Prof. Dr. R. Kruse / Pascal Held

## Exercise Sheet 9

Exercise 26 Learning from Data
Assume the following conditional independencies between the four attributes $A, B, C$ and $D$ (as in former exercises, the notation $X \Perp Y \mid Z$ states that $X$ is independent of $Y$ given $Z)$ :

$$
A \Perp B|\emptyset, \quad A \Perp D| C, \quad B \Perp D \mid C
$$

Assume further that only these independencies as well as those that are deducible by the graphoid axioms (cf. lecture slides) hold true (i.e. the symmetric conuterparts $B \Perp A \mid \emptyset$ etc. are satisfied). All other conditional independencies do not hold true. Which conditional independence graph over the four attributes can be read from this information?
(Hint: Remember the special properties of converging edges.)

## Exercise 27 Learning from Data

A simple approach to learn a graphical model from data consists in constructing an optimal spanning tree w.r.t. edge weights that represent the strengths of the attributes connected by that edge. Such a tree is named after its inventors Chow-Liu tree. We consider here the construction of a maximal spanning tree in the relational setting with the Hartley information gain

$$
\begin{aligned}
I_{\text {gain }}^{(\text {Hartley })}(A, B) & =\log _{2}\left(\sum_{i=1}^{n_{A}} R\left(A=a_{i}\right)\right)+\log _{2}\left(\sum_{j=1}^{n_{B}} R\left(B=b_{j}\right)\right) \\
& -\log _{2}\left(\sum_{i=1}^{n_{A}} \sum_{j=1}^{n_{B}} R\left(A=a_{i}, B=b_{j}\right)\right) \\
& =\log _{2} \frac{\left(\sum_{i=1}^{n_{A}} R\left(A=a_{i}\right)\right)\left(\sum_{j=1}^{n_{B}} R\left(B=b_{j}\right)\right)}{\sum_{i=1}^{n_{A}} \sum_{j=1}^{n_{B}} R\left(A=a_{i}, B=b_{j}\right)} .
\end{aligned}
$$

as the measure to assess the strength of dependence between attributes $A$ and $B$ : Determine for the relation from exercise 13 (repeated below) the Chow-Liu tree w.r.t. the Hartley information gain! Compare the result with the result of exercise 13!

| $A$ | $a_{1}$ | $a_{1}$ | $a_{2}$ | $a_{2}$ | $a_{2}$ | $a_{2}$ | $a_{3}$ | $a_{3}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $B$ | $b_{1}$ | $b_{1}$ | $b_{1}$ | $b_{1}$ | $b_{3}$ | $b_{3}$ | $b_{1}$ | $b_{2}$ |
| $C$ | $c_{1}$ | $c_{2}$ | $c_{2}$ | $c_{3}$ | $c_{2}$ | $c_{3}$ | $c_{2}$ | $c_{2}$ |

## Exercise 28 Learning from Data

Consider the following probability distribution:

|  | $C=c_{1}$ |  | $C=c_{2}$ |  |
| :--- | ---: | ---: | ---: | ---: |
|  | $B=b_{1}$ | $B=b_{2}$ | $B=b_{1}$ | $B=b_{2}$ |
| $A=a_{1}$ | $4 / 35$ | $12 / 35$ | $4 / 35$ | $1 / 35$ |
| $A=a_{2}$ | $1 / 35$ | $3 / 35$ | $8 / 35$ | $2 / 35$ |

Determine the Chow-Liu tree for that distribution w.r.t. the Shannon information gain

$$
I_{\text {gain }}^{(\text {Shannon })}(A, B)=\sum_{i=1}^{n_{A}} \sum_{j=1}^{n_{B}} P\left(A=a_{i}, B=b_{j}\right) \log _{2} \frac{P\left(A=a_{i}, B=b_{j}\right)}{P\left(A=a_{i}\right) \cdot P\left(B=b_{j}\right)},
$$

i.e. use the Shannon information gain as the edge weight and determine the maximal spanning tree! Does the result represent a correct decomposition?

