

Identifiability and Transportability in Dynamic Causal Networks

Gilles Blondel, Marta Arias, Ricard Gavaldà
Universitat Politècnica de Catalunya, Barcelona

KDD 2016 - Workshop on Causal Discovery
San Francisco - August 2016

Contact: gillesblondel@yahoo.com

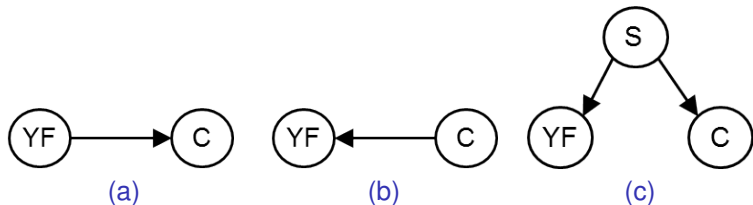
Causality vs Correlation

Correlation gives no information about causes and effects:

- ▶ yellow fingers and lung cancer
- ▶ smoking and yellow fingers
- ▶ lung cancer and smoking

Causal graphs:

- ▶ Cause to effect relations
- ▶ How do we know what causal relations exist?



Causal Graphs: How to build them?

Performing experiments:



- ▶ World Health Organisation: "Processed meat causes cancer"
- ▶ Result based on experiments (animals, cell based research); not on observation alone

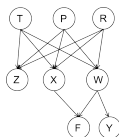


From observational data:

- ▶ Experiments may be expensive, unethical, impossible
- ▶ Observational data contains hints towards causal relations
- ▶ Causal discovery algorithms (since 90's)
- ▶ PC, IC, IC*, FCI, RFCI...

Causal Reasoning

Once we have a causal graph...



Causal reasoning:

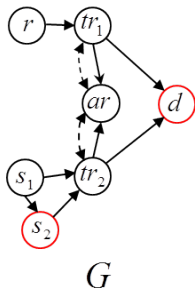
- ▶ Intervention: force a variable and evaluate the effect
- ▶ Expressed as $P(Y|do(X))$
- ▶ All natural causes of X (incoming edges to X in the causal graph) are disabled

Tool: rules of do-calculus (Pearl):

1. $P(Y|Z, W, do(X)) = P(Y|W, do(X))$ if $(Y \perp Z|X, W)_{G_{\bar{X}}}$
2. $P(Y|W, do(X), do(Z)) = P(Y|Z, W, do(X))$ if $(Y \perp Z|X, W)_{G_{\bar{X}Z}}$
3. $P(Y|W, do(X), do(Z)) = P(Y|W, do(X))$ if $(Y \perp Z|X, W)_{G_{\overline{XZ}(W)}}$

Identification of Causal Effects

- ▶ $P(Y|do(X))$ is 'Identifiable': If it can be uniquely computed from observational probability distributions in G
- ▶ Apply do-calculus rules
- ▶ Not all effects are identifiable (due to hidden confounders)
- ▶ Identification algorithm (Shpitser/Pearl 2006)
- ▶ Example: $P(d|do(s_2)) =$ expression without $do()$ terms; or fail

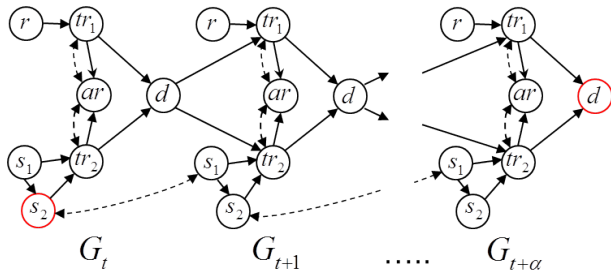


Identification of Dynamic Causal Effects

Adding time component to the identification problem:

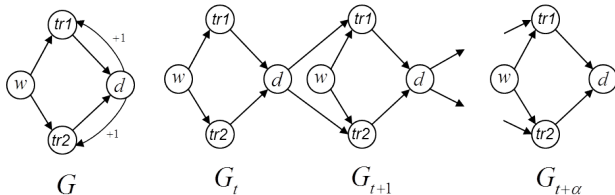
- ▶ Existing research did not formally address dynamic causal identifiability via do-calculus
- ▶ Our paper formally addresses dynamic causal settings with do-calculus
- ▶ Algorithm DCN-ID for **Dynamic Causal Network** identification

Example: calculate the probability of d some time α after doing an intervention on s_2



Dynamic Causal Networks

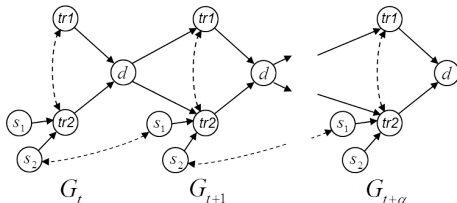
- ▶ DCN: DBN where relations are causal



(a) DCN

(b) DCN expanded graph (bi-infinite)

- ▶ Hidden confounders: Static vs Dynamic



DCN Analysis with Do-Calculus

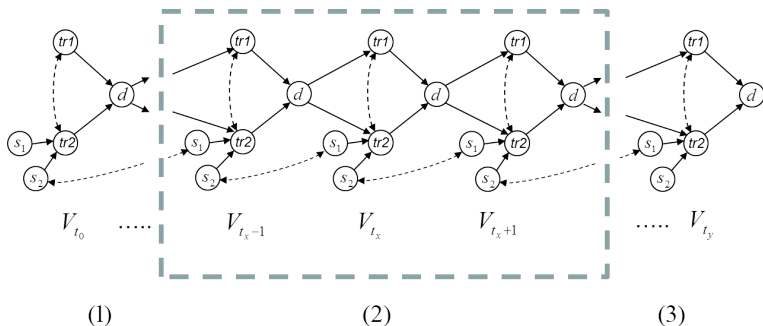
How to apply do-calculus to DCN:

- ▶ Exploit time slice d-separation by careful conditioning
- ▶ Heavy dependence on static/dynamic hidden confounders

DCN causal effect identification:

- ▶ we can **limit time scope** of graph (attention: confounders)
- ▶ reduce complexity of identification algorithms
- ▶ **past** (before intervention): no effect
- ▶ **present** (local graph around intervention): apply existing 'static' id algorithms
- ▶ **future** (after intervention): DCN may or may not recover 'natural' behaviour (static vs dynamic hidden confounders)

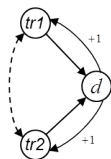
DCN Identification Algorithm



- ▶ Markov chain: $P(V_{t+1}) = TP(V_t)$; transition matrix T
- ▶ Intervention at t_x :
 1. transition matrix T
 2. transition matrix $A \neq T$
 3. transition matrix T (static hidden confounders)
 transition matrix $M_t \neq T$ (dynamic hidden confounders)

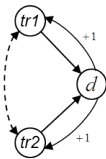
DCN Transportability Algorithm

- ▶ Two domains D_1, D_2
- ▶ Modeled with the same dynamic causal graph
- ▶ We perform experiments in D_1
- ▶ Causal effect identification in D_2 may use experiments from D_1



D_1

Experimental results

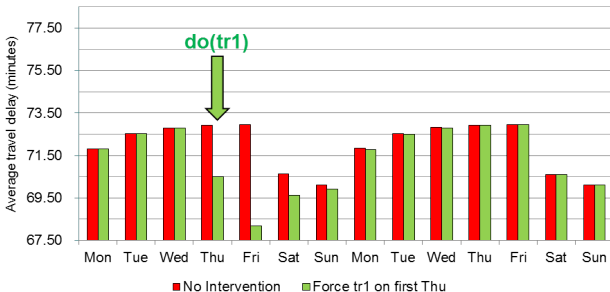
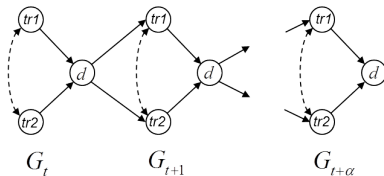


D_2

*Experiments from D_1
may help identifiability in D_2*

Example: DCN Causal Effect Identification

Two roads between two cities with traffic $tr1$, $tr2$
Find average traffic delay evolution $P(d|do(tr1))$



Conclusions

- ▶ Dynamic causal identification with do-calculus algorithms
- ▶ DCN-ID algorithm for static, dynamic hidden confounders
- ▶ DCNs with static hidden confounders do recover pre-intervention behaviour after intervention
- ▶ DCNs with dynamic hidden confounders may not recover pre-intervention behaviour

Identifiability and Transportability in Dynamic Causal Networks

Gilles Blondel, Marta Arias, Ricard Gavaldà
Universitat Politècnica de Catalunya, Barcelona

KDD 2016 - Workshop on Causal Discovery
San Francisco - August 2016

Contact: gillesblondel@yahoo.com