Indirect Causes in Dynamic Bayesian Networks Revisited

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Introduction

- Dynamic **Bayesian Networks**.
- **Indirect** Causes.
- DAG constraints **limit causal expressiveness**.
- Solution in DBN semantics on **cyclic graph**.

Running example

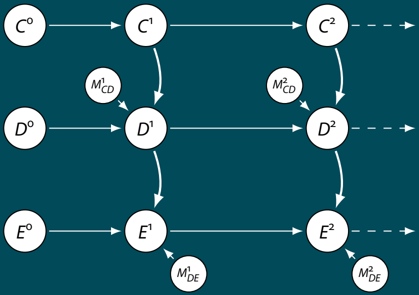
- **Regulatory compliance** of employees.
- A "creduluous" employee might **manipulate documents**.
- A credulous employee might (undeliberately) **influence other employees**.
- Might become credulous too, etc.

- Influences occur through **exchanged messages**.

- Track probabilistic credulousness-state over *time*.

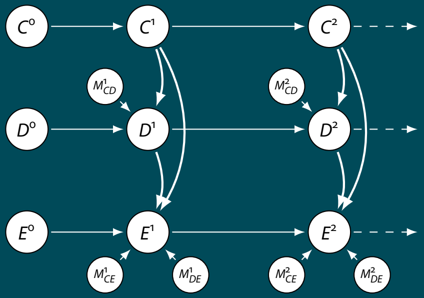
- Employees: ***C*laire, *D*on** and ***E*earl**.

Problem as a DBN



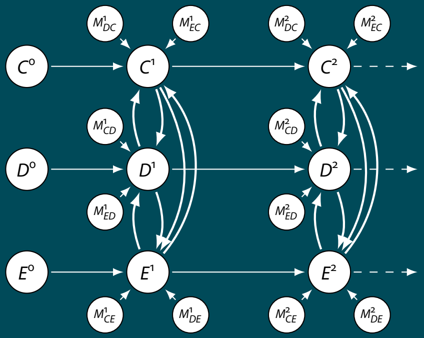
- Say, only *C*laire influences *D*on, influences *E*arl.
- i.e. *C* **influences** *E* **indirectly.**
- Typical DBN. ✓
- Problem correctly represented. ✓

Problem as a DBN



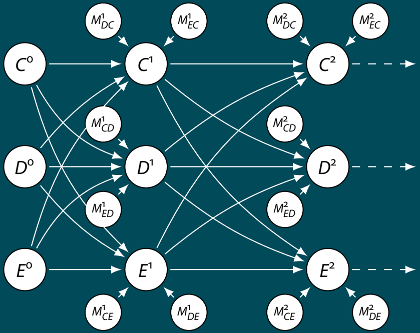
- Let's add some **more influences**.
- Claire *can* also influence Earl *directly*.
- Typical DBN. ✓
- Problem correctly represented. ✓

Problem as a DBN



- Say, **everybody** *can* influence **everybody**.
- "A BN is a **DAG**".
- Not a DBN. ✗
- Problem correctly represented. ✓?

Problem as a DBN



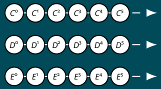
- Resolve cycles over time.
- "Diagonal" inter-state dependencies.
- Common DBN . ✓
- Problem correctly represented. ✗ ?

DBN Restrictions

- "Diagonal" encodes "**incubation** time":
  t: Receive Message. $t+1$*: Read and become influenced.*

a) Enforces **infinitesimal resolution of time** (e.g., seconds)

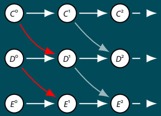
✗ High computation cost.



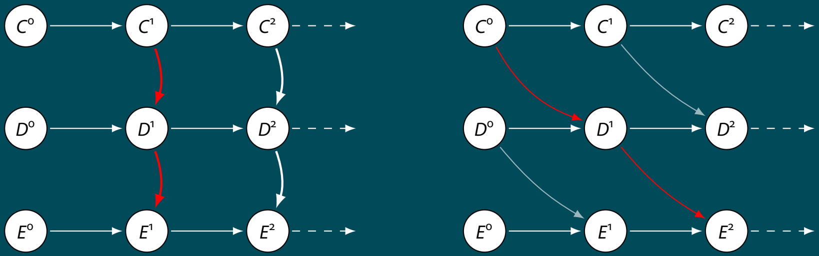
Observations not available this fine (e.g., only daily)?
Computation too costly? Transition only known hourly?

b) **Indirect influences not considerable**.

✗ Does not explain the world.

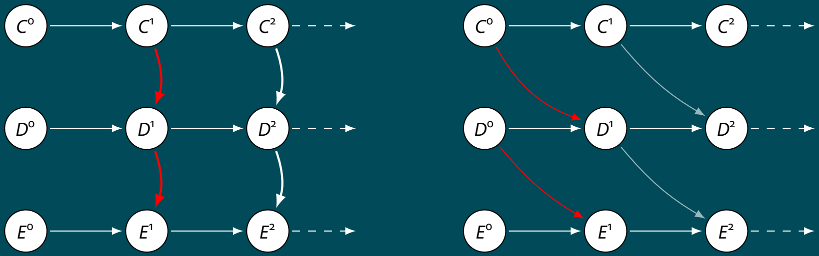


Classic DBNs spread indirect effects over time



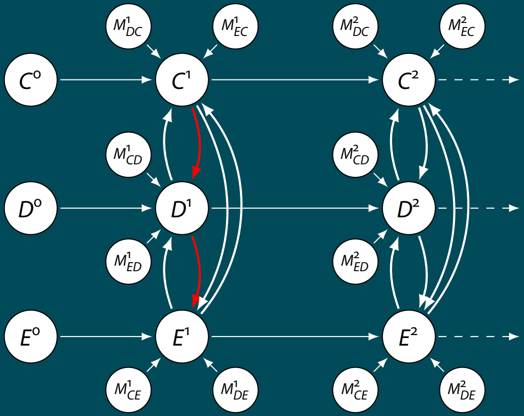
I.e., **observations** that require anticipations of **indirect effects** are **not supported**.

Classic DBNs spread indirect effects over time



I.e., **observations** that require anticipations of **indirect effects** are **not supported**.

Intuitive Design



Activator Random Variables

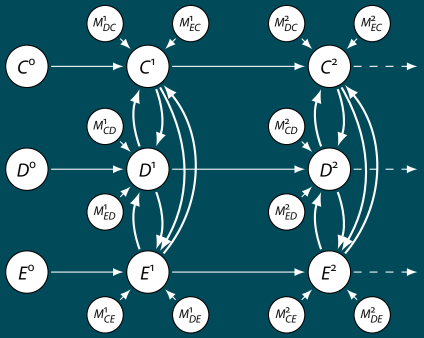
- Random variables M^t_{XY} representing exchanged messages are special
- We see M^t_{XY} as **Activator Random Variables**

$$\forall x, x' \in \mathrm{dom}(X), \forall y \in \mathrm{dom}(Y), \forall \vec{z} \in \mathrm{dom}(\vec{Z}):$$
$$P(y|x, \neg a_{XY}, \vec{z}) = P(y|x', \neg a_{XY}, \vec{z}) = P(y|*, \neg a_{XY}, \vec{z})$$

$*$ wildcard, $\vec{z}$ further dependencies

$$\exists x, x^* \in \mathrm{dom}(X), \exists y \in \mathrm{dom}(Y), \exists \vec{z} \in \mathrm{dom}(\vec{Z})$$
$$P(y|x, a_{XY}, \vec{z}) \neq P(y|x^*, a_{XY}, \vec{z})$$

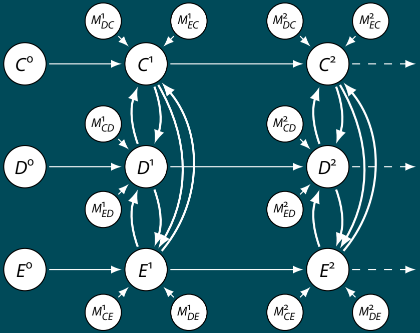
Activator Dynamic Bayesian Networks



- Is an *Activator Dynamic Bayesian Network*

- We show: **Semantically a (D)BN**, despite being based on a **cylic graph**!
- Straight forward semantic as joint probability as usual.

Activator Dynamic Bayesian Networks



- Is an *Activator Dynamic Bayesian Network*
- We show: **Semantically a (D)BN**, despite being based on a **cylic graph**!
- Straight forward semantic as joint probability as usual.
- Under some restrictions...

ADBN Restrictions Formally

Theorem (Bayesian Network Soundness)

For every set of instantiations $\vec{\mathcal{A}}_*^{1:t}$ ***an ADBN corresponds to a Bayesian network*** *(BN), if for all t, $\vec{\mathcal{A}}_*^{t}$ satisfies a new acyclicity constraint:*

$$\forall x, y, z \in \vec{X}^t : \mathfrak{A}(x,z)^t, \mathfrak{A}(z,y)^t \rightarrow \mathfrak{A}(x,y)^t$$
$$\neg \exists q : \mathfrak{A}(q,q)^t ,$$

$$\mathfrak{A}(i,j)^t = \begin{cases} \mathit{false} & \mathit{if} \quad A_{ij}^t = \neg a_{ij}^t \\ \mathit{true} & \mathit{otherwise} \end{cases} .$$

ADBN's semantics are well-defined as usual in a DBN,

$$P(\vec{X}^{0:t^\top}, \vec{\mathcal{A}}^{1:t^\top}) = P(\vec{X}^{0:t-1^\top}, \vec{\mathcal{A}}^{1:t-1^\top}) \cdot \prod_i P(X_i^t | \vec{X}^{t^\top} \setminus X_i^t, \vec{A}_i^{t^\top}, X_i^{t-1}) \cdot P(\vec{\mathcal{A}}^{t^\top}) .$$

Restrictions Comparison

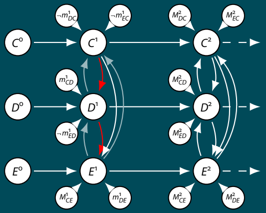
Cyclic ADBN

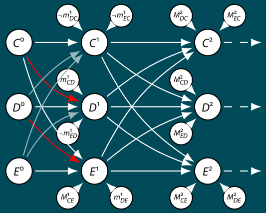
- No cyclic M^t_{XY} observations allowed.
- Activator set must form **DAG**.

"Diagonal" DBN

- No "interlocking" M^t_{XY} obs. allowed.
- must form **bipartite** graph.

#DAG >> #Bipartite





ADBN Contributions

- Bayesian networks can syntactically be based on **cyclic** graphs.
- Cyclic graphs are **causally required** for some problems.
- Acyclic graphs run into causal problems.

ADBNs provide

✓ **Free choice** of time granularity.
✓ Anticipation of **indirect influences**.
✓ **Well-defined DBN** semantics.
✓ **Filtering, Smoothing** same as usual.
✓ BN as world-representing first-class declaration.