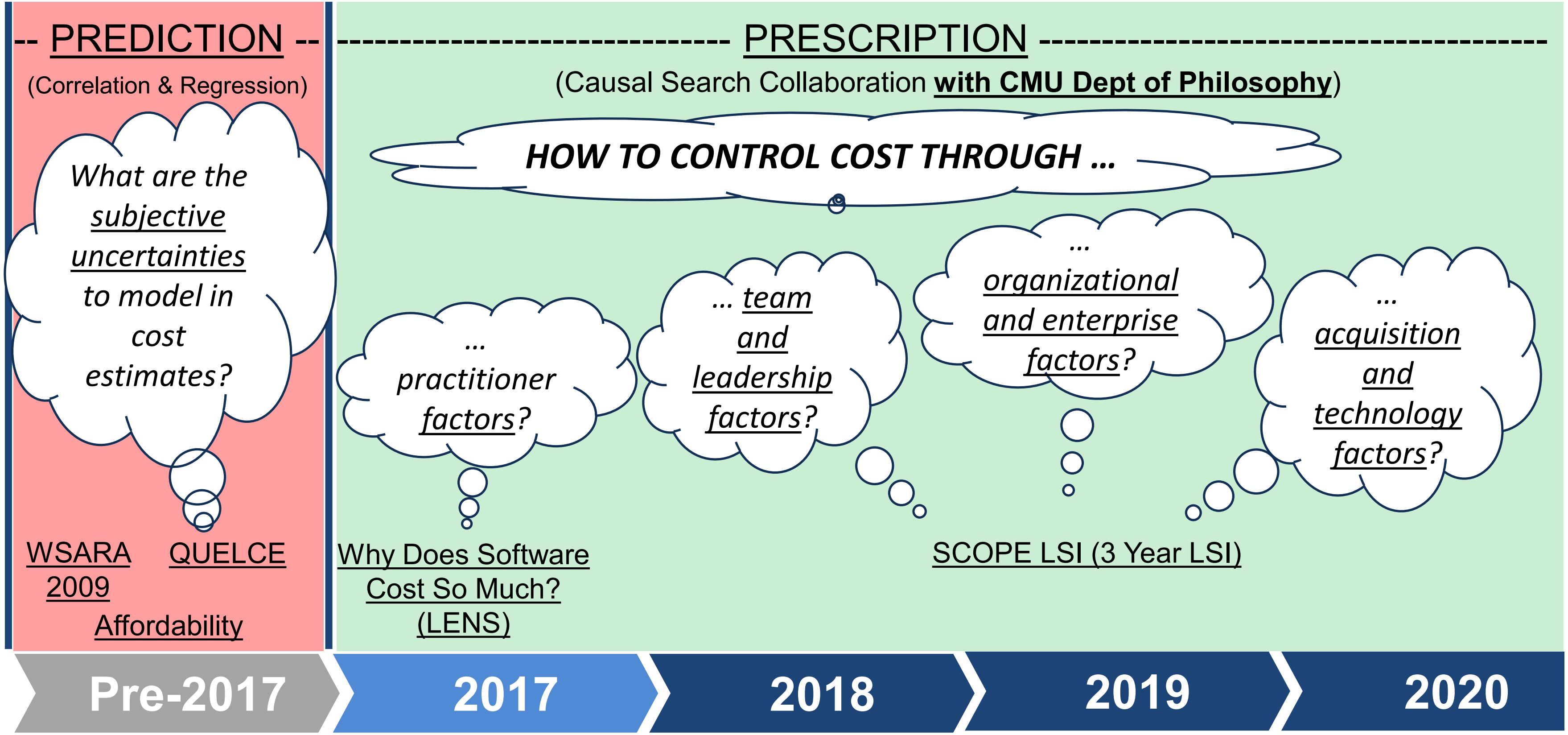
Use of BayesiaLab

Causal Learning

Comparison of ML and CL outputs

Questions Posed for Future Collaboration?

Context of Causal Models for Software Cost Control (SCOPE)



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Use of BayesiaLab

1. Supervised machine learning (ML) with cost, schedule and quality as targets
2. Multi-variate outlier analysis
   a) Aid in data quality analysis
   b) Possible data segmentation strategies
3. Data imputation, when needed
4. Prediction of “what-if” scenarios of factors against outcomes
5. Classifier to assign probability of a binary outcome (e.g. good vs bad outcomes)
6. Diagnostic of most likely factors associated with a given outcome
7. All in support of DoD cost estimation and affordability analysis

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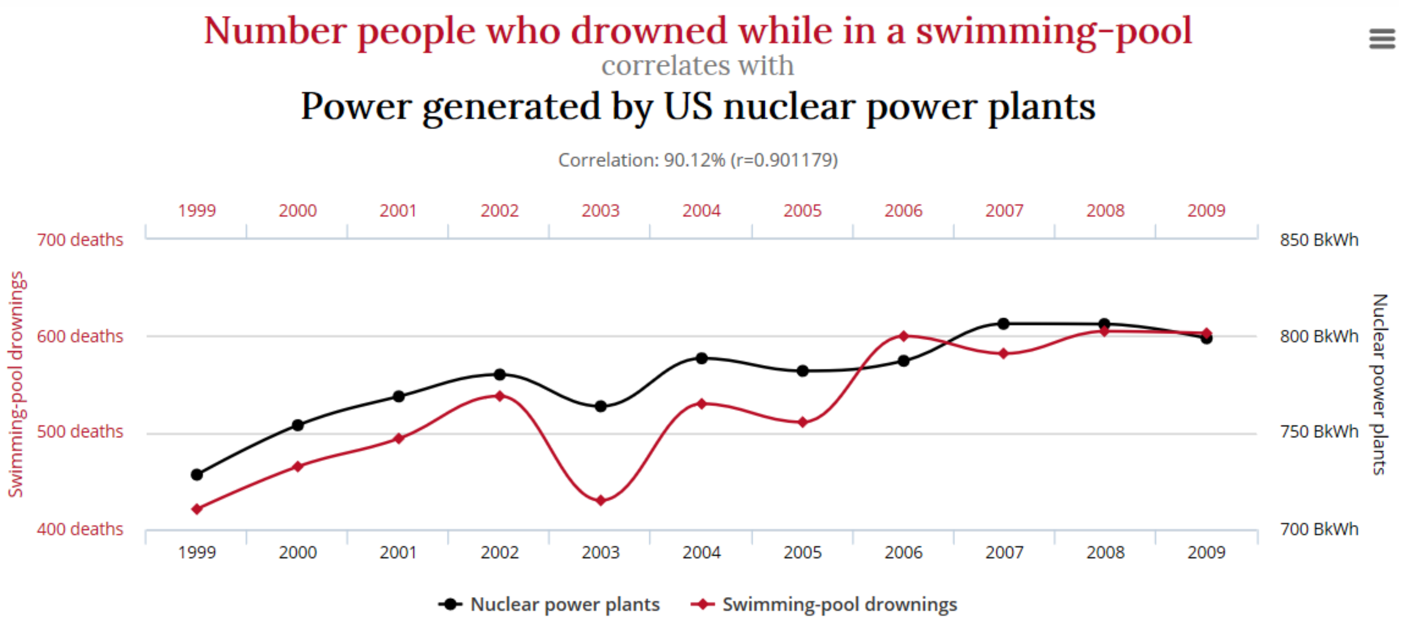
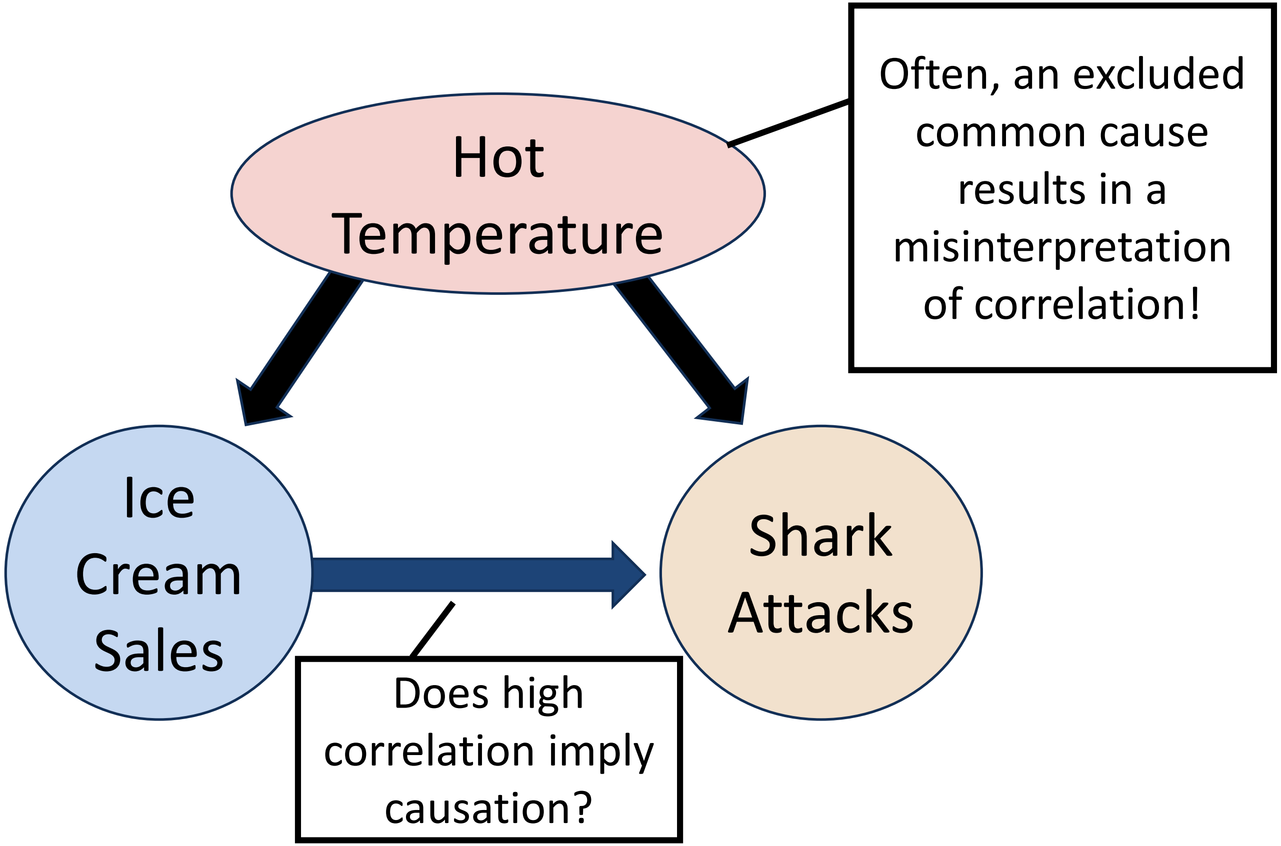
Why Do We Care about Causation?



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

More about Misinterpreting Correlation!



Regression & ML benefit from a Structural Causal Model!

Regression and ML may be fooled by spurious association!

Need a structural causal model (SCM) representing our theory and context

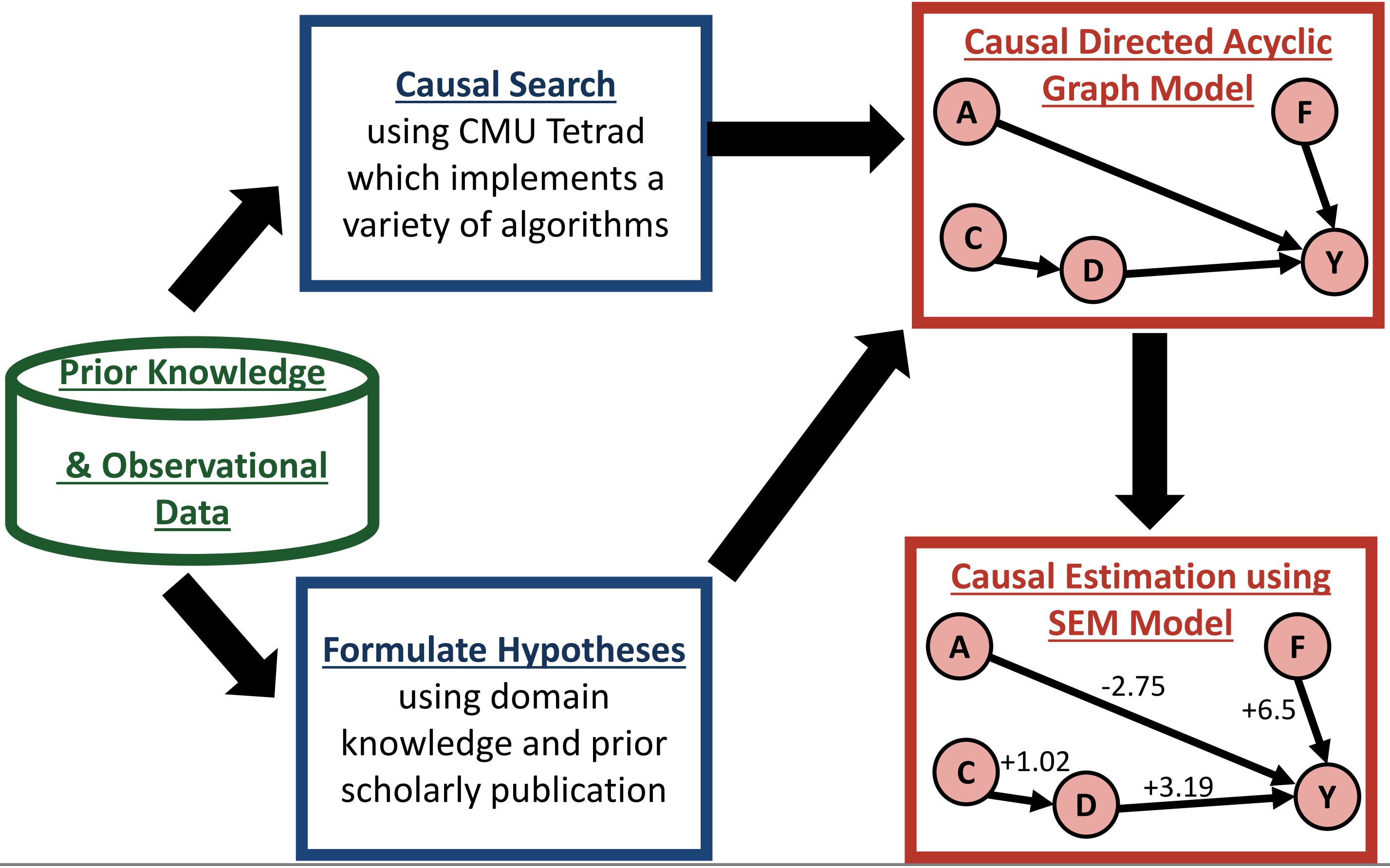
Need to determine which paths are causal versus non-causal

Must block non-causal paths

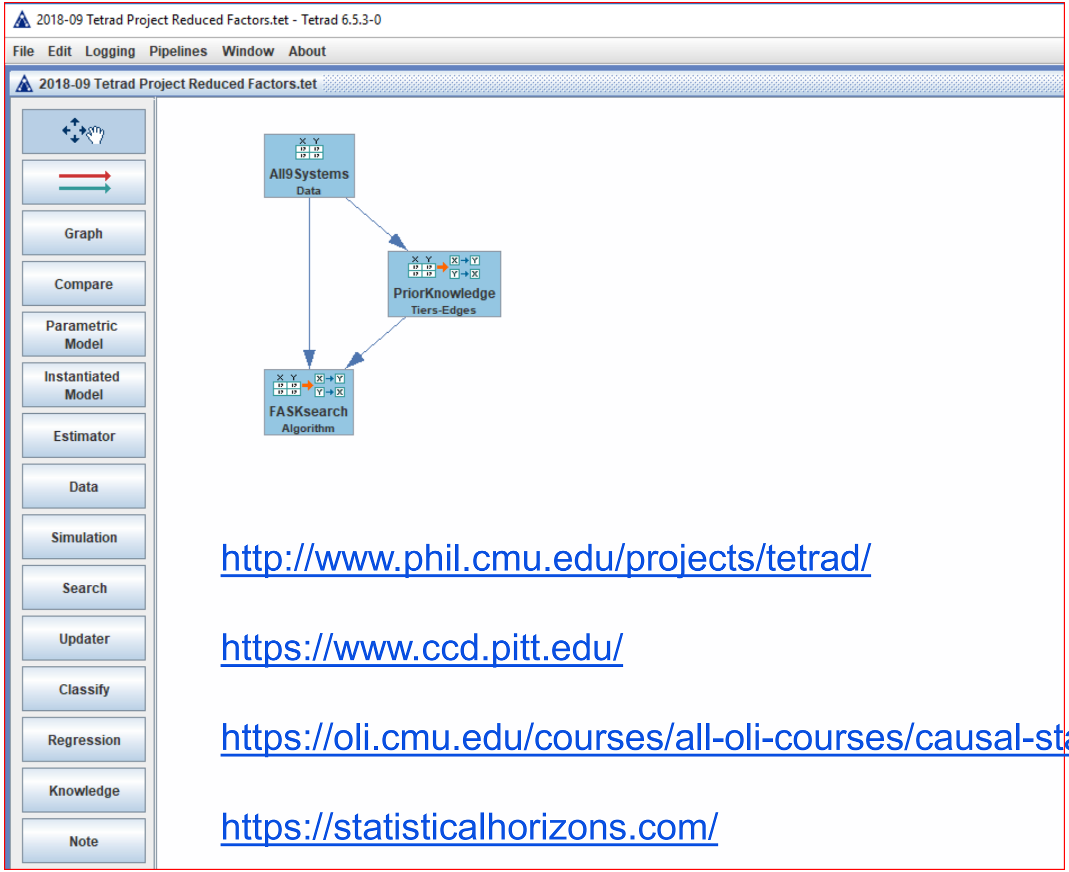
Then conduct regression and ML with the correct set of factors!

Suitability of the model depends on the SCM!

The Causal Learning Landscape



Conduct Causal Search using Tetrad



http://www.phil.cmu.edu/projects/tetrad/

https://www.ccd.pitt.edu/

https://oli.cmu.edu/courses/all-oli-courses/causal-statistical-reasoning/

https://statisticalhorizons.com/

A View of the Data File Loaded into Tetrad

All9Systems (Data)

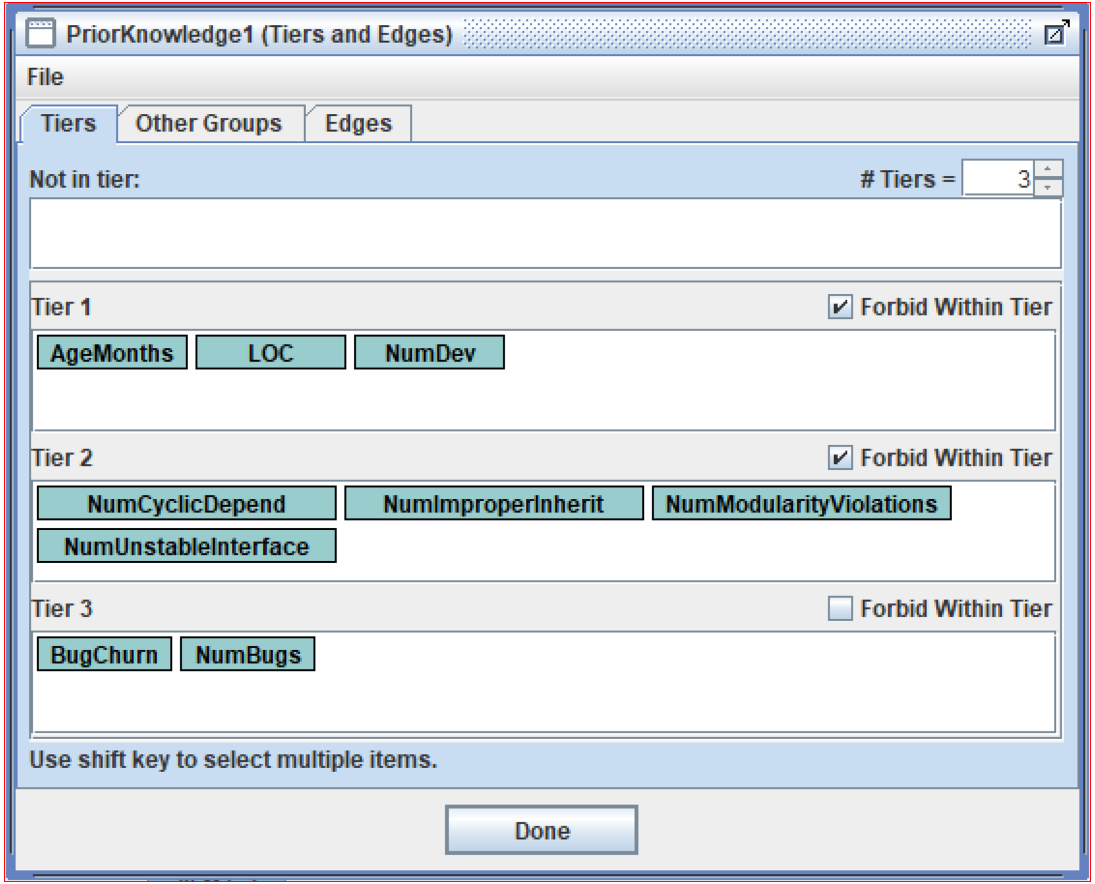
File Edit Tools

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



Causal Learning Algorithms

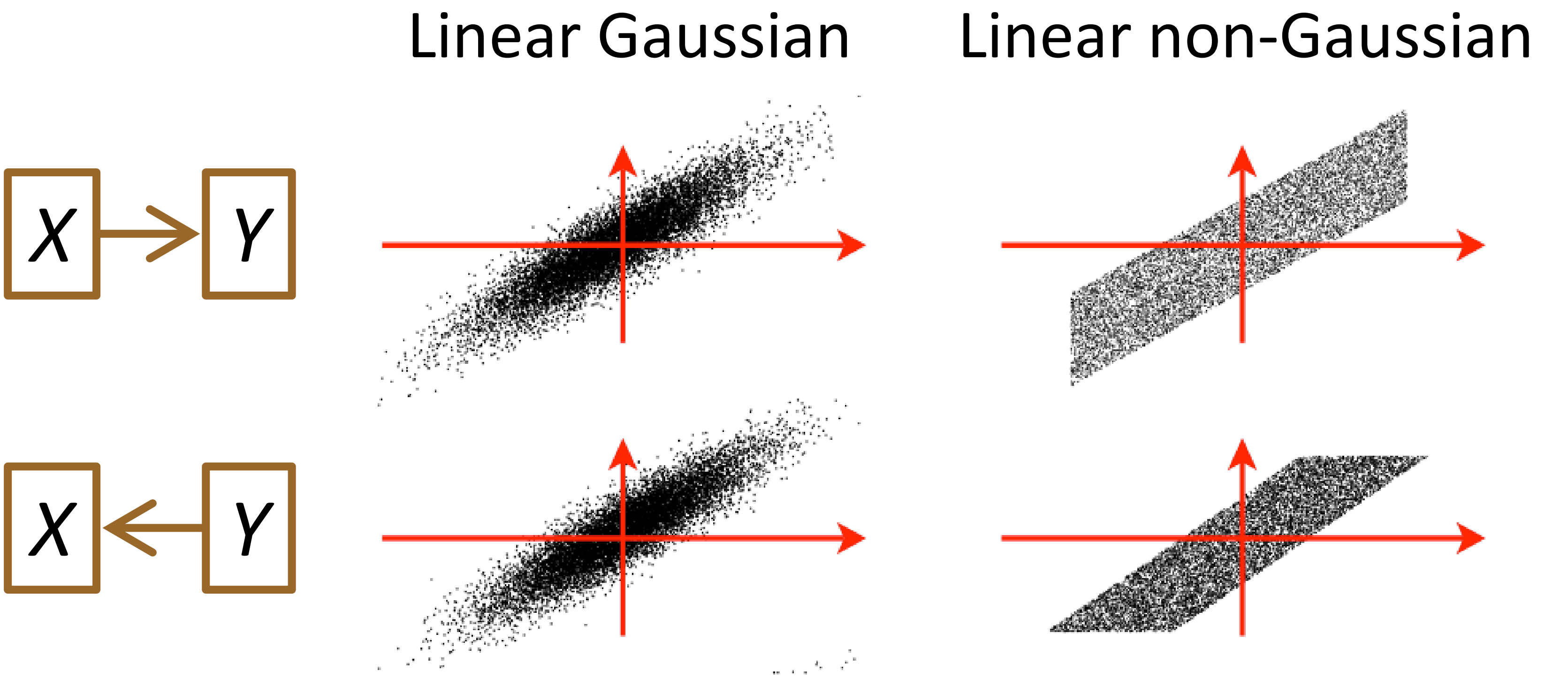
Constraint-based: Calculate independences in the data and do “backwards inference”; used to minimize the degree of false negative edges

Score-based (Bayesian): Calculate the likelihood of different DAGs given the data; used to minimize the degree of false positive edges

Hybrid: Use constraint-based to get “close,” then Bayesian search around neighborhood

A B	No evidence of a causal link
A $\longrightarrow$ B	Evidence of a causal link from A to B
A $\longleftarrow$ B	Evidence of a causal link from B to A
A $\longleftrightarrow$ B	Evidence of an unmeasured confounder

Some Algorithms Exploit Non-Gaussianality



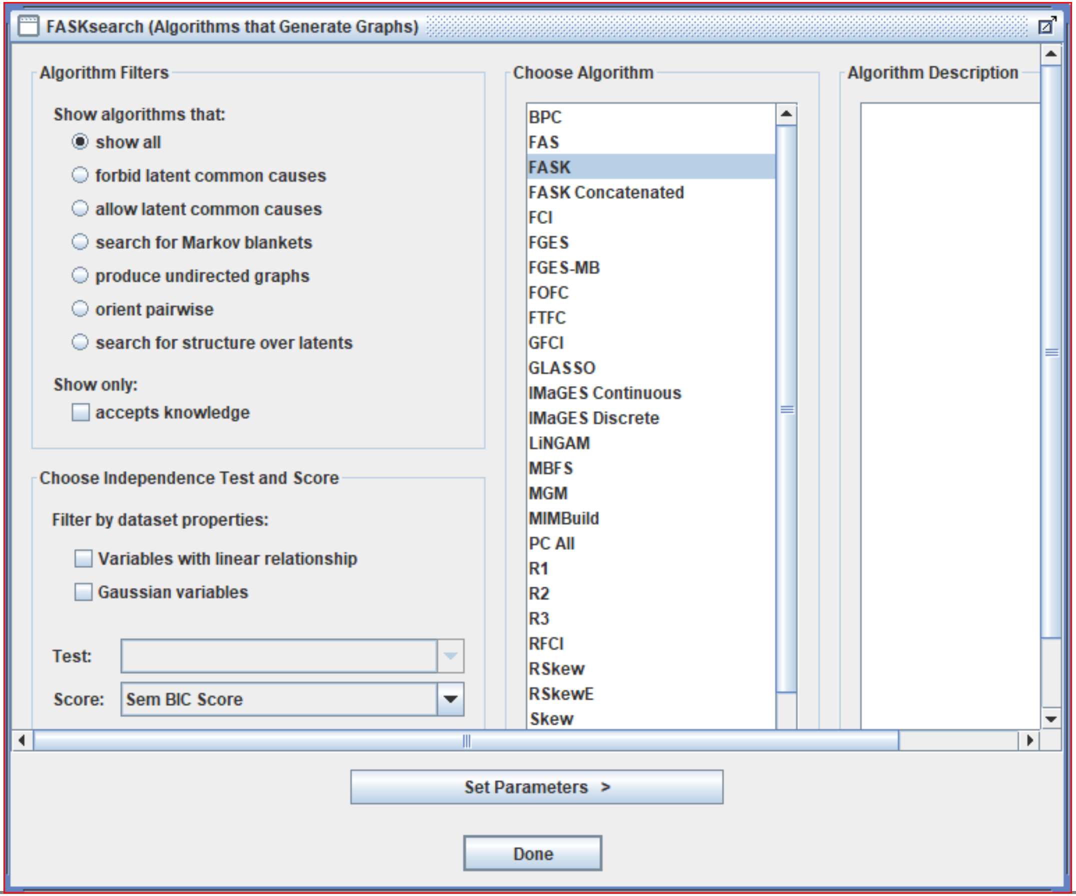
Causal Search Capable with Small Data

Challenge: Which genes regulate flowering time in Arabidopsis thaliana?

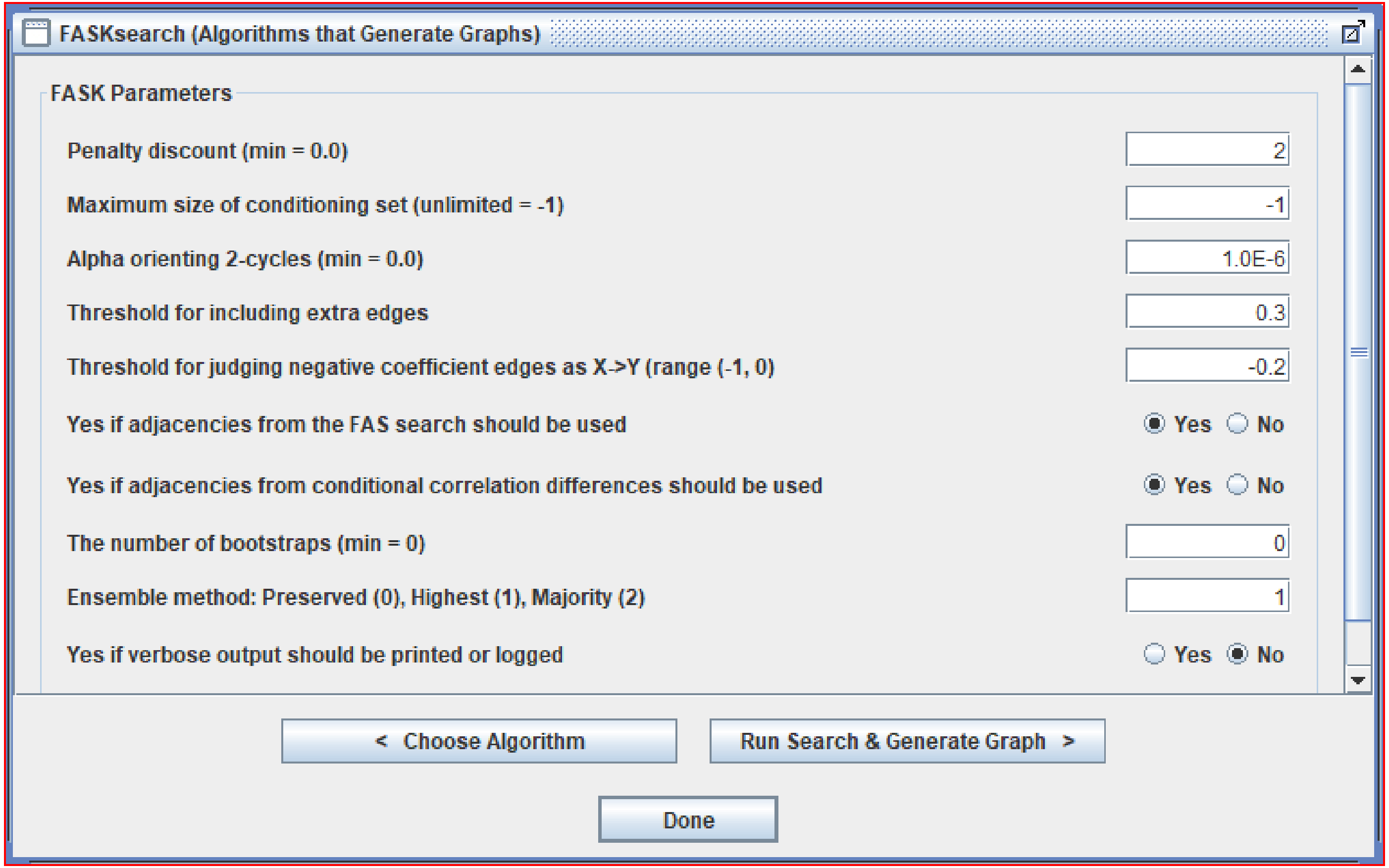
Using only 47 observations, causal search identified 9 out of 21,326 genes as causal on gene activation

Subsequent greenhouse study, that used knockout variants, confirmed that 4 of the 9 were actual regulators

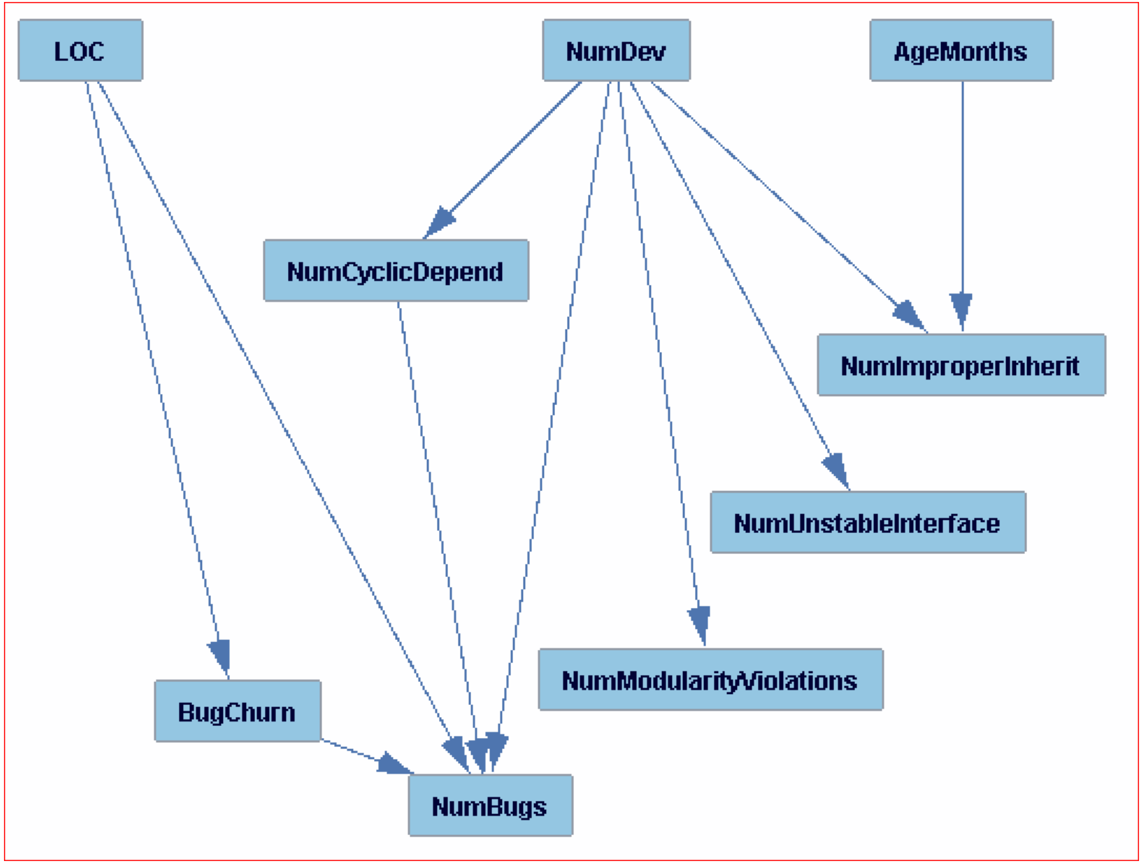
Using FASK Search with Associated Parameters



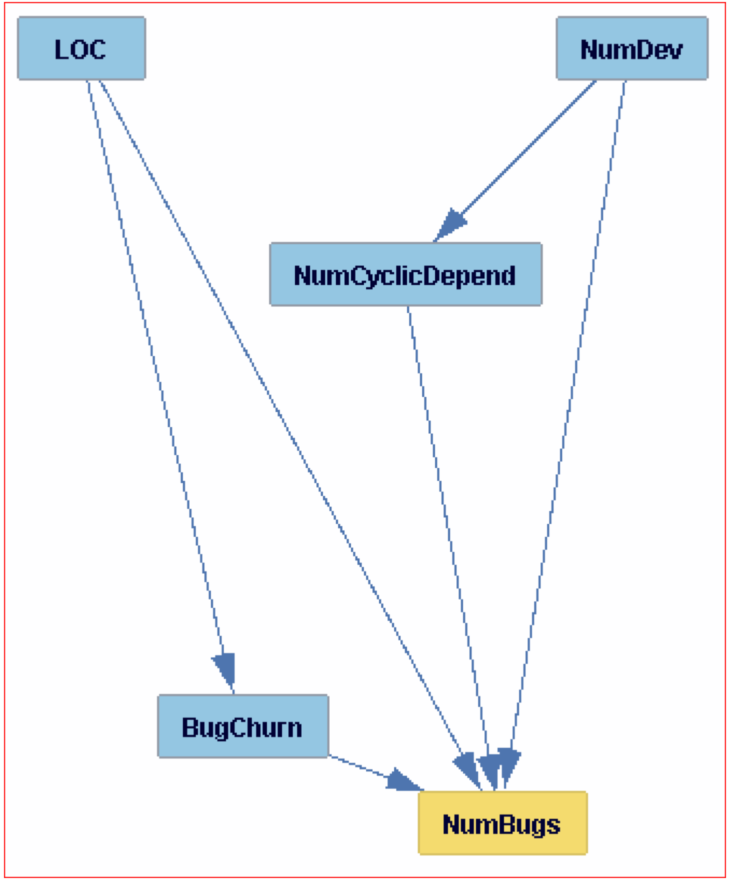
Additional FASK Search Parameter Settings



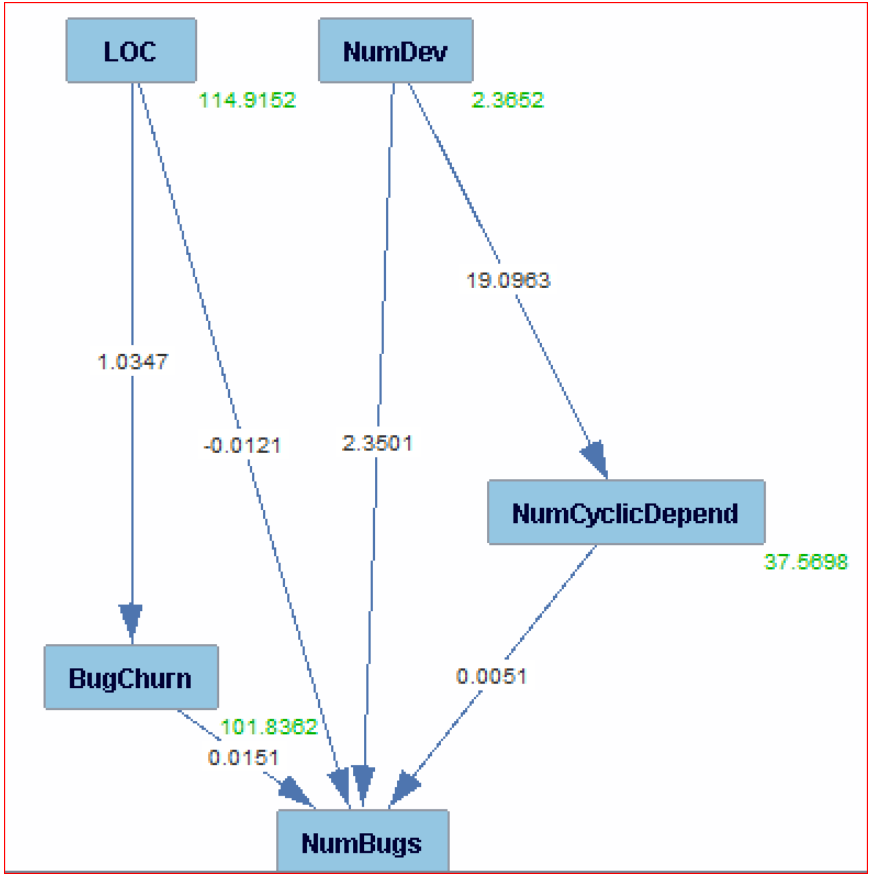
Causal Structure Graph Result

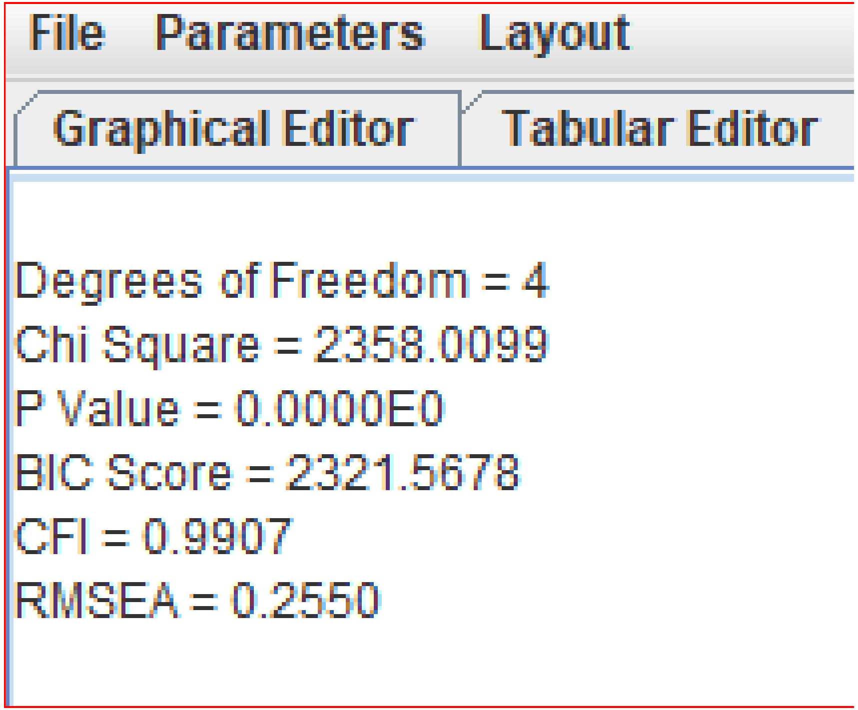


Markov Blanket of the NumBugs Factor



Traditional SEM Results from Tetrad



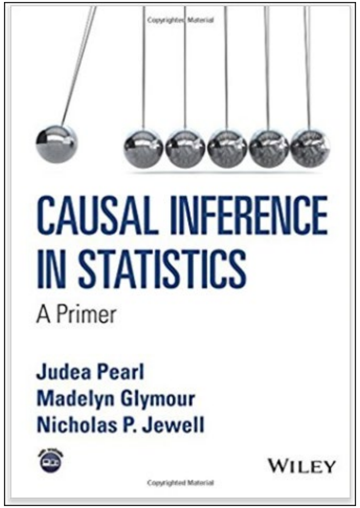


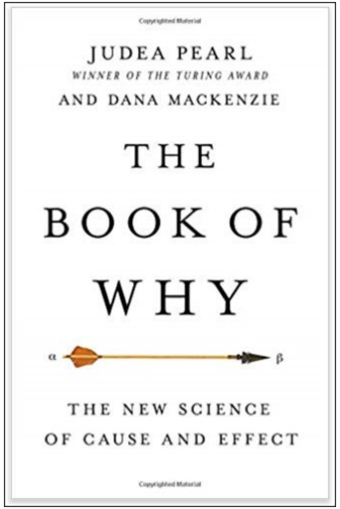
Additional Causal Learning Topics

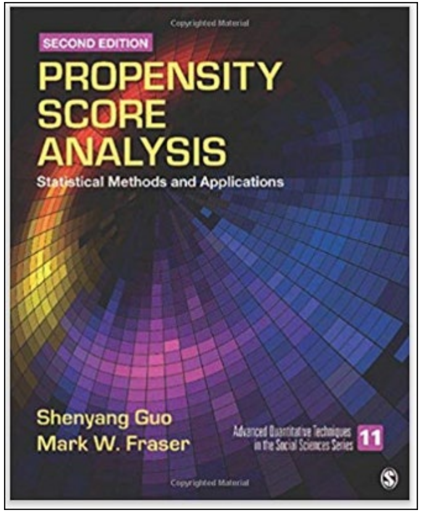
1. Algorithms operating on the Structural Causal Model (see Judea Pearl, 2018, “The Book of Why”)

2. Propensity Scoring (see Shenyang Guo and Mark W. Fraser, 2014, “Propensity Score Analysis”)

3. Instrumental Variables (see Felix Elwert, publications on Instrumental Variables)







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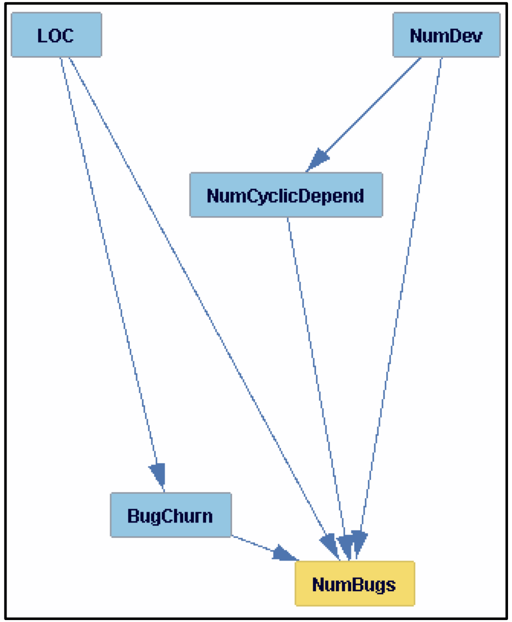
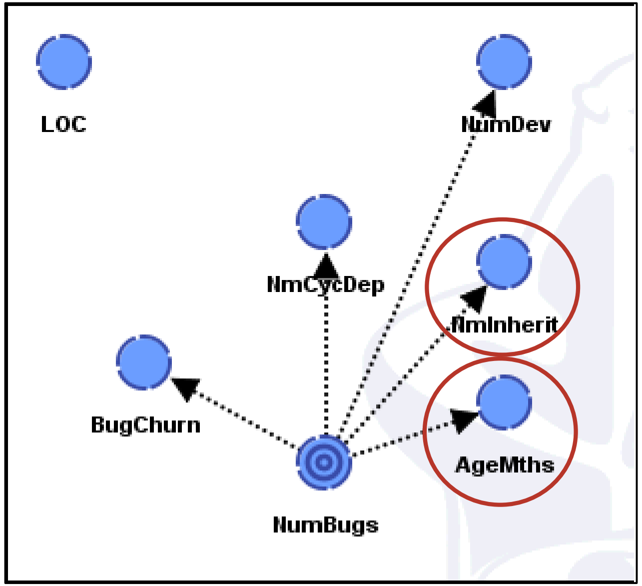
ML and CL Graph Structures May Be Different

CL Markov Blanket



ML Markov Blanket



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When ML and CL Graph Structure Results Differ?

1. Choose to instantiate the Tetrad causal structure in BayesiaLab as a PSEM?

2. Use BayesiaLab to conduct Pearl graph surgery or Jouffe's likelihood matching for causal modeling?

3. Pursue metrics such as Average Causal Effect (ACE) and Total Causal Effect (TCE)?

Opportunities to Integrate ML & CL? - 01

1. Can a ML association graph structure result inform a CL causal search?

2. For extremely large datasets and # variables, would ML require significantly less computer time than a CL causal search? If so, could ML serve as a pre-screen of a CL causal search?

3. Could ML graph structure results inform opportunities for research into new CL causal search algorithms?

4. Could/should CL causal search be combined with ML graphical results for a new, superior output?

Opportunities to Integrate ML & CL? - 02

5. Is there a possible superior understanding obtainable from graphical structural results of both ML and CL?

   a) Can differences between the two graphs provide insight?

   b) Can commonality across the two graphs provide insight?

   c) More generally, is there greater knowledge of combining Shannon Information Theory with Causal Theory?

6. Can combined use of ML and CL graphical structures enable an improved method of "stitching together" separate, but overlapping results towards a more holistic result?

Conclusion

We are seeking research collaboration in two ways:

1. Collaboration and data access for software project cost estimation and control, and

2. Collaboration to gain insight and answer the questions posed in this presentation

Contact Information

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