

# Recitation

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Hetunandan

# Review

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- Topics covered in class this week:
  - Structure Learning In BNs
  - Expectation Maximization
- Main topic for review today: Structure Learning

# BN structure learning

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- Two approaches
  - Independence tests
    - Given data, determine all independencies
    - Typically using a chi square/mutual information test
    - Can be very sensitive to noise.
    - Used when number of variables are few and lot of data
  - Score-based search

# Score based Structure Learning

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- Idea:

- Associate score with each model
- Search over all models and find one with best score
  - Hard!
  - Do greedy search and stop when score doesn't improve

# How to score?

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- **Wishlist for scoring function**
  - **Consistency**
    - Given enough data, best BN must have highest score
    - I-equivalent BNs should have same score
  - **Decomposability**
    - $\text{Score} = \sum_{\text{fam}} \text{Score}(\text{fam})$
    - For computational convenience: greedy search can quickly compute scores of its moves

# Scoring Functions

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- Maximum Likelihood score
- $\text{Score}(\text{Graph}, \text{Data}) = \log\text{-likelihood}(G, \theta_{ML}, D)$ 
  - $\theta_{ML}$  is the ML estimate of  $\theta$  for this skeleton  $G$
  - Can rewrite as sums of single variable entropy terms and mutual information over family
  - Therefore, decomposable

# Bad News: ML score overfits

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- To see this, consider two node graphical model over  $X, Y$
- Score of model with one edge always  $\geq$  score of model with no edges
  - Since mutual information always  $\geq 0$
- True in general:  $I(X, Y \cup Z) \geq I(X, Y)$

# Bayesian Score

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- $\text{Score}(G,D) = \log P(D|G) + \log P(G)$ 
  - $\log P(D|G) = \int_{\theta} P(D|\theta,G) P(\theta|G) d\theta$
  - $\log P(G)$  is from structure prior
- We would like to fulfill wishlist
  - Good News: Bayesian score is consistent!
  - Need to work on making it decomposable

# Decomposability: Sufficient Conditions

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- Global Parameter Independence
- Parameter modularity

# Encoding Priors

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- K2 prior
  - Choose a dirichlet prior for each value of  $P(X|Pa(X)=u)$
  - Pro: Simple
  - Weight of prior depends on number of parents
  - Con: Lose Score Equivalence(hw3!)

# BDe prior

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- Prior is encoded in the form of some observed num of instances( $M'$ ) of all variables
- $\alpha_{X|Pa(X)} = M'P'(X, Pa(X))$
- Weight of prior on variable now independent of number of parents