Conditional Independence in Testing Bayesian Networks

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Fuse Knowledge with Expressiveness

DEEP LEARNING

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

Pr (Label \ Feature)

Sampled functions that are represented using a simple neural network.
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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  Best fit for BN

Universal Approximator
Testing Bayesian Network

A SET OF DISTRIBUTIONS

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

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

\[
Pr^{x=0.6, y=0.4}(z = 1 \mid x = 0.6, y = 0.4)
\]
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 $z$
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Model Assumptions Bayesian Networks

Testing Bayesian Networks

Universal Approximators Neural Networks
Thank You

Conditional Independence in Testing Bayesian Networks