

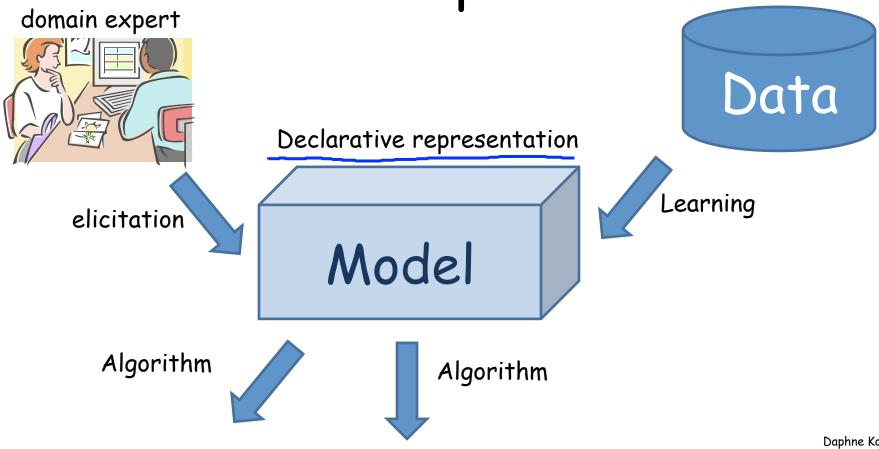
#### Summary

# Probabilistic Graphical Models

# Why PGMs?

- PGMs are the marriage of statistics and computer science
  - Statistics: Sound probabilistic foundations
  - Computer science: Data structures and algorithms for exploiting them

Declarative Representation



Daphne Koller

#### When PGMs?

- When we have noisy data and uncertainty
- When we have lots of prior knowledge
- When we wish to reason about multiple variables
- When we want to construct <u>richly structured</u> <u>models from modular building blocks</u>

# Intertwined Design Choices

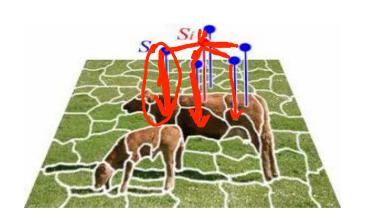
- Representation
  - affects cost of inference & learning
- Inference algorithm
  - Used as a subroutine in learning
  - Some are only usable in certain types of models
- Learning algorithm
  - Learnability imposes modeling constraints

Example: Image Segmentation

- BNs vs MRFs vs CRFs
  - Naturalness of model white
- ->Using <u>rich</u> features
  - Inference costs (associative, regular)
  - Training cost
  - Learn with missing data X CRF -

## Mix & Match: Modeling

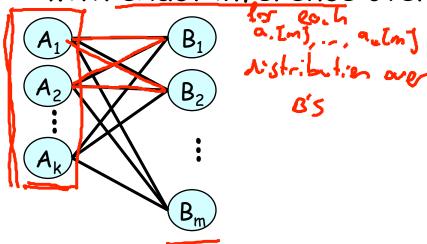
- Mix directed & undirected edges
- E.g., image segmentation from unlabeled images
  - Undirected edges over labels S natural directionality
  - Directed for  $P(X_i \mid S_i)$  easy learning (w/o inference)



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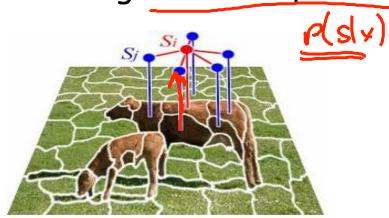
### Mix & Match: Inference

- Apply different inference algorithms to different parts of model
- E.g., combine approximate inference (BP or MCMC)
   with exact inference over subsets of variables



## Mix & Match: Learning

- Apply different learning algorithms to different parts of model
- E.g., combine high-accuracy, easily-trained model (e.g., SVM) for node potentials P(S | X) with CRF learning for higher-order potentials



## Summary

- Integrated framework for reasoning and learning in complex, uncertain domains
  - Large bag of tools within single framework
- Used in a huge range of applications
- Much work to be done, both on applications and on foundational methods