

# Open-access datasets for time series causality discovery validation

I. Guyon, C. Aliferis, G. Cooper,

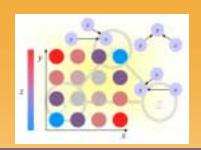
A. Elisseff, O. Guyon, J.-P. Pellet,

A. Statnikov, P. Spirtes

http://clopinet.com/causality/

causality@clopinet.com

# The challenges of causality discovery



What affects...



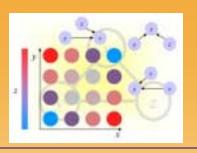




and...

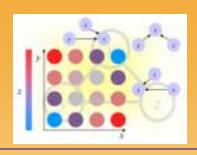
which actions will have beneficial effects?

### Causality and time

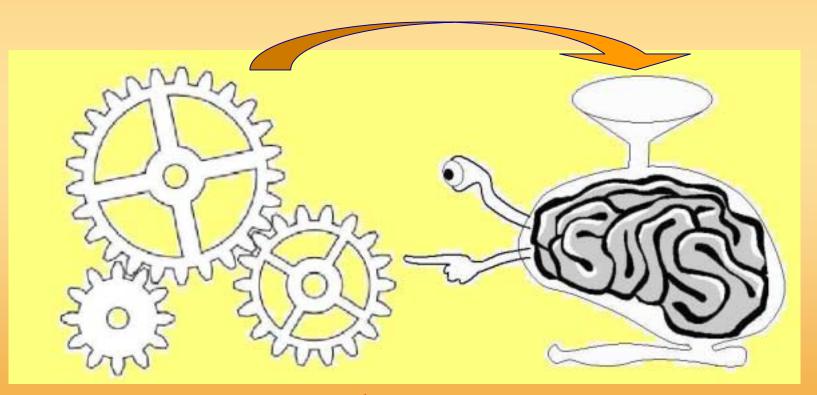


- Everyday notion of causality involves time:
  - The causes precede their effects
- Is that always true?
  - Delayed/weak measurements; reverse causation
  - Final cause (objective)
- Time does not resolve:
  - Variability
  - Confounding
  - Sample bias
- Other difficulties:
  - Non i.i.d. samples: redundancy; correlation misleading.
  - Seasonality.
  - Censored data.

### Experimenting is needed...

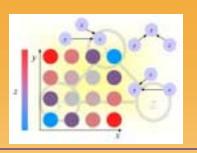


# Experimenting is usually needed to determine cause-effect relationships



but ...

### but...



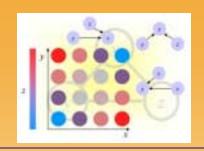
- Experiments are often:
  - Costly
  - Unethical
  - Infeasible

Non-experimental
"observational" data is abundant and costs less.





## The Causality Workbench



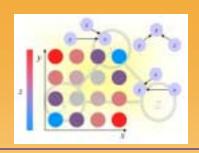
#### Our goal:

#### Identify algorithms both

- efficient to identify causes
- cost effective



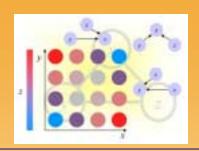
### The Causality Workbench



#### Our challenges:

- Finding adequate data
  - Ground truth of causal relationships
  - Experimental data
  - Large sample size
- Conducting "life" experiments
  - Costly
  - Impractical in a challenge setting

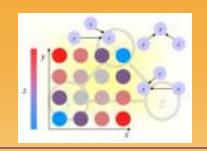
### The Causality Workbench



#### Our methodology:

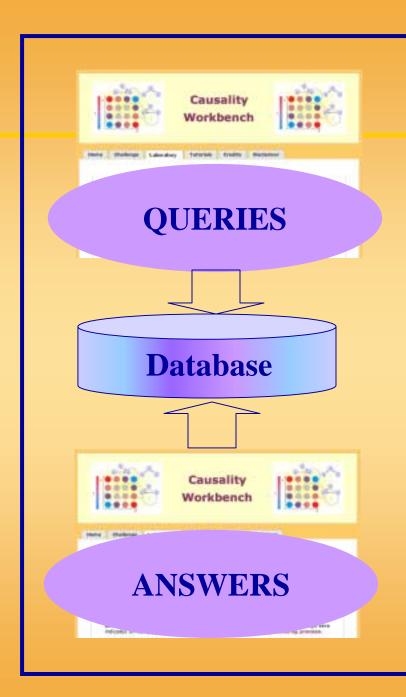
- Collecting donations or real data
- Acquiring or designing good simulators of real systems
  - Trained with real data
  - Used in the field to simulate systems, or
  - Including real data + artificial "probe" variables
- Defining tasks with well defined objectives

# To benchmark algorithms, we built a ...

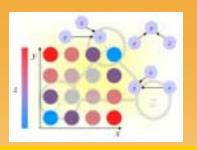


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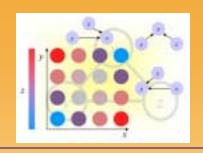
### Virtual Lab







### Virtual Lab



#### What we can do for you:

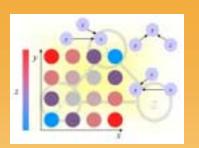
- Let you intervene on the system
  - Perform virtual experiments
- Serve you the data you want
  - For a virtual cash fee



- Real data
- Semi-artificial data
- Simulated data



# Causation and Prediction challenge



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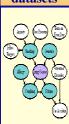






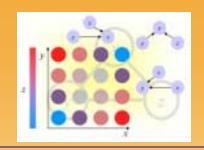
	Dataset (click for info)	Description	Test data	Variables (num)	Tanget	Training examples	Test examples	Ovenicad (text forms)	Souniusd (Maliab incos)
ı	REGEDO	Genomics re-simulated data	Not manipulated	Numeric. (999)	Sinary	596	29608	35 195	25198
	RECED1	Genomics re-simulated data	Manipulated (see list of manipulated variables)	Numeric (999)	Binary	580	20008	35 MB	25 MB
	RECED'2	Genomics re-simulated data	Manipulated	Numeric (999)	Binary	500	20000	36 466	25-ME
ľ	SIDOO	Pharmacology real data w. probes	Not manipulated	Binary (4932)	Binary	12678	10000	3.2 MB	54 ME
	SIDO1	Pharmacology real data w. probes	Manipulated	Binary (4932)	Binery	12678	10000	2.2 10%	54 965
	SIDO2	Pharmacology real data w. probes	Manipulated	Binary (4932)	Binery	12678	16006	12195	54 1985
	CINAO	Census real data w. probes	Not manipulated	Mixed (132)	Binary	18033	10000	1.005	186
	CINA1	Census real data w. grobes	Manipulated	Mixed (132)	Sinary	16633	19998	2.865	2.008
	CINA2	Census real data w. probes	Manipulated	Mixed (132)	Sinary	1f633	19008	3 968	S 198
1	MARTIO	Genomics re-simulated data w. noise	Not manipulated	Numeric (1824)	Binary	500	29000	47 ME	35.MB
I	MARTI1	Genomics re-simulated data w. noise	Manipulated	Numeric (1024)	Bisary	500	20000	47 ME	35 MB
١	MARTI2	Genomics re-simulated data w. noise	Manipulated	Numeric (1024)	Binary	256	20000	47 165	35 MB





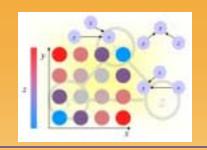
Dataset (click for info)	Description	Test data	Variables {nom}	Target	Training examples	Test examples	Oownload (text format)	Soundsaf (MaSab Somat)	
LUCA50	Toy medicine data	Not manipulated	Binary (11)	Binary	2000	10000	33.WB	2292	
LUCAS1	Toy medicine data	Manipulated	Binary (11)	Einary	2000	10000	22 KB	22.68	
LUCAS2	Toy medicine data	Manipulated	Sinary (££)	Sincery	2006	10000	32.408	2.3:63E	
LUCAPO	Toy medicine data w. probes	Not manipulated	Sinary (143)	Sinary	2006	10000	341 83	262 93	
LUCAPI	Toy medicine data w. probes	Manipulated	Binary (143)	Binary	2000	10000	342 KB	-554 W3:	
LUCAP2	Toy medicine data w. probes	Manipulated	Elinary (143)	Einary	2096	10800	342 KB	263 KB	

### Pot-Luck challenge



	Task	Views	Type	Time dep.		
1776						
000	CYTO	609	real self eval			
	LOCANET	1372	real artif			
PROMOTICALS	PROMO	862	artif self eval			
<ul><li>⊕ ⊕ N</li><li>⊕ ⊕ N</li><li>⊕ ⊕ N</li></ul>	SIGNET	918	artif			
	TIED	551	artif			
® — ®	CauseEffectPairs	580	real			
1	Stemmatology	372	real self eval			

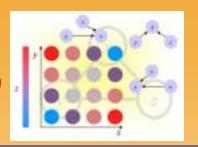
### Other donated datasets



	Task	Views	Type	Time dep.		
	WebLogs	272	real self eval			
$Q_{out} \longrightarrow Q_{out}$ $P \longrightarrow P$	MIDS	232	artif			
***	NOISE	247	real artif			
	SECOM	297	real			
<b>%</b> -	SEFTI	280	real			

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### Active Learning Challenge



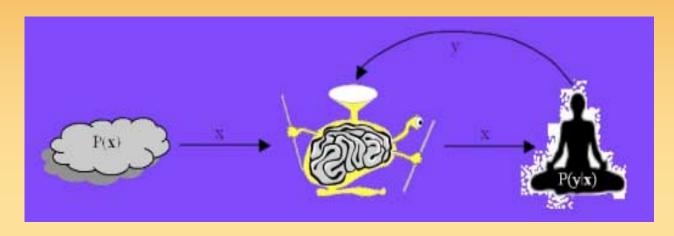








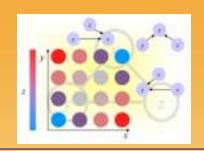




Dataset	Domain	Feat. Type	Feat. num.	Sparsity %	Missing %	Label	Train num.	Test num.	Positive labels %	Seed	Data (zip)	Data (Matlab)
HIVA	Chemo- informatics	binary	1617	90.88	0	binary	21339	21339	3.52	1	5.9 MB	9.3 MB
IBN_SINA	Handwriting recognition	mixed	92	80.67	0	binary	10361	10361	6.53	4	346 KB	537 KB
NOVA	Text processing	binary	16969	99.67	0	binary	9733	9733	28.45	11	2.3 MB	2.3 MB
ORANGE	Marketing	mixed	230	9.57	65.46	binary	25000	25000	7.34	54	6.8 MB	6.4 MB
SYLVA	Ecology	mixed	216	77.88	0	binary	72626	72626	6.15	4	14.5 MB	20.2 MB
ZEBRA	Embryology	continuous	154	0.04	0.004	binary	30744	30744	4.58	23	28.6 MB	53.2 MB

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# Next: Causality and Time Series



### With your help:

- Get more datasets
  - of practical and scientific interest
- Get good simulators of real systems
  - paired with the real datasets
- Define tasks and objectives
  - and practical challenge protocols

### Organize the next challenge!