Summary of Literature on IK and Bayesian Networks

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Outline

- Kinematics and Inverse Kinematics
  - [Elias04]
- Character Physics
  - [Jakobsen03]
- Bayesian Networks
  - [Tozour04], [Ghahramani01], [Russell03]
- Hierarchical Hidden Markov Models
  - [Ueda04]

Kinematics

- Motion of objects w/o concerning force
  - Includes acceleration, velocity, position
- Top-down approach
- In skeletal animation, typically angles are defined for each joint in hierarchy
- Transforming by each angle gives final orientation/position of object

Inverse Kinematics

- Reverse of kinematics, bottom-up
- Given: position of “effecter” e.g. hand
- Find: orientations/positions of everything else higher up in hierarchy

Inverse Kinematics

- Can have infinite solutions
- Basically a minimization problem
- [Elias04] uses simple gradient descent
- Using only IK can look bad
- Typically used for small adjustments
  - Climbing stairs (terrain following)
  - Grabbing objects

Character Physics

- [Jakobsen03] describes physics used for *Hitman: Codename 47*
- Uses Verlet integration (not Euler)
  - Velocity is kept implicitly -> more stable
  - Euler: $v' = v + a*dt$; $s' = s + v' * dt$
  - Fix timestep and assume $v' = s - s_{old}$
  - $s = 2s – s_{old} + a * dt^2$

Character Physics

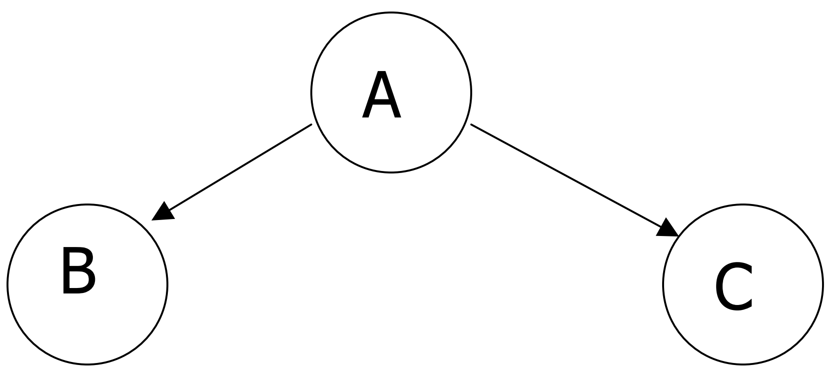
- Everything is a particle system
- System has constraints e.g.
  - stick – keep certain distance
  - bound – keep within this area
- Each frame, for particle:
  - feelForces();
  - Verlet integration i.e. update pos.
  - Satisfy (or relax) constraints
  - Relaxation could give better visuals

Character Physics

- Used for everything from cloth, to rigid bodies, to articulated bodies (chars)
- Works as an IK solver e.g.
  - Constrain hand to certain position
  - Satisfy other constraints
  - Used for dragging bodies in *hitman*
  - Also used for animation of being hit

Bayesian Networks

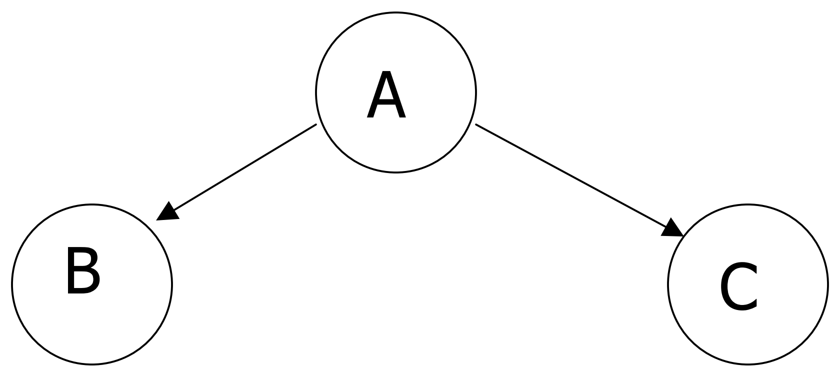
- Concise representation of full joint prob. dist.
- DAG showing dependencies
  - B directly dependent on A
  - B and C conditionally independent given A



Bayesian Networks

- Each node has conditional prob. table

$P(A) = 0.7 \quad P(\neg A) = 0.3$



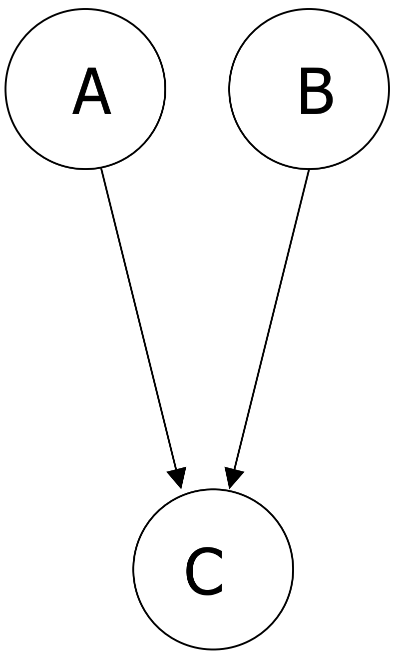
$P(B|A) = 0.6 \quad P(\neg B|A) = 0.4$

$P(B|\neg A) = 0.3 \quad P(\neg B|\neg A) = 0.7$

$P(C|A) = 0.2 \quad P(\neg C|A) = 0.8$

$P(C|\neg A) = 0.4 \quad P(\neg C|\neg A) = 0.6$

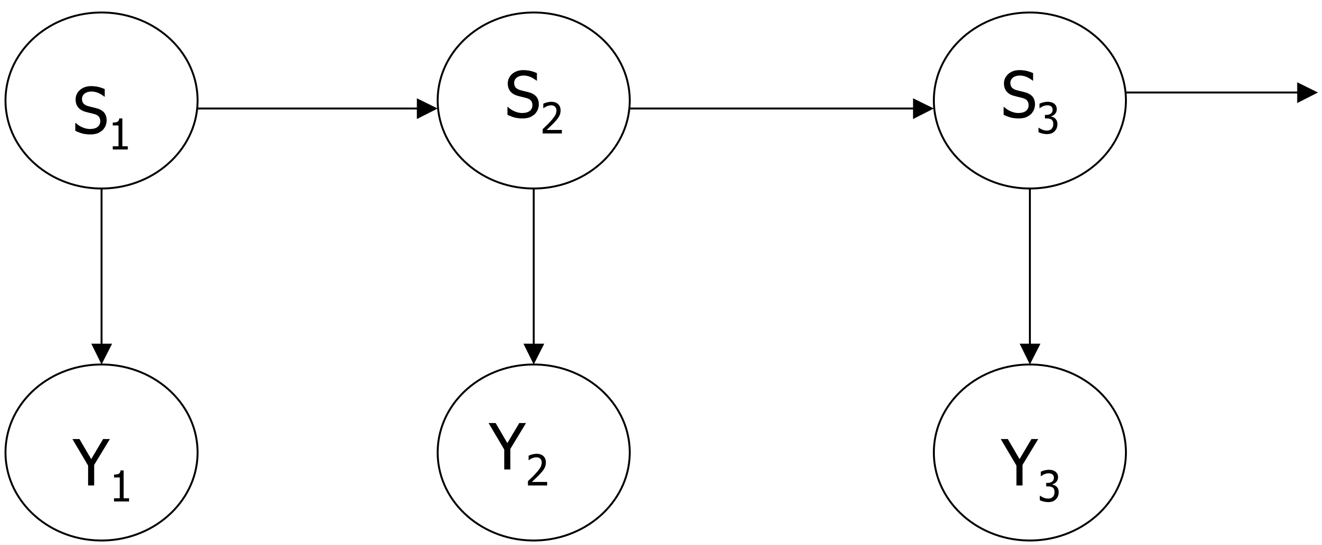
Bayesian Networks - Uses



- Causal Inference (Prediction): given A what’s prob. C
- Diagnostic Inference (Induction): given C what’s prob. A using Baye’s Theorem
  $P(A|B) = P(B|A)\ P(A)/P(B)$
- Intercausal Inference (“Explaining away”): given C, how does prob. A affect prob. B.

HMM as Bayesian Network

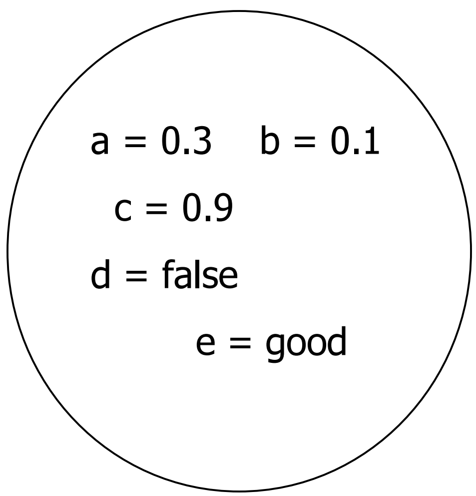
- HMM is really a special case of Dynamic Bayesian Network (BN with time)
- One *can* represent HMM as a DAG



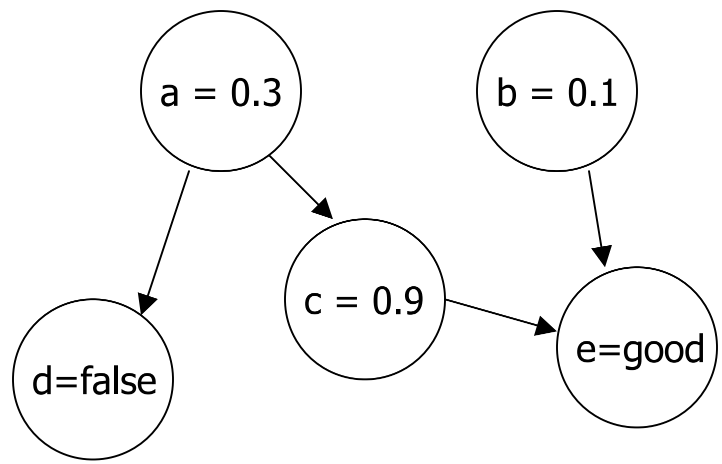
S_t = hidden state at time t. Y_t = observation

HMM as DBN

- Difference is HMM is allowed only one "Megavariable", whereas DBN is "locally-structured". DBN = Concise HMM



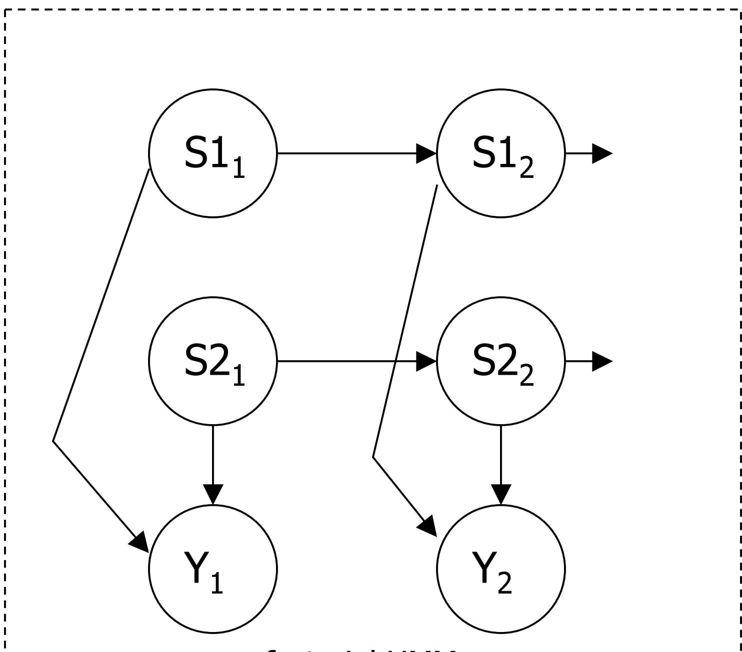
HMM state



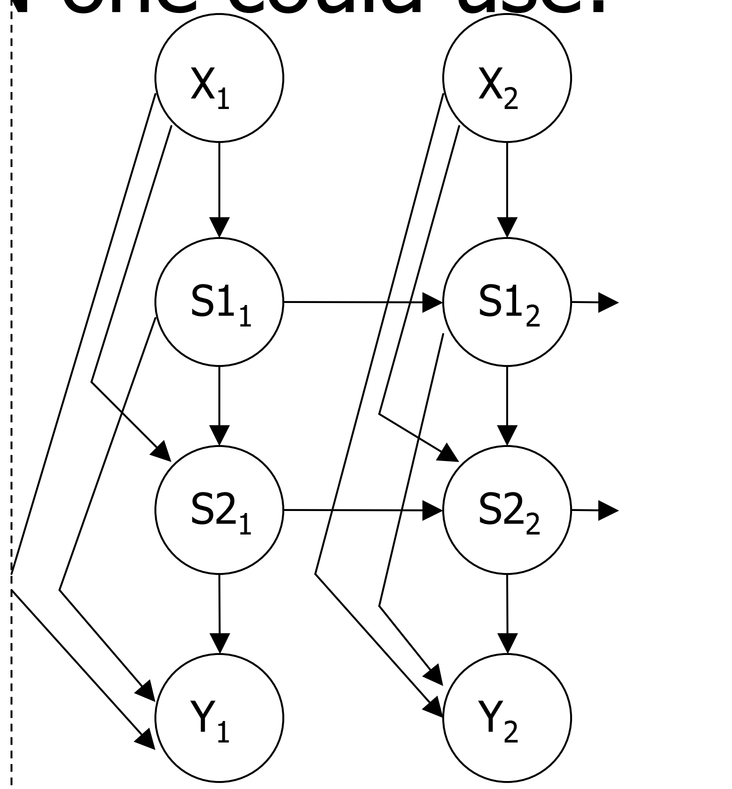
DBN state

Problem with HMMs

- Overfitting and inefficiency
- Without going DBN one could use:



factorial HMM



tree structured HMM

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