Identifiability and Transportability in Dynamic Causal Networks

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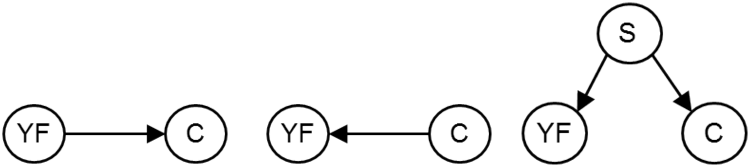
Causality vs Correlation

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?



(a) (b) (c)

Causal Graphs: How to build them?

Performing experiments: 

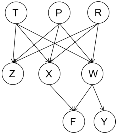
- World Health Organisation: "Processed meat causes cancer"
- Result based on experiments (animals, cell based research); not on observation alone

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:

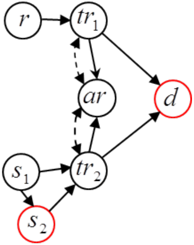
- Intervention: force a variable and evaluate the effect
- Expressed as $P(Y|do(X))$
- All natural causes of X (incoming edges to X in the causal graph) are disabled

Tool: rules of do-calculus (Pearl):

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

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



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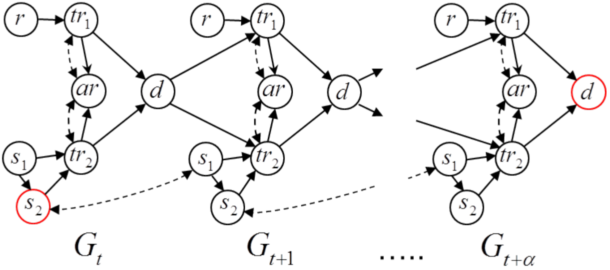
Identification of Dynamic Causal Effects

Adding time component to the identification problem:

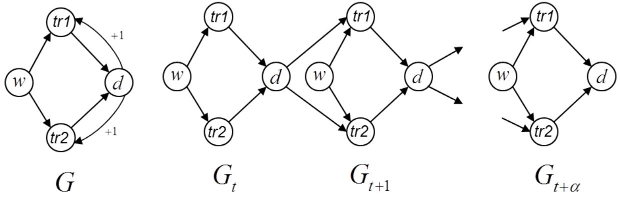
- Existing research did not formally address dynamic causal identifiability via do-calculus
- Our paper formally addresses dynamic causal settings with do-calculus
- Algorithm DCN-ID for **Dynamic Causal Network** identification

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



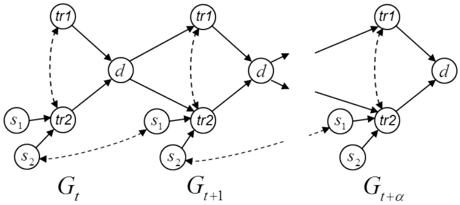
Dynamic Causal Networks

- DCN: DBN where relations are causal



(a) DCN (b) DCN expanded graph (bi-infinite)

- Hidden confounders: Static vs Dynamic



DCN Analysis with Do-Calculus

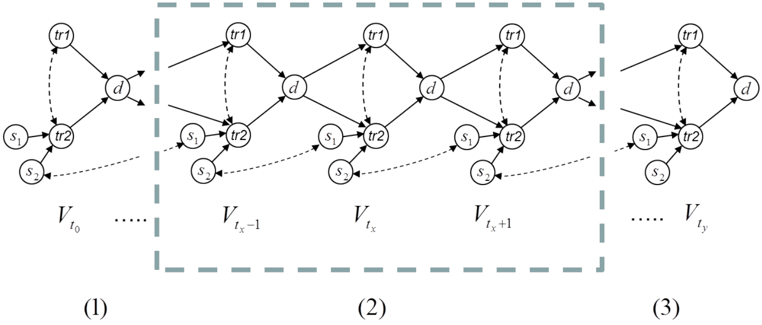
How to apply do-calculus to DCN:

- 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)

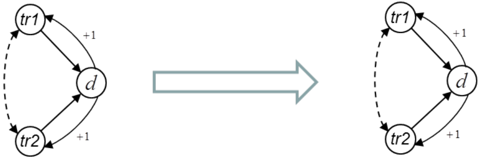
DCN Identification Algorithm



- 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 *D_2*

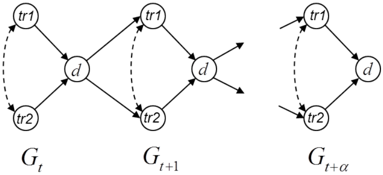
Experimental results

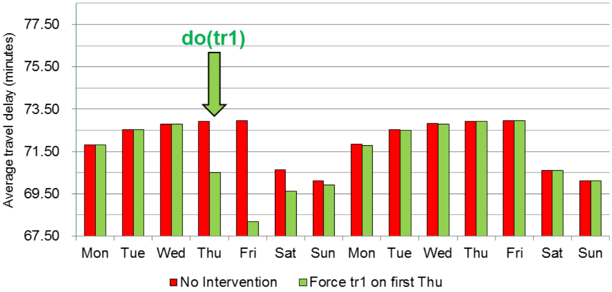
Experiments from D_1 may help identifiability in D_2

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

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