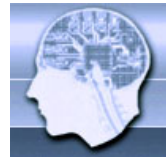


UCLA

**Computer
Science**



Automated
Reasoning
Group

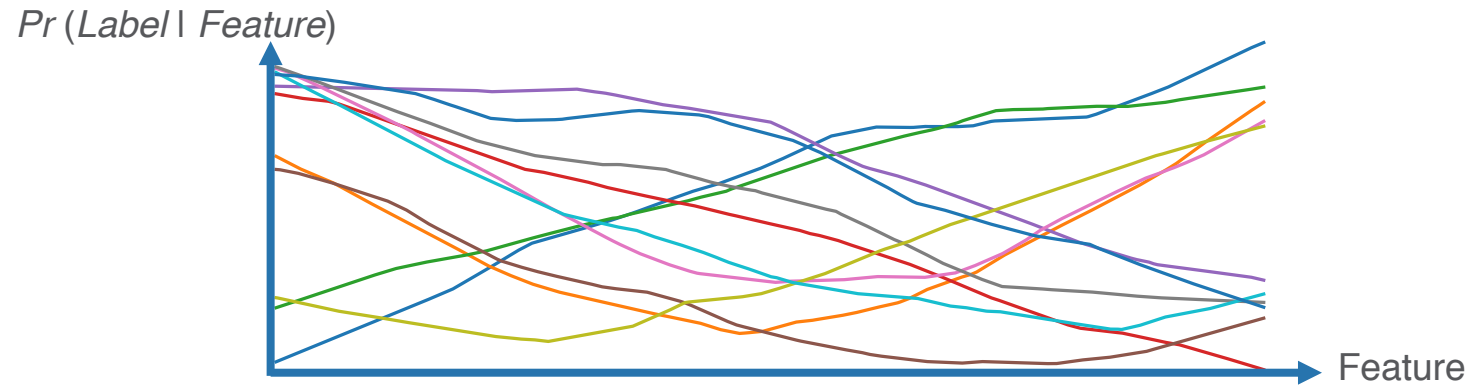
Conditional Independence in Testing Bayesian Networks

Yujia Shen, Haiying Huang, Arthur Choi, Adnan Darwiche.
Computer Science Department, UCLA

Fuse Knowledge with Expressiveness

DEEP LEARNING

- Neural networks are universal approximators.
- They are data hungry.

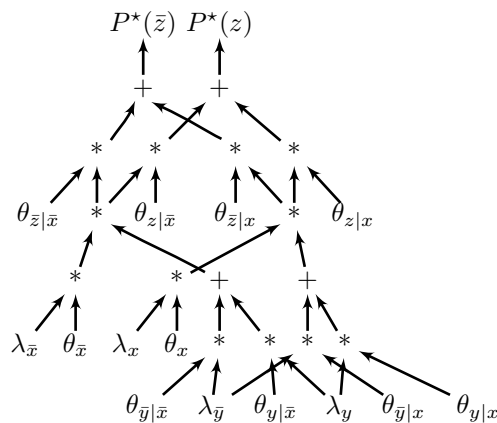
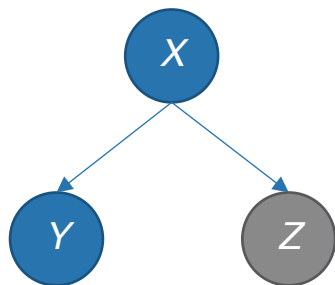


Sampled functions that are represented using a simple neural network.

Fuse Knowledge with Expressiveness

BAYESIAN NETWORKS

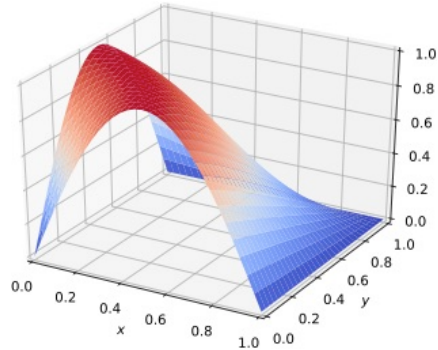
- BNs utilize data efficiently using conditional independence assumptions.



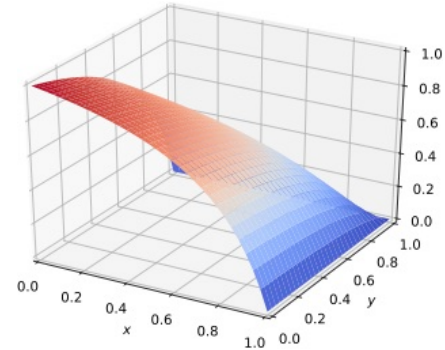
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EXPRESSIVENESS IN BAYESIAN NETWORKS

- BNs utilize data efficiently using conditional independence assumptions.
- Marginal queries are not universal approximators.



Ground truth

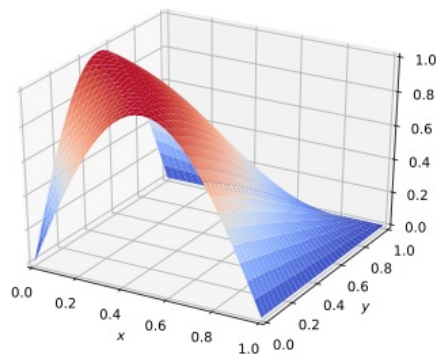


Best fit for BN

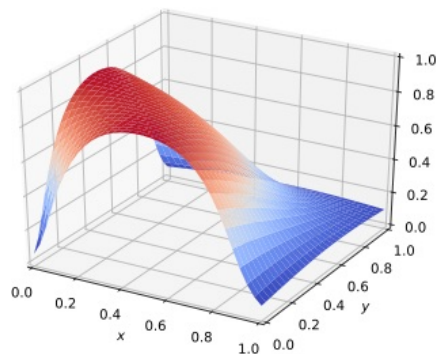
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TESTING BAYESIAN NETWORK

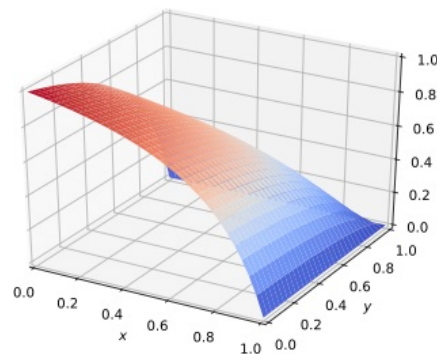
- Testing Bayesian networks are universal approximators [Choi, Darwiche(2018)].



Ground truth



Best fit for TBN
Universal Approximator



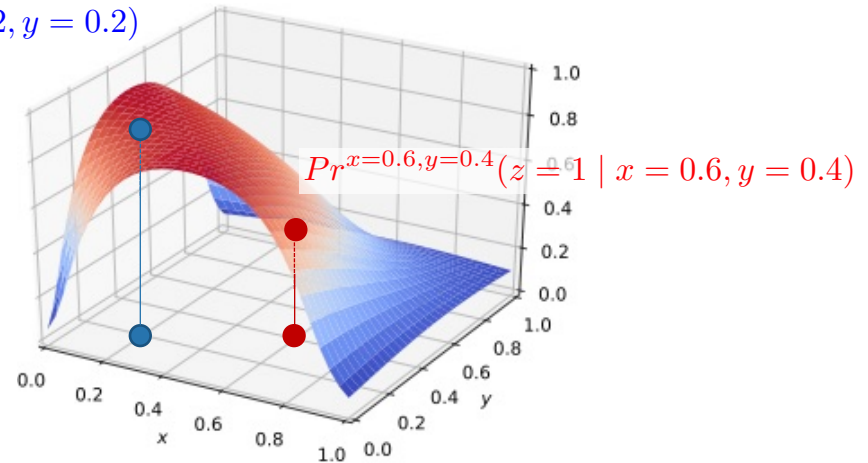
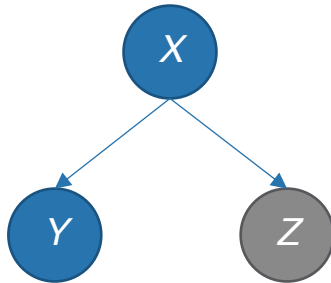
Best fit for BN

Testing Bayesian Network

A SET OF DISTRIBUTIONS

- TBN represents a set of distributions.
 - Different evidence selects different distribution for inference.

$$Pr^{x=0.2,y=0.2}(z = 1 \mid x = 0.2, y = 0.2)$$



Conditional Independence in TBN

Suppose X is d-separated from Y given Z .

In classical Bayesian networks,

$$Pr(x|yz) = Pr(x|z) .$$

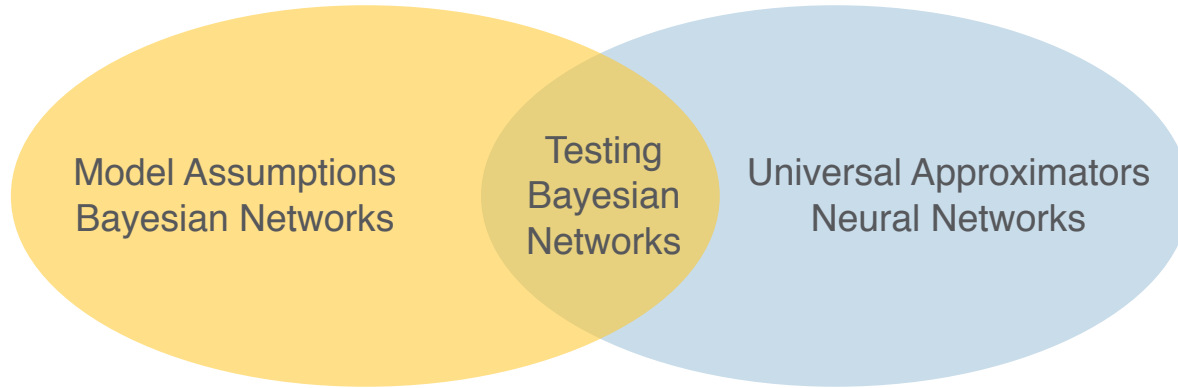
In testing Bayesian networks,

$$Pr^{yz}(x|yz) = Pr^z(x|z) .$$

Pr^{yz} is the joint distribution selected under evidence yz

Pr^z is the joint distribution selected under evidence z

Fuse Knowledge with Expressiveness



Thank You

Conditional Independence in Testing Bayesian Networks