

# Graphical Models

## Lecture 5:

## Template-Based Representations

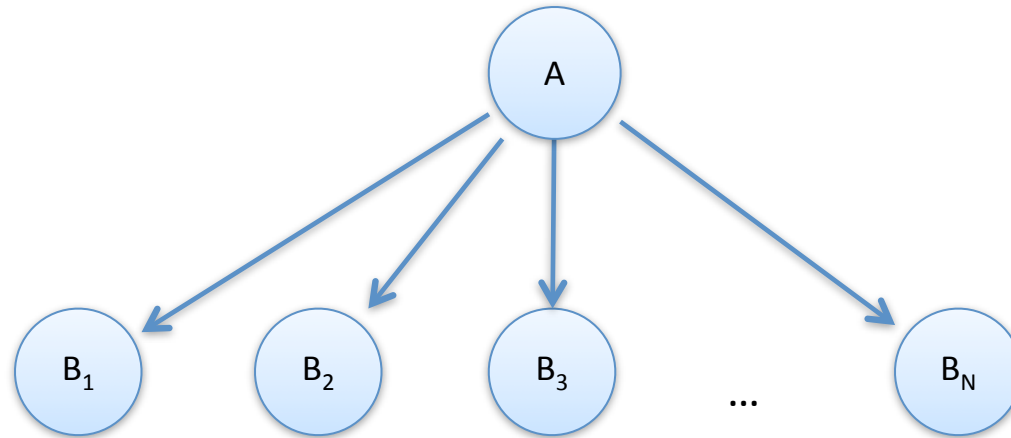
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Thanks to Noah Smith and Carlos Guestrin for some slide materials.

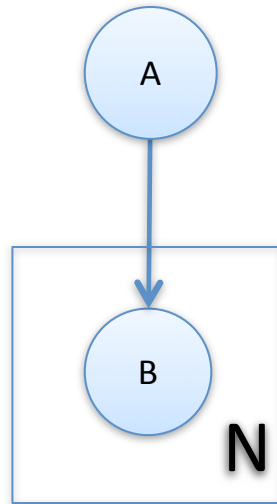
# Administration

- Homework #3 won't go out until early March.  
Push back HW#2 due date?
- Lagrange Multipliers?
- Calendar.

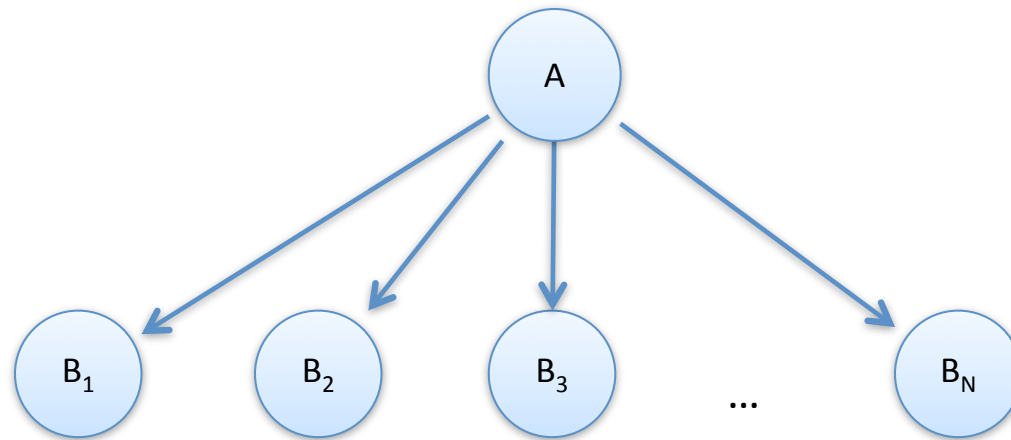
# BN with Repeated Structure



# Plate Model

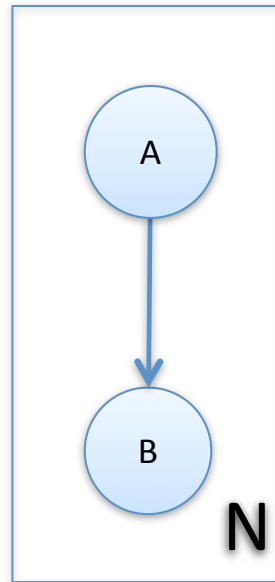


# “Unrolled” Ground Network



Ground network

# Students and their Grades

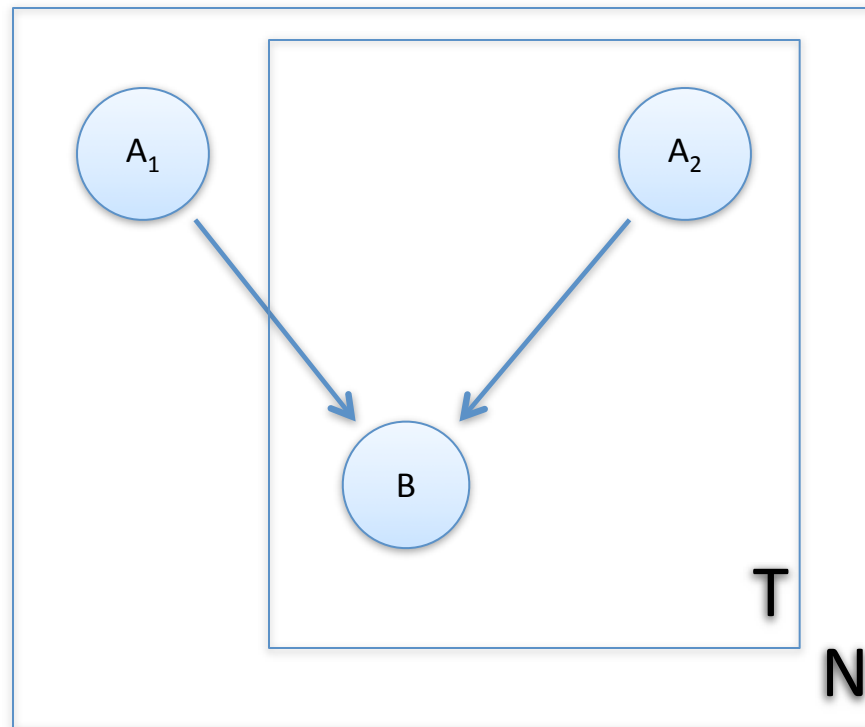


Example: A = student, B = grade

# Student, Course, Grade, Difficulty

Each student takes only one course

Nesting

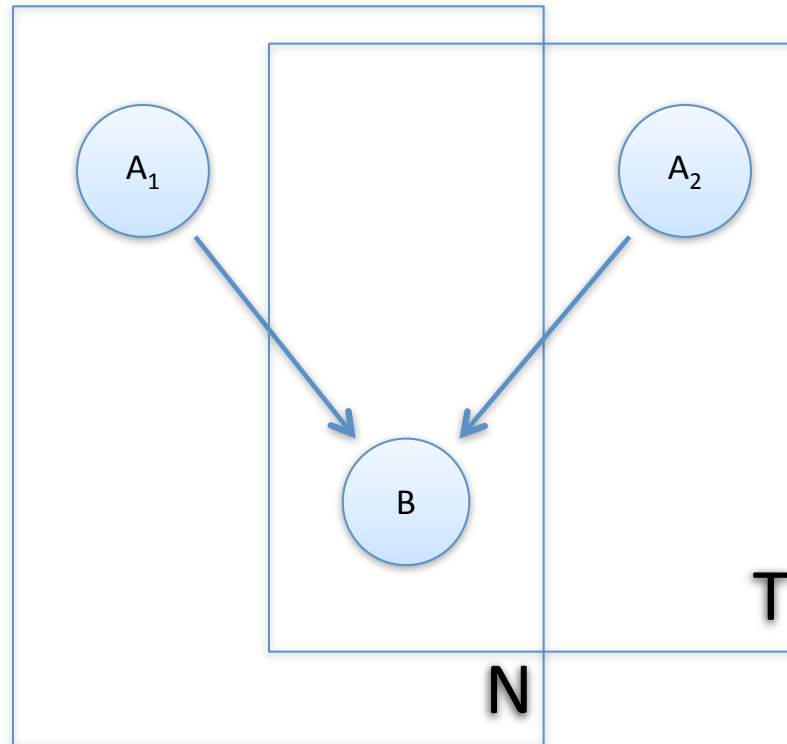


Example:  $A_1$  = course difficulty,  $A_2$  = student aptitude for the area,  $B$  = grade

# Student, Course, Grade, Difficulty

Multiple courses per student

Intersecting



Example:  $A_1$  = assignment difficulty,  $A_2$  = intelligence, B = grade



# Plate Models:

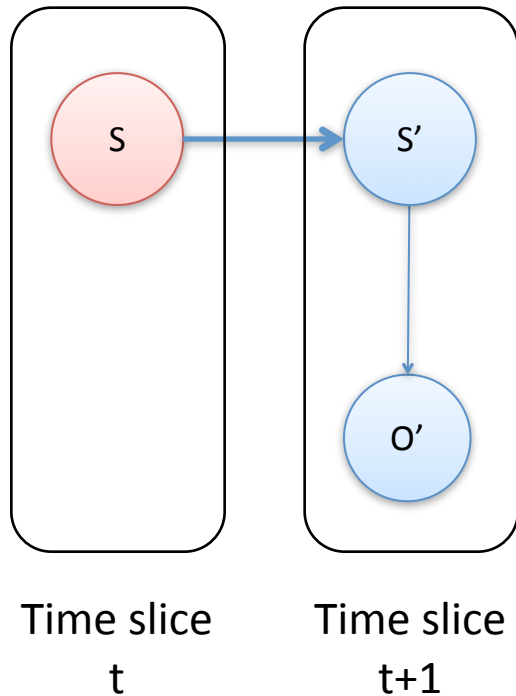
## Limitations and Alternatives

- Limitations:
  - can't have edges between two “copies” of the same variable, (e.g. *position* at time  $t$  depends on *position* at time  $t-1$ )
  - can't have edges between particular pairs selected by some other relation, (e.g.  $\text{Genotype}(U_1)$  depends on  $\text{Genotype}(U_2)$ , where  $U_2$  is mother of  $U_1$ ).
- Alternatives
  - Dynamic Bayesian Networks (DBNs)
    - Specific to repetitions over time
  - Probabilistic relational models
    - More flexible; see K&F 6.4.2.

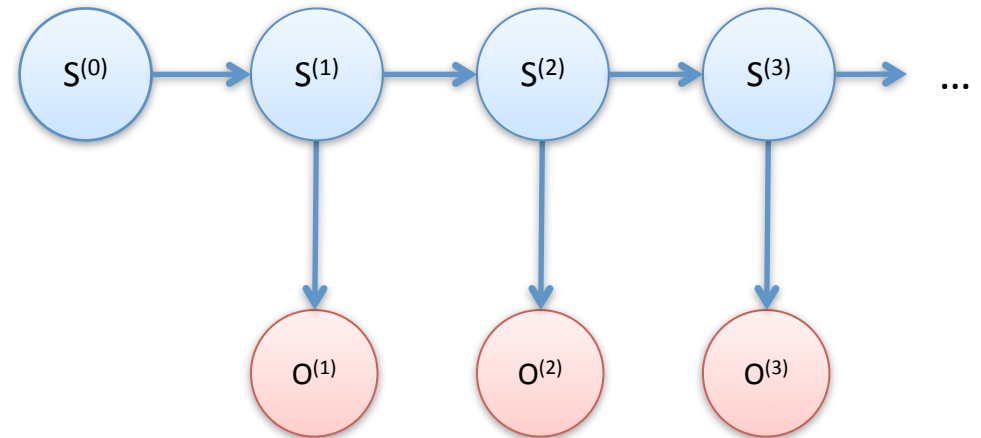
# Temporal Models

- $\mathbf{X}$  takes different values at each (discrete) time step.
  - $\mathbf{X}^{(t)}$  is the random variable at time  $t$
- Markov Assumption:  
 $\mathbf{X}^{(t+1)} \perp \{\mathbf{X}^{(0)}, \dots, \mathbf{X}^{(t-1)}\} \mid \mathbf{X}^{(t)}$
- Stationary Assumption (*aka time invariant or homogeneous*)  
 $P(\mathbf{X}^{(t+1)} \mid \mathbf{X}^{(t)})$  is the same for all  $t$ .
- Can use *conditional Bayesian network* to define  
 $P(\mathbf{X}^{(t+1)} \mid \mathbf{X}^{(t)})$

# Hidden Markov Model



**2-time-slice *conditional BN***

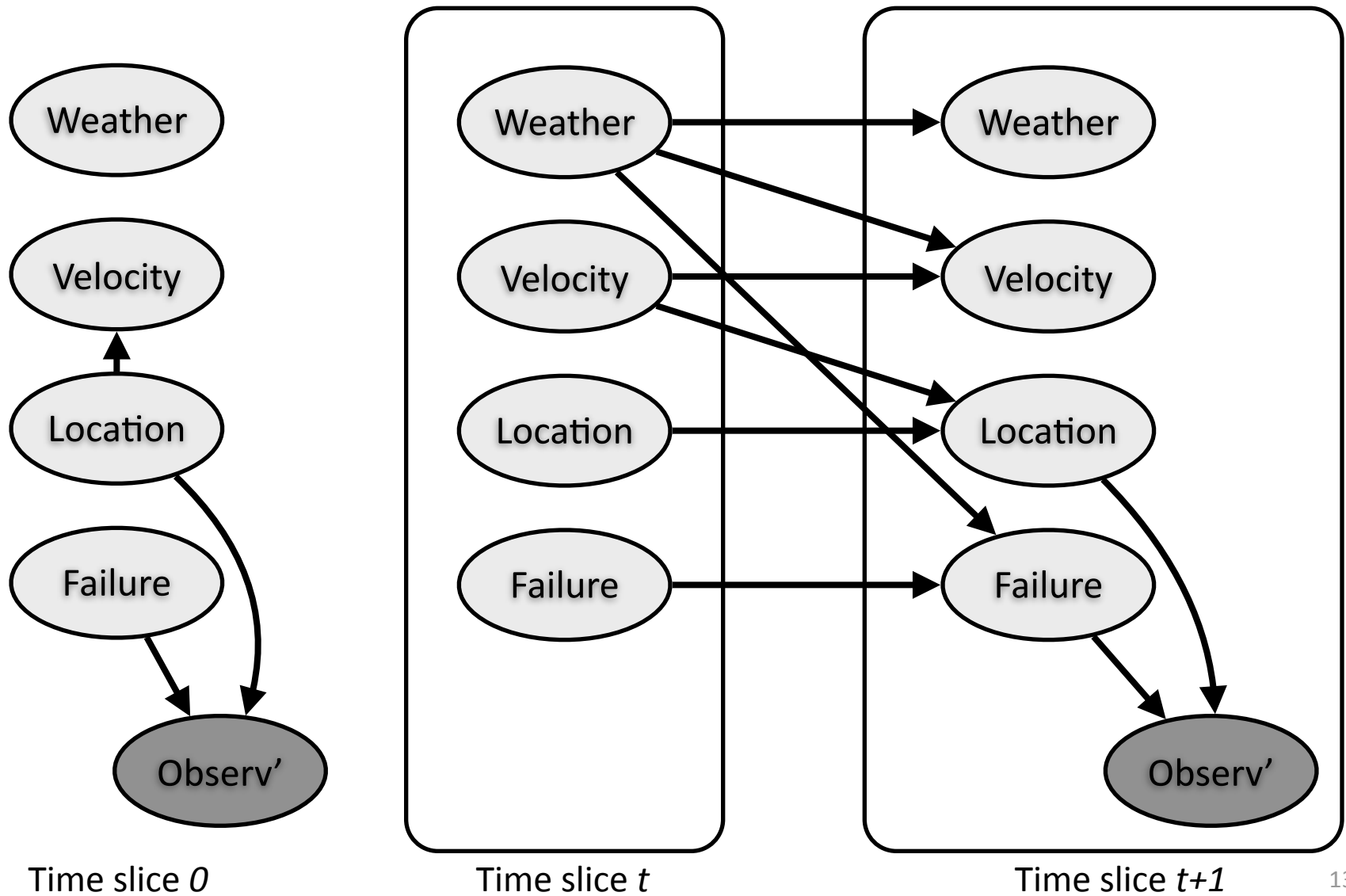


**unrolled or ground Bayesian network**

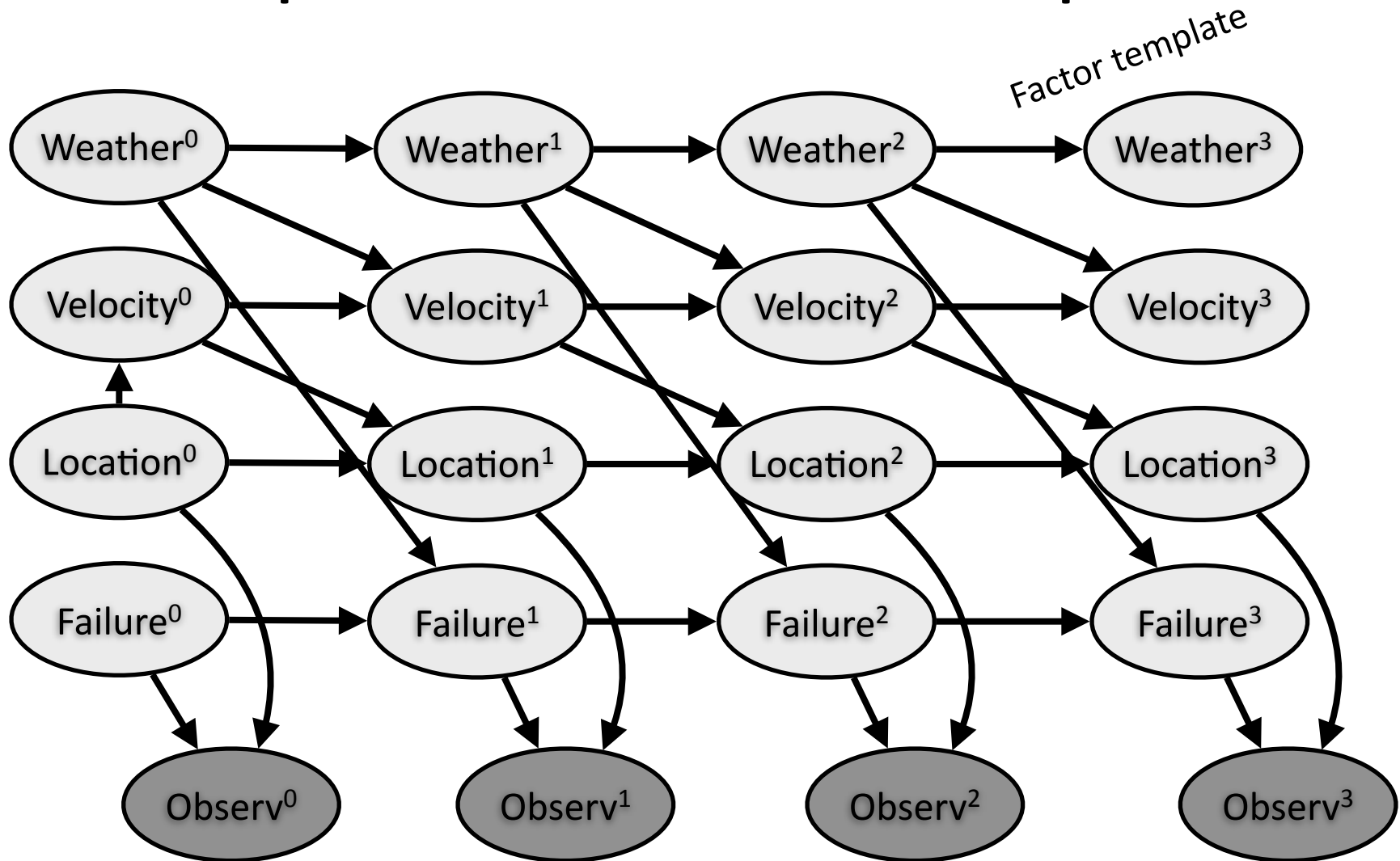
# Dynamic Bayesian Network

- Bayesian network over  $\mathbf{X}^{(0)}$ ,  
conditional Bayesian network for  $\mathbf{X}^{(t+1)}$  given  $X^{(t)}$   
(2-time-slice)
  - HMM is a special case.
  - Kalman filter (linear dynamical system) is a special case.

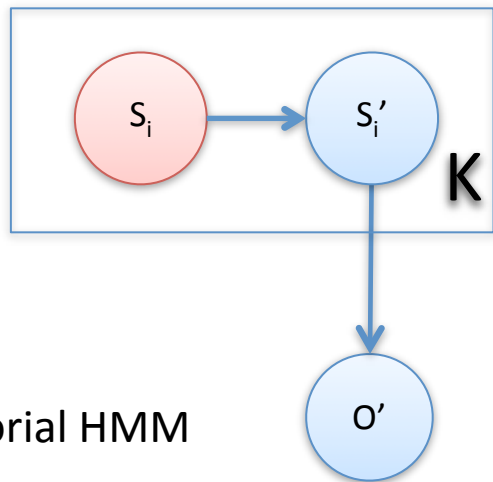
# Example: DBN for vehicle position



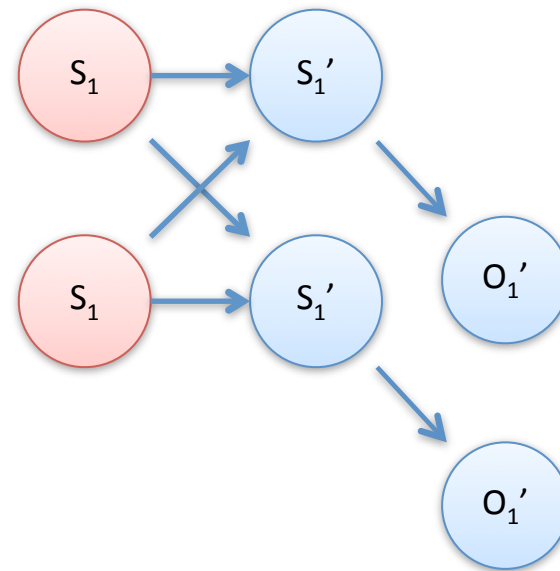
# Example: DBN for vehicle position



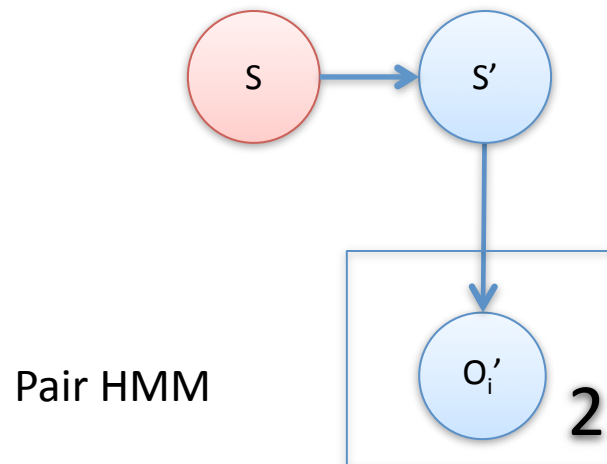
# Dynamic Bayesian Networks



Factorial HMM



Coupled HMM



Pair HMM

# Probabilistic Relational Models

- Contingent Dependency
  - specifies the context in which some dependency holds, with a “guard”—a formula that must hold for the dependency to be applicable.
  - e.g. Location(V) depends on Location(U) contingent on Precedes(U,V)
  - e.g. Genotype(V) depends on Genotype(U) contingent on Mother(U,V)
- Relational Uncertainty (one kind of structural uncertainty)
  - The “guard” predicates are random variables!



# Object Uncertainty



[Milch et al “BLOG”]

- The set of objects is not predetermined.
  - Get list of authors in 100 BibTeX files.  
“Stuart Russell” “Stuart Rusell” “S. Russell”  
How many people are mentioned?
- Introduce
  - person-objects* (represents entity)
  - person-reference objects* (represents mention)
  - refers-to(m,o)* relation
- Model generates (a) # of people, (b) person objects, (c) their reference objects.

# Directed Factor Graph Notation

[Laura Dietz 2010]

# Variables and Constants

	Directed factor graph	Pseudocode
Latent variable / latent parameter		
Observed variable		
Constant / hyper parameter	const	

# Factors and Densities

	Directed factor graph	Pseudocode
Factor with one input parameter		1: <b>draw</b> $out \sim \text{Density}(in)$
Example: Gaussian		1: <b>draw</b> $x \sim \mathcal{N}(\mu, \sigma)$

# Replication with Plates

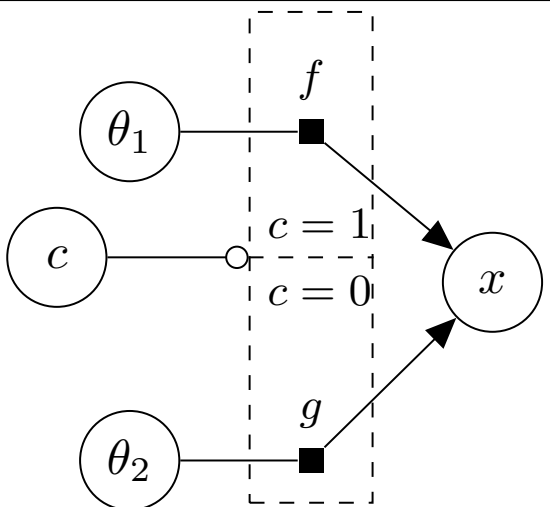
	Directed factor graph	Pseudocode
Plate		<ol style="list-style-type: none"> <li>1: <b>for all</b> <math>\forall i \in \{1..N\}</math> <b>do</b></li> <li>2:     <b>draw</b> <math>\text{var}_i \sim \text{global}</math></li> </ol>
Example: repeated Gaussian		<ol style="list-style-type: none"> <li>1: <b>for all</b> <math>\forall i \in \{1..N\}</math> <b>do</b></li> <li>2:     <b>draw</b> <math>x_i \sim \mathcal{N}(\mu, \sigma)</math></li> </ol>

# Nested Plates

	Directed factor graph	Pseudocode
Nested plates	<p> <math>\sigma</math>  <math>\mu</math>  <math>\mathcal{N}</math>  <math>x</math>  <math>\forall i \in \{1..N\}</math>  <math>\forall k \in \{1..K\}</math> </p>	<pre> 1: for all <math>\forall k \in \{1..K\}</math> do 2:   for all <math>\forall i \in \{1..N\}</math> do 3:     draw <math>x_{k,i} \sim \mathcal{N}(\mu_k, \sigma)</math> </pre>

# Conditioning with *Gates*

Minka & Winn 2008

	Directed factor graph	Pseudocode
Unrolled boolean gate	 <p>The diagram shows a directed factor graph with three parent nodes: <math>\theta_1</math>, <math>c</math>, and <math>\theta_2</math>. <math>\theta_1</math> and <math>\theta_2</math> are connected to a square node <math>f</math>. <math>c</math> is connected to a circle node <math>g</math>. Both <math>f</math> and <math>g</math> are connected to the child node <math>x</math>. A dashed box encloses the nodes <math>f</math>, <math>g</math>, and the connection between <math>c</math> and <math>g</math>. Labels <math>c = 1</math> and <math>c = 0</math> are placed near the dashed box.</p>	<pre>1: <b>if</b> <math>c = 1</math> <b>then</b> 2:   <b>draw</b> <math>x \sim f(\theta_1)</math> 3: <b>else</b> 4:   <b>draw</b> <math>x \sim g(\theta_2)</math></pre>

# Plates & Gates (and implicit combo)

	Directed factor graph	Pseudocode
Replicated gate		1: <b>draw</b> $x \sim \text{Multi}(\theta_c)$
Implicit notation for replicating gates		1: <b>draw</b> $x \sim \text{Multi}(\theta_c)$



# Latent Dirichlet Allocation

[Blei, Ng, Jordan]

