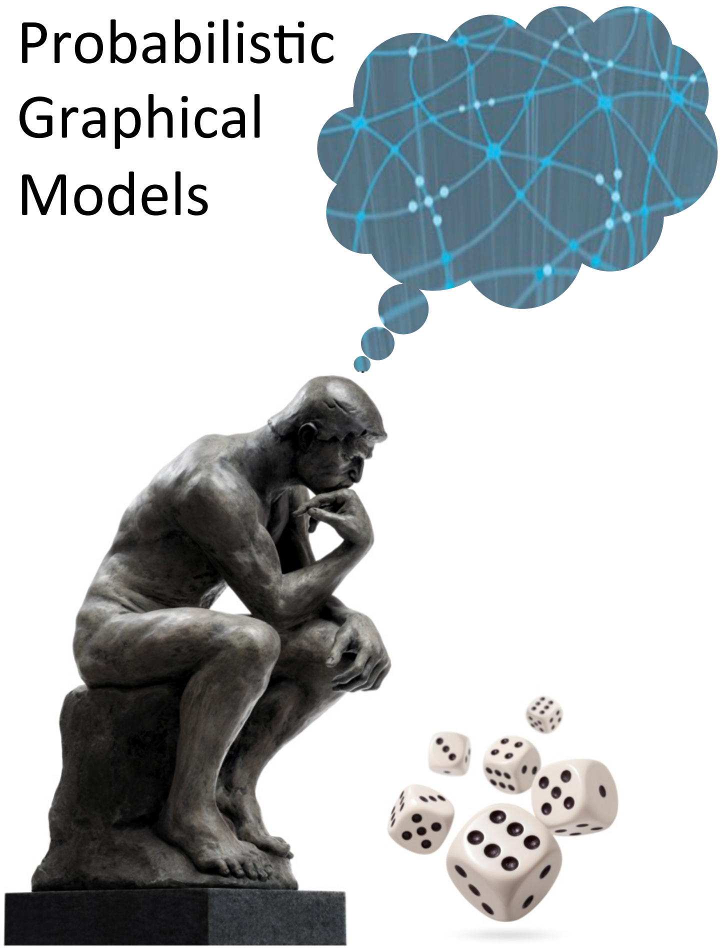
Probabilistic
Graphical
Models

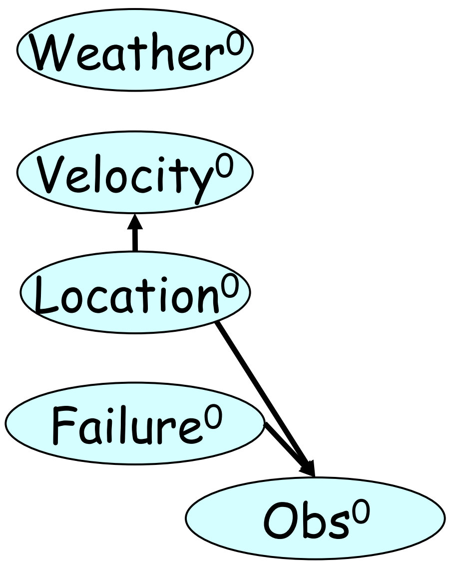


Inference

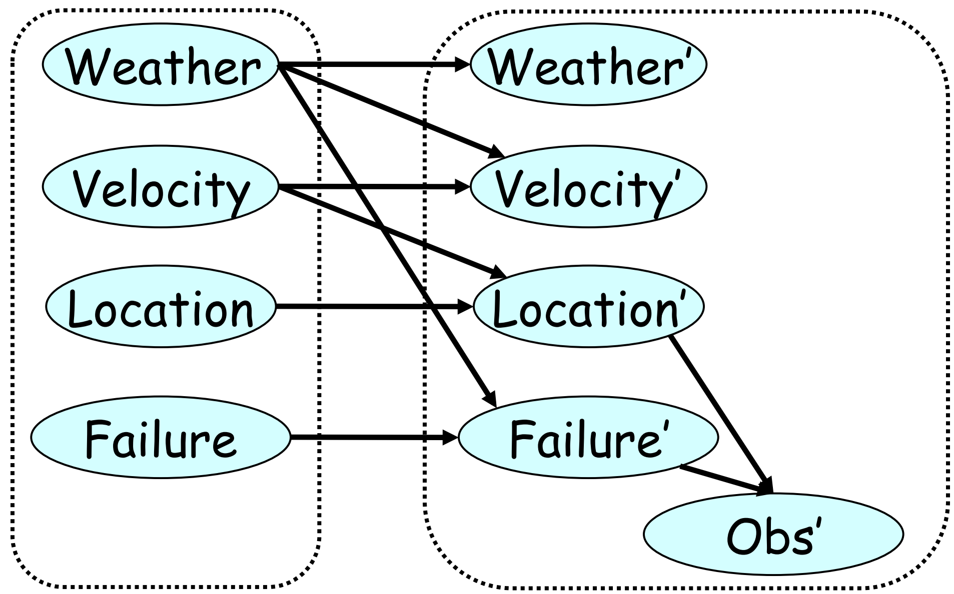
Sampling Methods

Inference In Template Models

DBN Template Specification



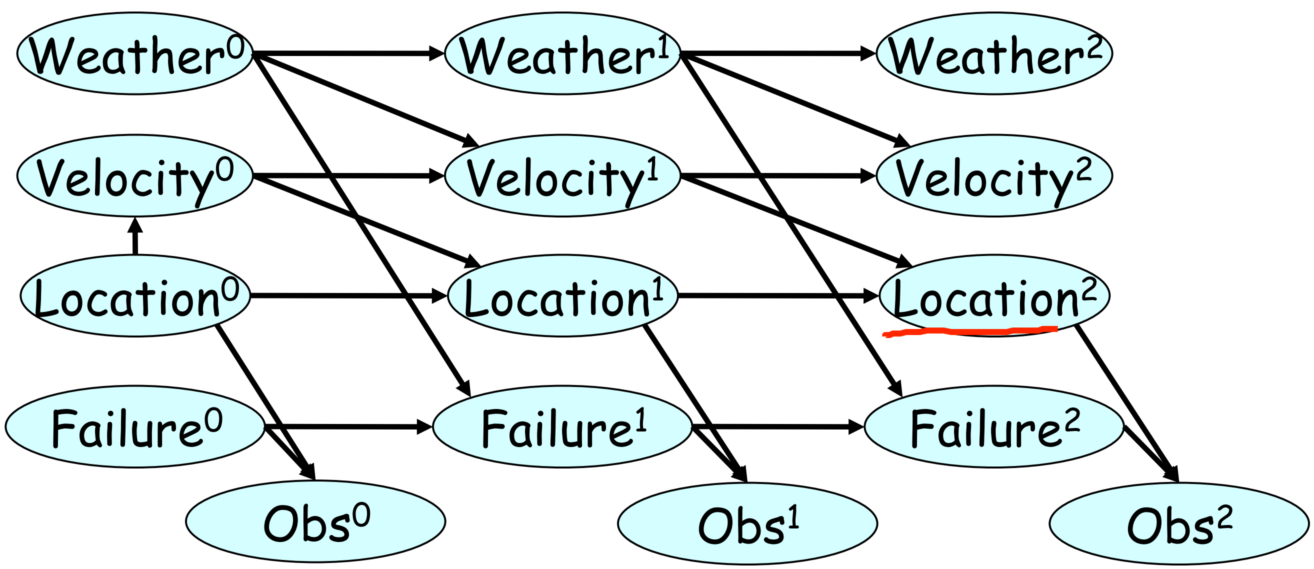
Time slice *0*



Time slice *t*   Time slice *t+1*

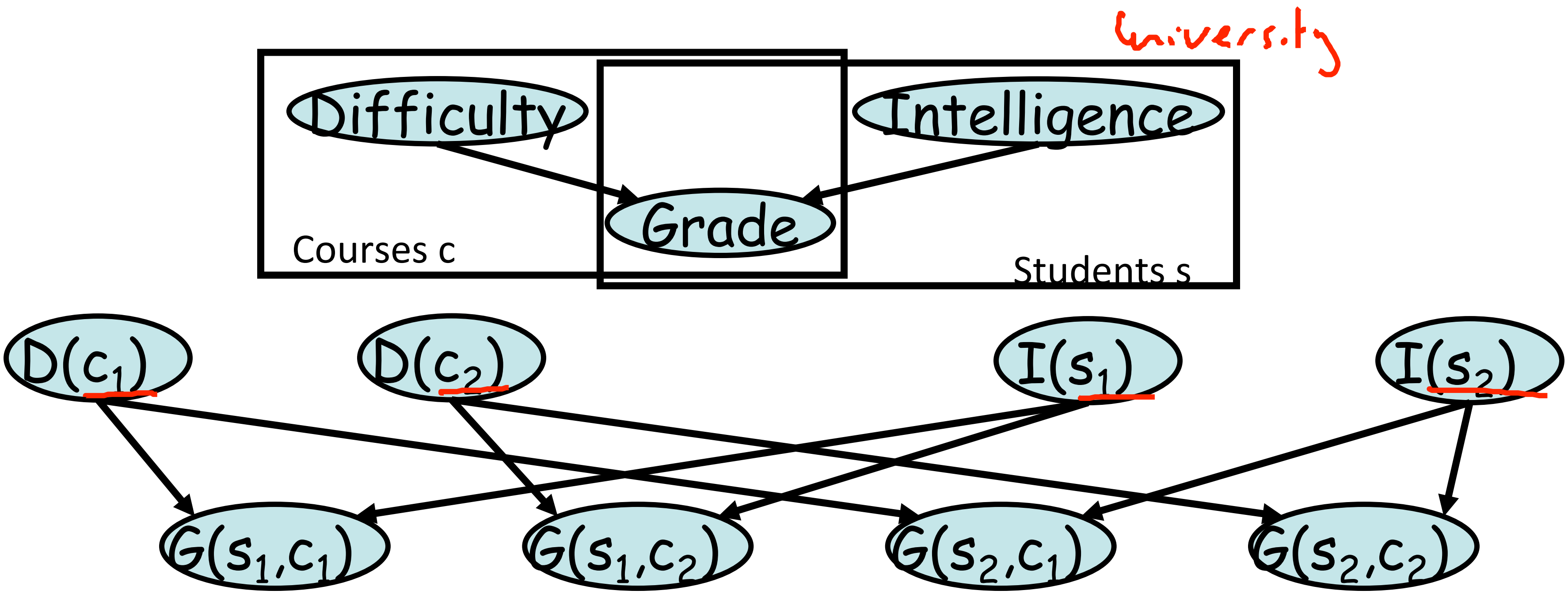
2TBN

Ground Bayesian Network



Can unroll DBN for given trajectory
and run inference over ground network

Plate Model



Can unroll plate model for given set of objects and run inference over ground network

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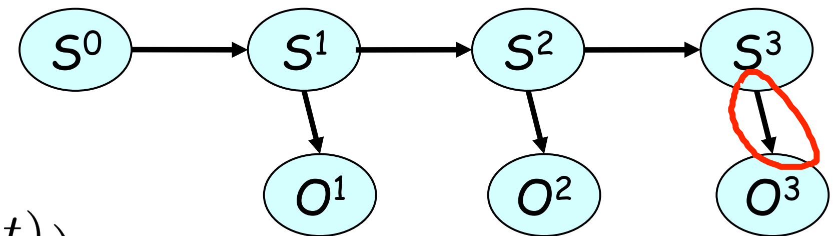
Belief State Tracking



$o^1, o^2, \ldots, o^t$

$$\sigma^{(t)}(S^{(t)}) = P(S^{(t)} \mid \boldsymbol{o}^{(1:t)})$$

$$\sigma^{(t+1)}(S^{(t+1)}) \triangleq P(S^{(t+1)} \mid o^{(1:t)})$$

$$= \sum_{S^{(t)}} P(S^{(t+1)} \mid S^{(t)}, o^{(1:t)}) P(S^{(t)} \mid o^{(1:t)})$$

$$= \sum_{S^{(t)}} P(S^{(t+1)} \mid S^{(t)}) \sigma^{(t)}(S^{(t)})$$

transition model

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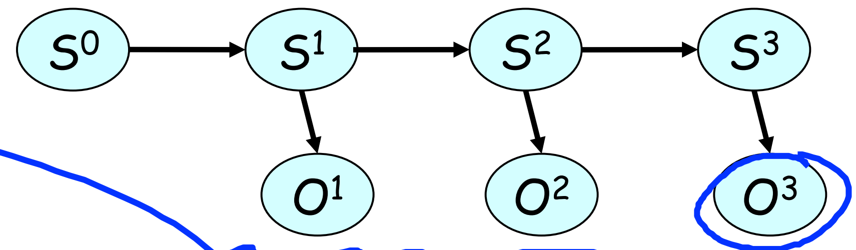
Belief State Tracking

$$\sigma^{(t)}(S^{(t)}) = P(S^{(t)} \mid \boldsymbol{o}^{(1:t)})$$

$$\sigma^{(\cdot t+1)}(S^{(t+1)}) \triangleq P(S^{(t+1)} \mid o^{(1:t)})$$



$$\sigma^{(t+1)}(S^{(t+1)}) = P(S^{(t+1)} \mid o^{(1:t)}, o^{(t+1)})$$

$$= \frac{P(o^{(t+1)} \mid S^{(t+1)}, \cancel{o^{(1:t)}})P(S^{(t+1)} \mid o^{(1:t)})}{P(o^{(t+1)} \mid o^{(1:t)})}$$

observations

$$= \frac{P(o^{(t+1)} \mid S^{(t+1)})\sigma^{(\cdot t+1)}(S^{(t+1)})}{P(o^{(t+1)} \mid o^{(1:t)})}$$

numerator + normalizing

normalizing constant

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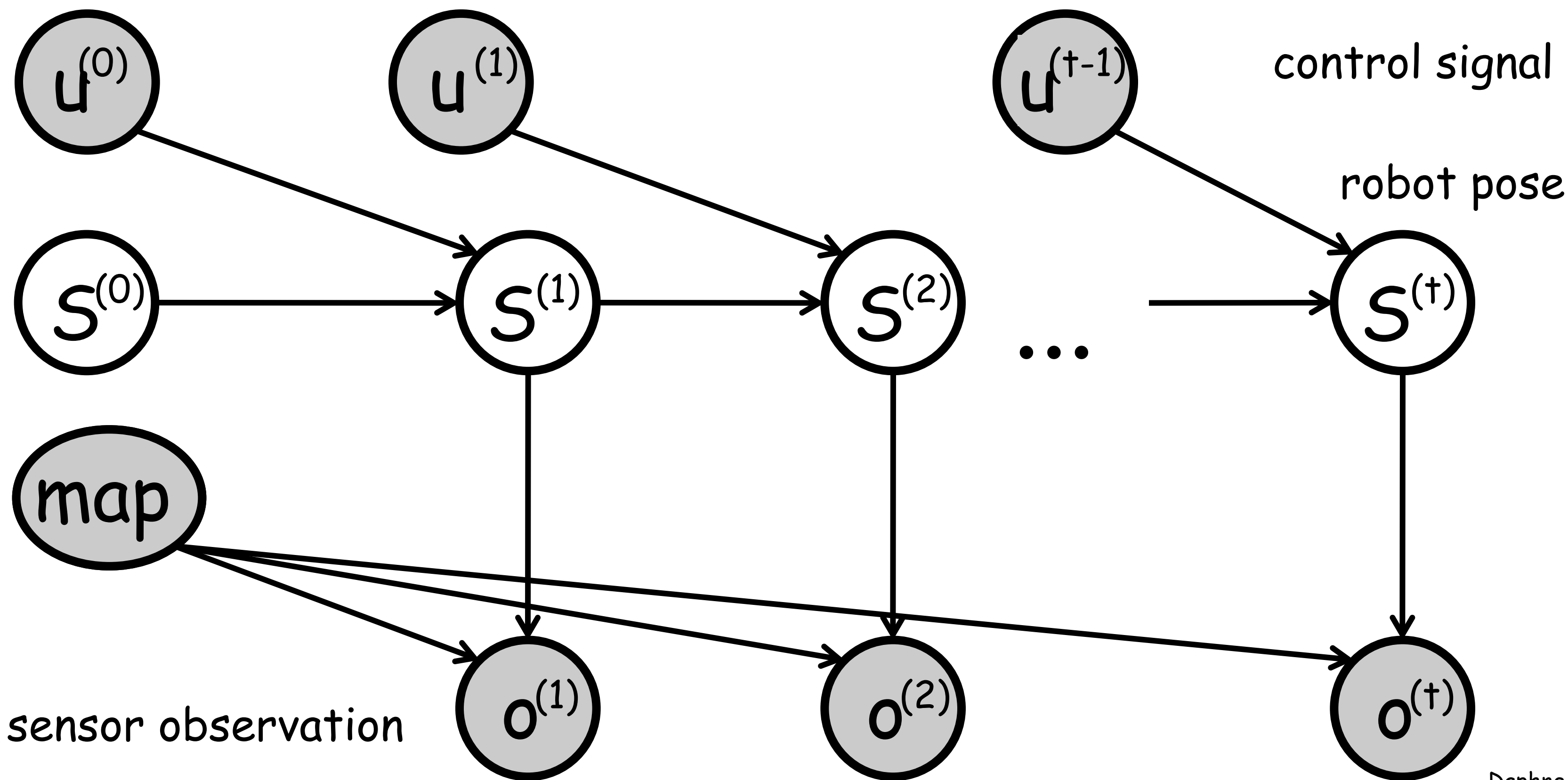
Robot Localization



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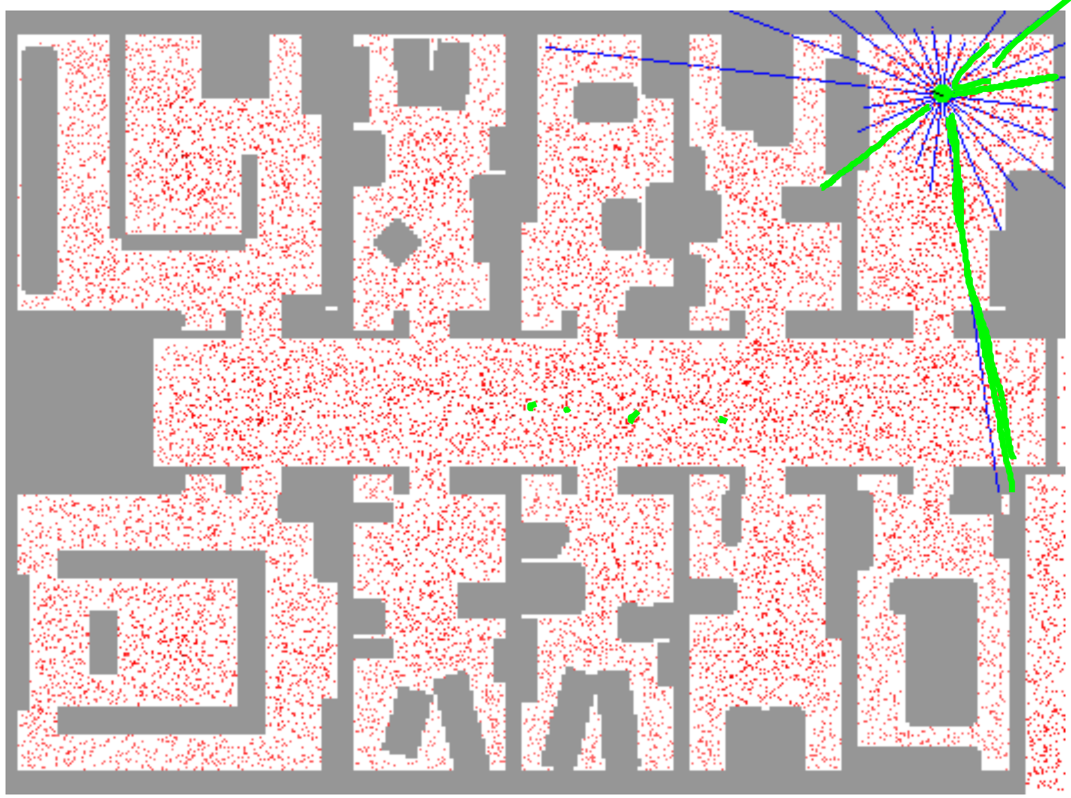
Robot Localization

robot true position



Fox, Burgard, Thrun

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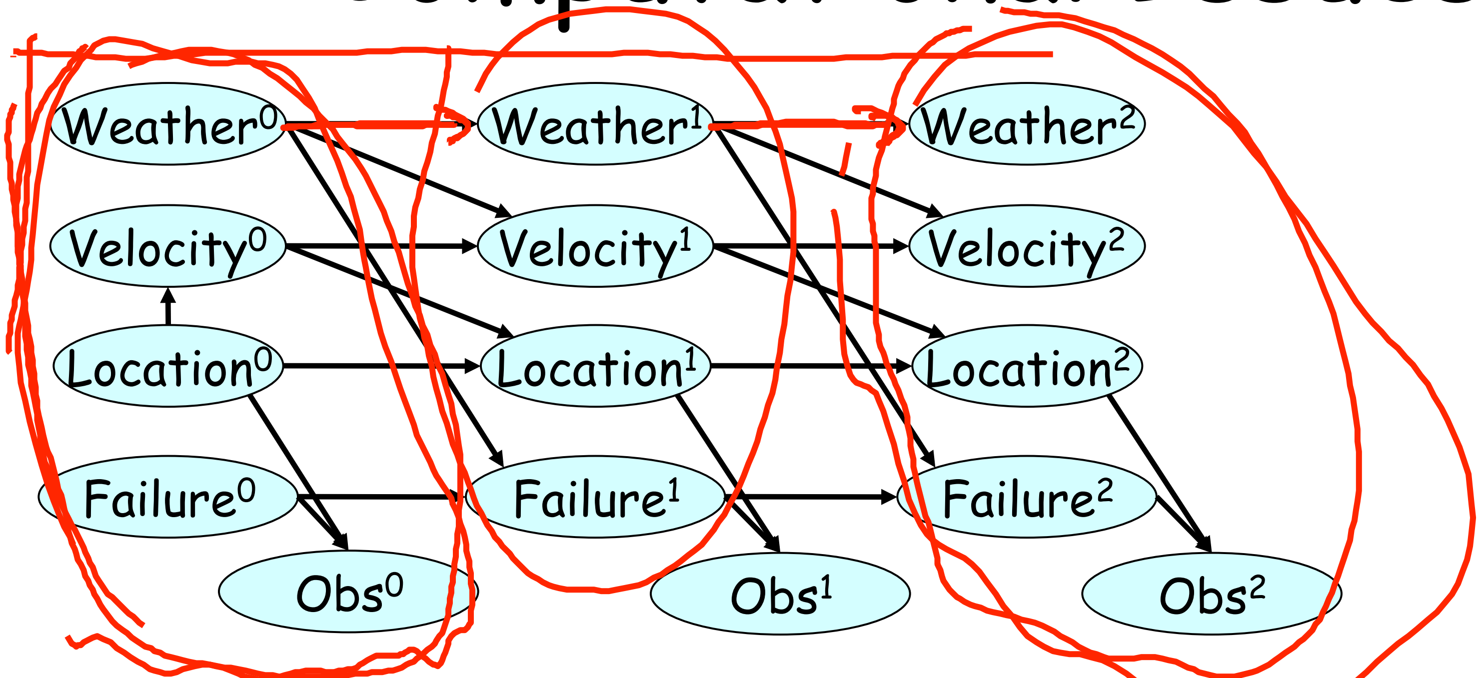
Computational Issues

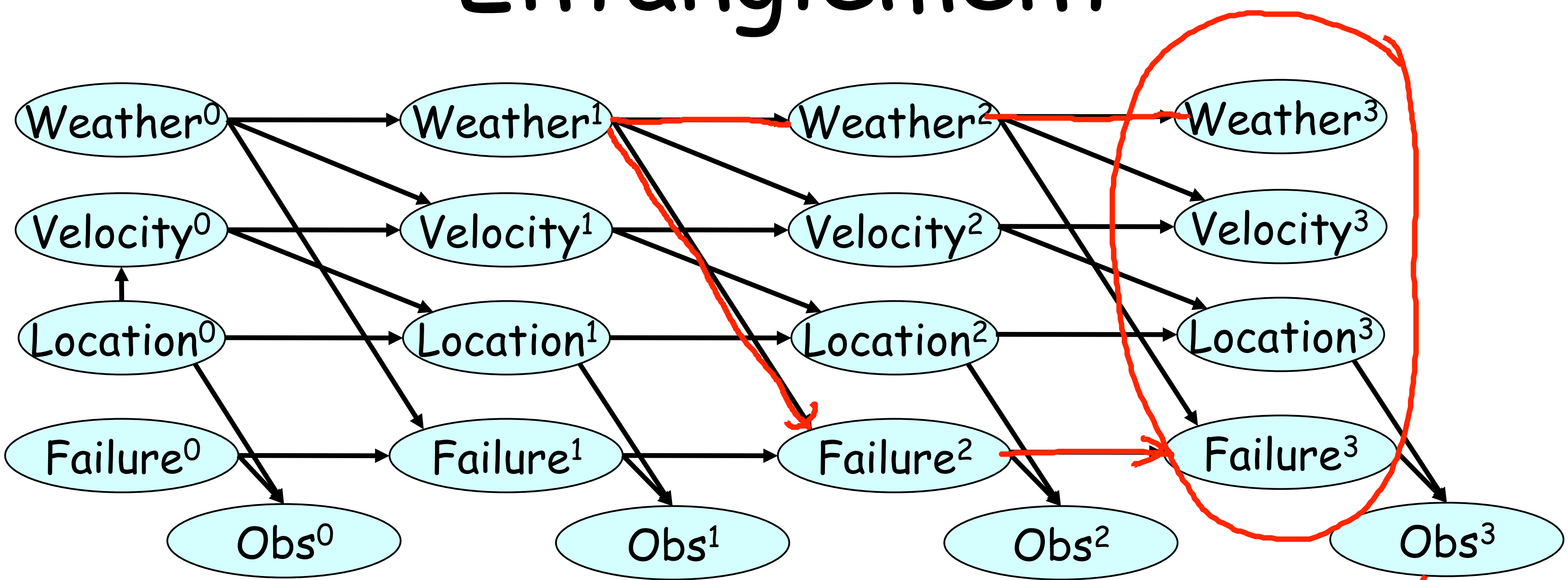


Minimal sepset must separate future from past

⇨ must involve at least all of the persistent variables

Entanglement

$\leftarrow^{(3)}$



no conditional independencies

exact belief state is fully correlated in most cases

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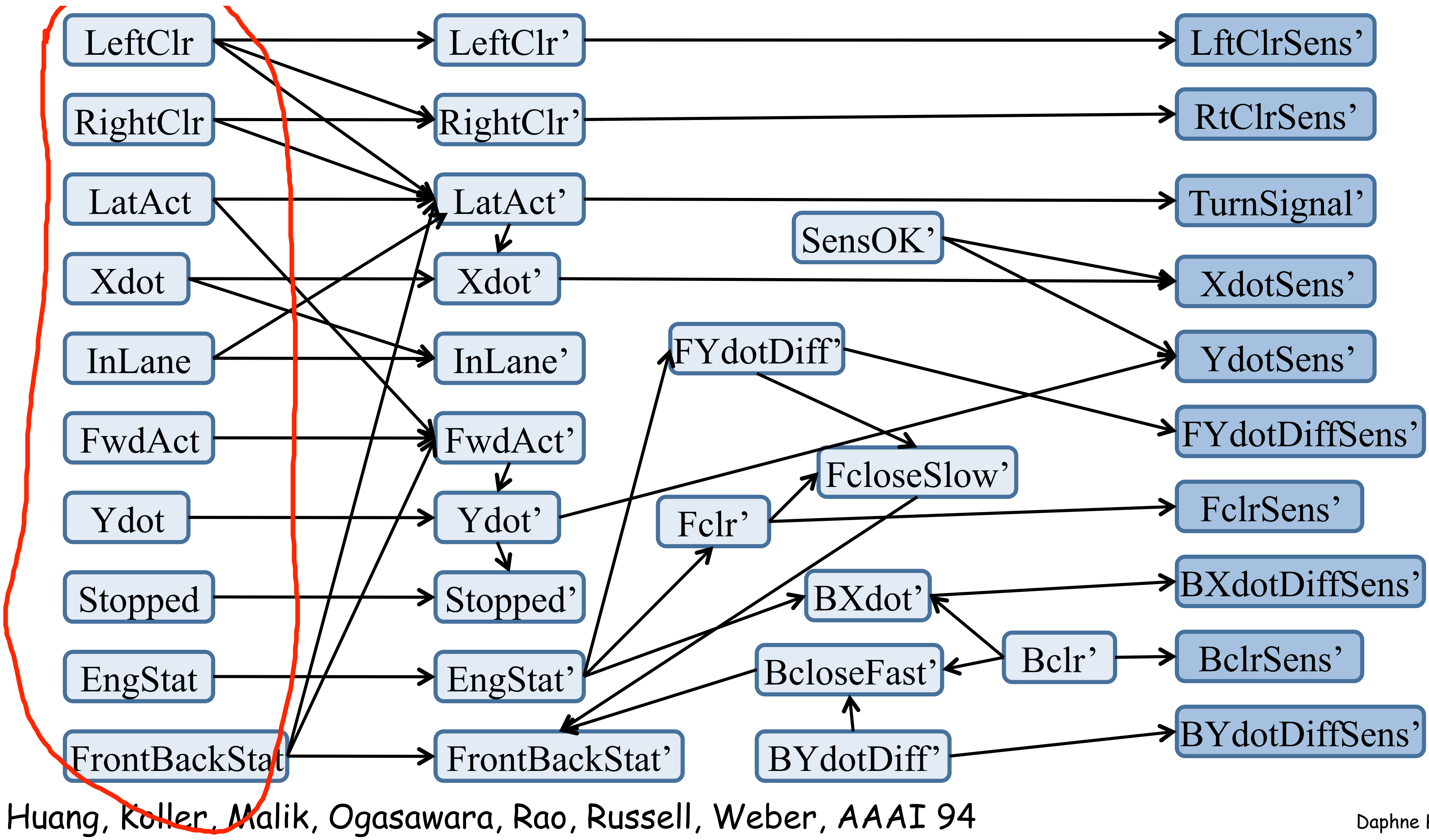
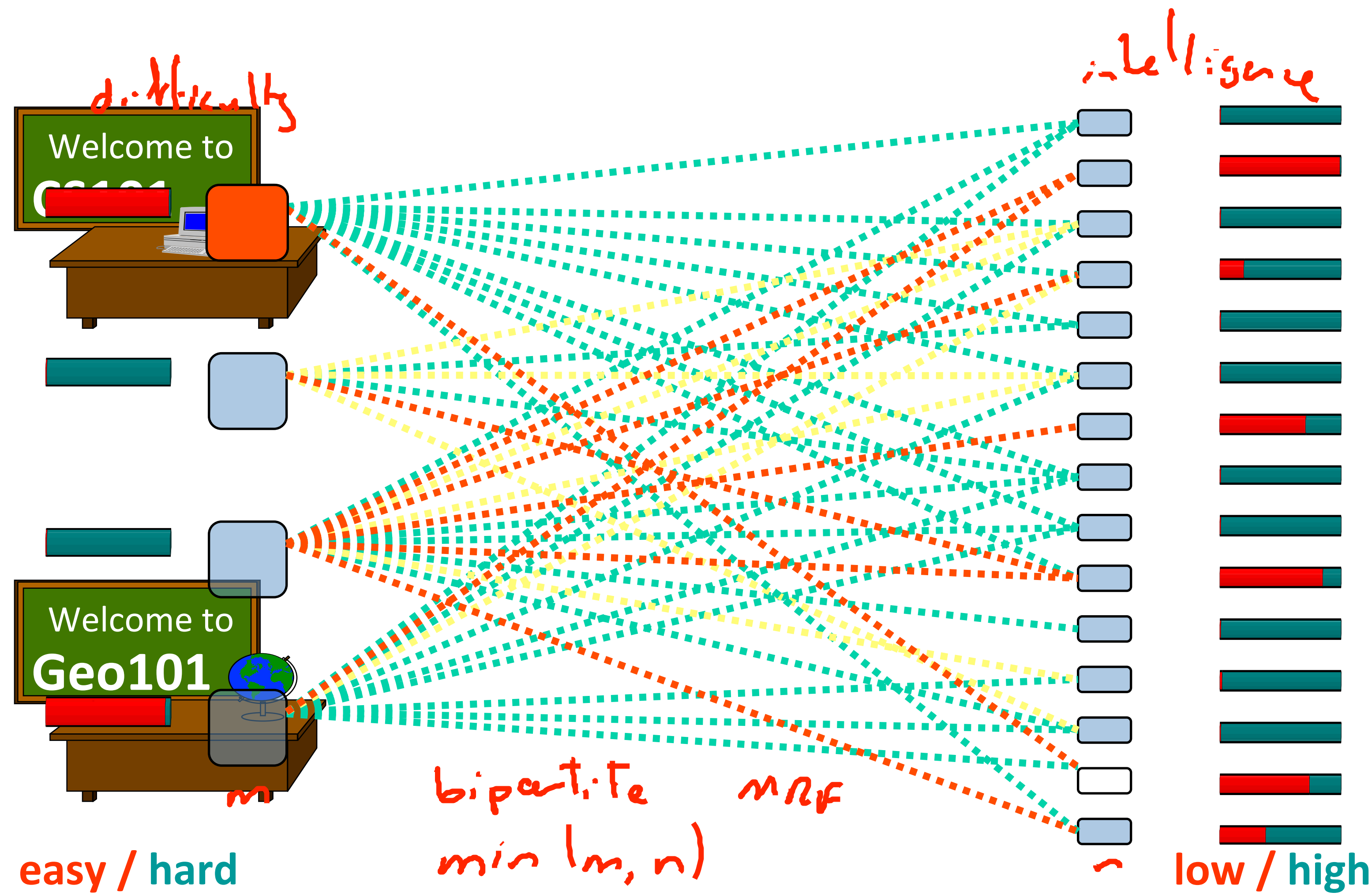


Huang, Koller, Malik, Ogasawara, Rao, Russell, Weber, AAAI 94



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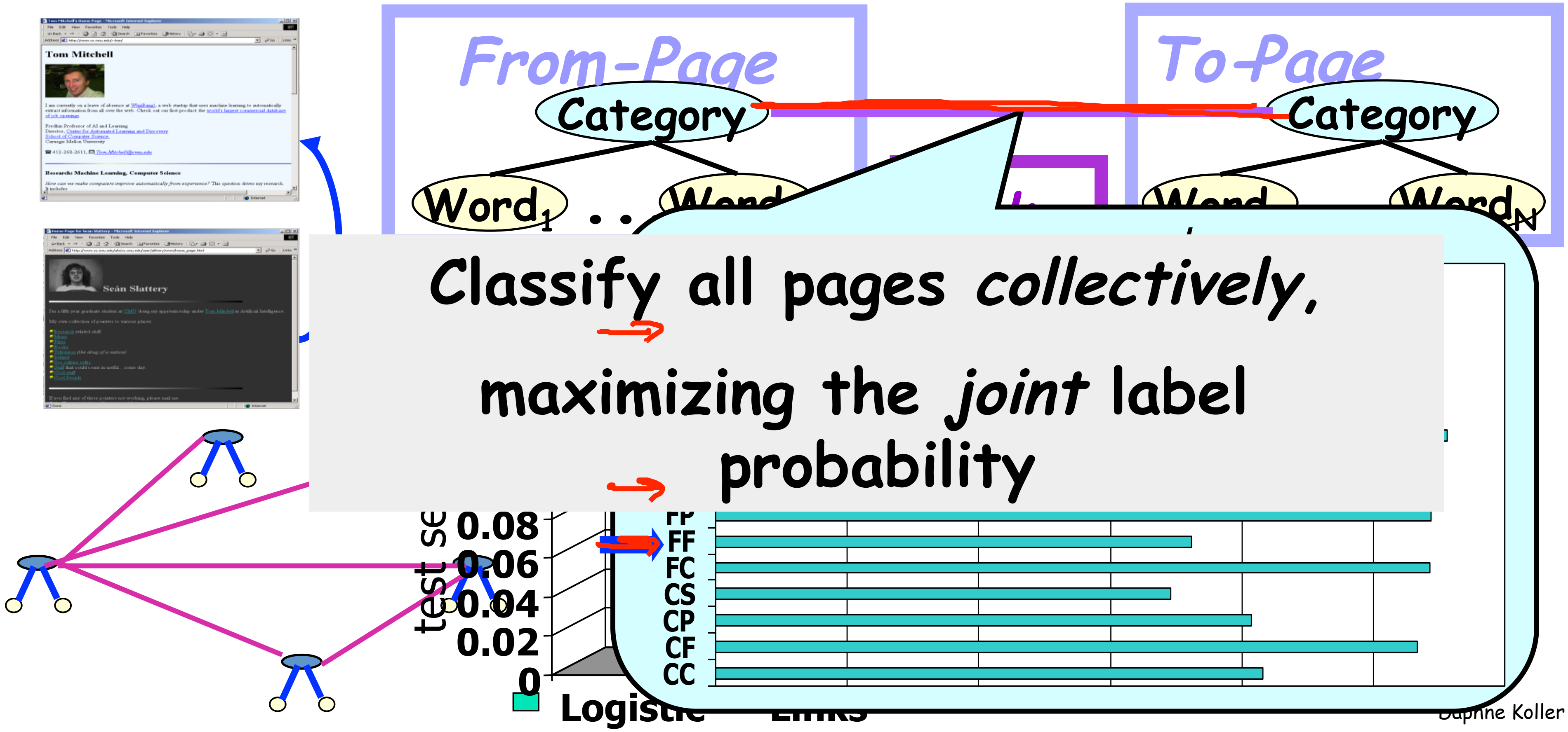
webkb (mitchell (Craven et al, Proc AAAI98; Tasker et al, UAI2002)

Collective Webpage Classification



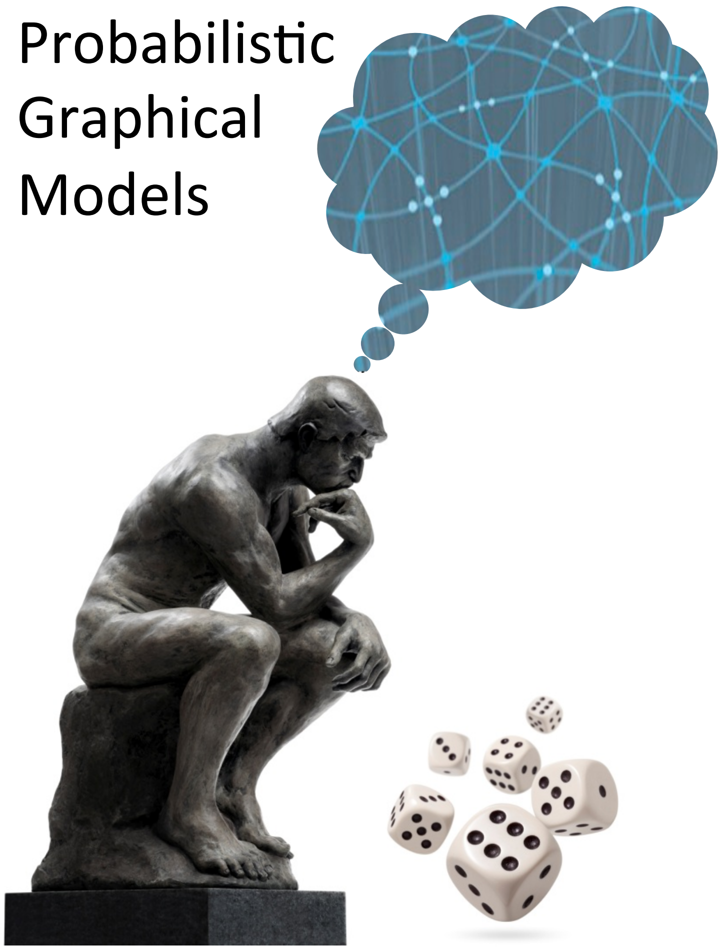
Classify all pages *collectively*,

maximizing the *joint* label probability

Summary

- Inference in template and temporal models can be done by unrolling the ground network and using standard methods
- Temporal models also raise new inference tasks, such as real-time tracking, which require that we adapt our methods
- Moreover, ground network is often large and densely connected, requiring careful algorithm design and use of approximate methods

Probabilistic
Graphical
Models



Inference

Summary

Inference Methods and Evaluation

MAP vs Marginals

Marginals

- Less fragile
- Confidence in answers
- Supports decision making

MAP

- Coherent joint assignment
- More tractable model classes
- Some theoretical guarantees

Approximate inference

- Errors are often attenuated
- Ability to gauge whether algorithm is working

Algorithms for Marginals

- Exact inference

  fits in memory ⇒ exact inference

- Loopy message passing
- Sampling methods

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Algorithms for MAP

- Exact inference
  low treewidth
  associative models
- Optimization methods:
  – exact or approximate (dual decomposition)
- Search-based methods (including sampling)
  hill-climbing MCMC

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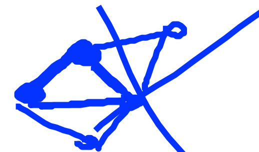
Factors in Approximate Inference

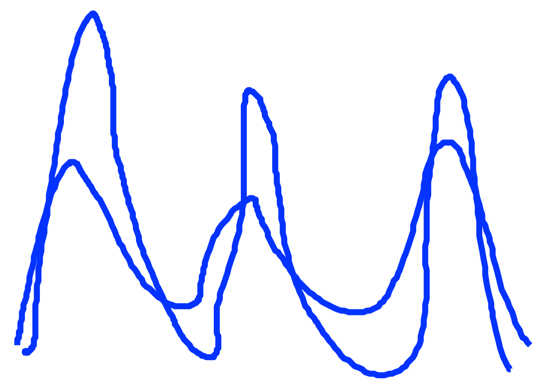
- Connectivity structure
- Strength of influence
- Opposing influences
- Multiple peaks in likelihood



message passing

convergence accuracy

coupling between variables



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So, now what?

- Identify "problem regions" in network
- Try to make inference in these regions more exact
  - Larger clusters in cluster graph
  - Proposal moves over multiple variables
  - Larger "slave" in dual decomposition