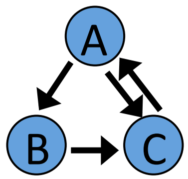
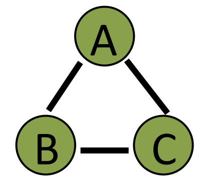
Closed-Form Learning of Markov Networks from Dependency Networks

Daniel Lowd, University of Oregon



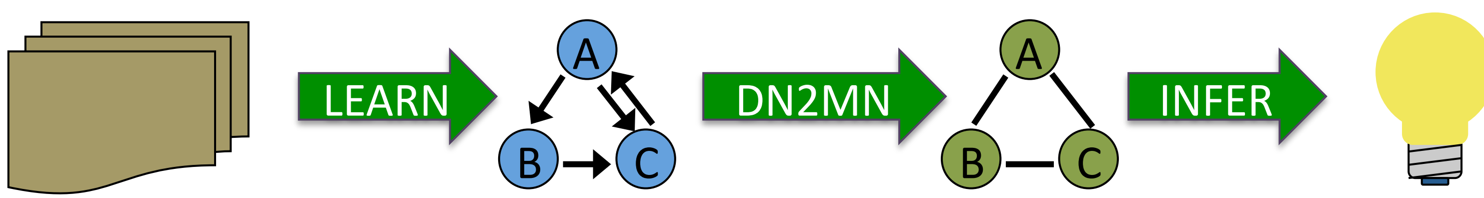
$$\{P_A(A \mid C), P_B(B \mid A), P_C(C \mid A,B)\}$$

Dependency networks (DNs):
Easy to learn, ugly semantics.



$$\frac{1}{Z}\phi_1(A)\phi_2(A,B)\phi_3(A,B,C)$$

Markov networks (MNs):
Hard to learn, nice semantics.



Best of both worlds: Learn a DN and convert it into an MN.

How do we convert a DN into an MN?

KEY IDEA: We can express probability ratios using only conditional probabilities, which are given by the DN:

$$\frac{P(A,B)}{P(a^0b^0)} = \underbrace{\frac{P(A|b^0)}{P(a^0|b^0)}}_{a^0 \rightarrow A} \cdot \underbrace{\frac{P(B|A)}{P(b^0|A)}}_{b^0 \rightarrow B}$$

Use the conditional probability ratios to construct MN factors:

$$\phi_1(A) = \frac{P(A|b^0)}{P(a^0|b^0)} \qquad \phi_2(A,B) = \frac{P(B|A)}{P(b^0|A)}$$

Exact for consistent DNs!
Runs in linear time!

How well does DN2MN work?

Methods: Learned DNs on 12 real-world datasets and converted to MNs by both DN2MN and weight learning.

Results: DN2MN has similar or better accuracy than weight learning and is orders of magnitude faster.

Complete source code: http://libra.cs.uoregon.edu

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