

Bayesian Networks: a Combined Tuning Heuristic

Janneke H. Bolt

2016



Universiteit Utrecht

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Sensitivity functions

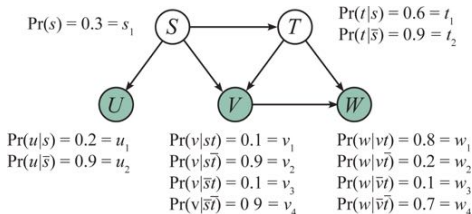
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Bayesian network tuning

Adaptation of one or more parameters of a Bayesian network to enforce output to meet some constraint.



For example: the current value of $\Pr(st|uvw)$ is 0.045 but it should be 0.25. Tuning by adapting multiple parameters may be preferred.

Sensitivity functions

A sensitivity function describes an output probability of a network as a function of one or more of its parameters. The general form of a sensitivity function is:

$$\Pr(\mathbf{w}|\mathbf{u})(\mathbf{z}) = \frac{\sum_{\mathbf{z}_k \in \mathcal{P}(\mathbf{z})} (c_k \cdot \prod_{z_i \in \mathbf{z}_k} z_i)}{\sum_{\mathbf{z}_k \in \mathcal{P}(\mathbf{z})} (d_k \cdot \prod_{z_i \in \mathbf{z}_k} z_i)}$$

A two-way sensitivity function in the parameters z_1 and z_2 for example, has the following general form:

$$\Pr(\mathbf{w}|\mathbf{u})(z_1, z_2) = \frac{c_0 + c_1 \cdot z_1 + c_2 \cdot z_2 + c_3 \cdot z_1 \cdot z_2}{d_0 + d_1 \cdot z_1 + d_2 \cdot z_2 + d_3 \cdot z_1 \cdot z_2}$$

Tuning heuristics

When a network is tuned by changing multiple parameters a choice has to be made with respect to the relative amount of parameter change.

- Locally optimal

- Balanced

- Combined

Tuning heuristics: locally optimal

Consider a set parameters $\mathbf{z} = \{x, y_1, \dots, y_{n-1}\}$. In a locally optimal tuning scheme, with respect to $\Pr(\mathbf{w}|\mathbf{u})$, all parameters $y_i \in \mathbf{z}$ are tied to x by:

$$y_i = \frac{sy_i^o}{sx^o} \cdot (x - x^o) + y_i^o$$

where sx^o and sy_i^o are the values of the partial derivatives of $\Pr(\mathbf{w}|\mathbf{u})(\mathbf{z})$ with respect to x and y_i at \mathbf{z}^o , respectively.

Advantage: locally optimal.

Disadvantage: the tuning range may be reduced.

Tuning heuristics: balanced

Consider a set parameters $\mathbf{z} = \{x, y_1, \dots, y_{n-1}\}$. In a balanced tuning scheme, with respect to $\Pr(\mathbf{w}|\mathbf{u})$, all parameters $y_i \in \mathbf{z}$ are tied to x by

$$y_i = \begin{cases} \frac{x \cdot (x^o - 1) \cdot y_i^o}{x^o \cdot (x - 1 + y_i^o) - x \cdot y_i^o} & \text{if } y_i \uparrow x \\ \frac{(x - 1) \cdot x^o \cdot y_i^o}{-x + x \cdot x^o + x \cdot y_i^o - x^o \cdot y_i^o} & \text{if } y_i \not\uparrow x \end{cases}$$

If $y_i \uparrow x$, y_i and x simultaneously increase/decrease and if $y_i \not\uparrow x$, an increase of x results in an decrease of y_i and vice versa. Moreover, x and y_i vary simultaneously in the entire interval $\langle 0, 1 \rangle$.

Advantage: in general a larger tuning range than the locally optimal heuristic.

Disadvantage: changes are locally not optimal.

Tuning heuristics: combined

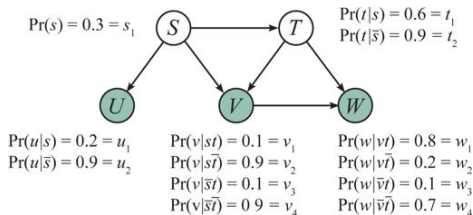
Consider a set parameters $\mathbf{z} = \{x, y_1, \dots, y_{n-1}\}$. In a combined tuning scheme, with respect to $\Pr(\mathbf{w}|\mathbf{u})$, all parameters $y_i \in \mathbf{z}$ are tied to x by:

$$y_i = \left\{ \begin{array}{l} \frac{x \cdot (sx^o \cdot y_i^o \cdot (y_i^o - 1) + sy_i^o \cdot (1 - x^o)) + sx^o \cdot y_i^o \cdot (1 - y_i^o) - sy_i^o \cdot x^o \cdot (1 - x^o)}{x \cdot (sx^o \cdot (y_i^o - 1) + sy_i^o \cdot (1 - x^o)) + sx^o \cdot (1 - y_i^o) - sy_i^o \cdot x^o \cdot (1 - x^o)} \\ \frac{x \cdot sx^o \cdot y_i^{o2}}{x \cdot (sx^o \cdot y_i^o - sy_i^o \cdot x^o) + sy_i^o \cdot x^{o2}} \\ \frac{x \cdot sx^o \cdot y_i^{o2} - sx^o \cdot y_i^{o2}}{x \cdot (sy_i^o \cdot (1 - x^o) + sx^o \cdot y_i^o) + sy_i^o \cdot x^o \cdot (x^o - 1) - sx^o \cdot y_i^o} \\ \frac{x \cdot (sx^o \cdot y_i^o \cdot (y_i^o - 1) - sy_i^o \cdot x^o) + sy_i^o \cdot x^{o2}}{x \cdot (sx^o \cdot (y_i^o - 1) - sy_i^o \cdot x^o) + sy_i^o \cdot x^{o2}} \end{array} \right.$$

where $sx^o, sy_1^o, \dots, sy_{n-1}^o$ are the values of the partial derivatives of $\Pr(\mathbf{w}|\mathbf{u})(\mathbf{z})$ with respect to respectively x, y_1, \dots, y_{n-1} at \mathbf{z}^o .

This heuristic is locally optimal, yet, it covers the same tuning range as the balanced heuristic.

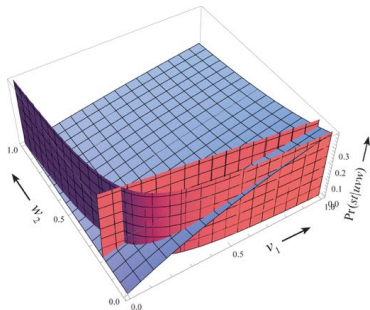
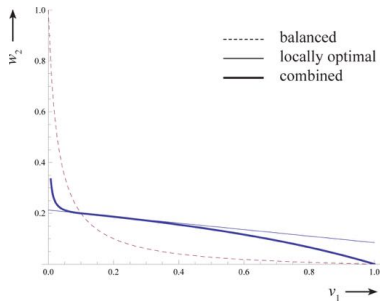
Example



$$\Pr(st | uvw)(v_1, w_2) = \frac{2.88 \cdot v_1}{2.88 \cdot v_1 + 7.83 \cdot w_2 + 4.54}$$

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$$\Pr(st|uvw)(v_1, w_2) = \frac{2.88 \cdot v_1}{2.88 \cdot v_1 + 7.83 \cdot w_2 + 4.54}$$

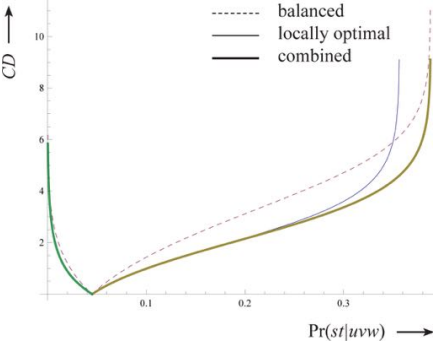
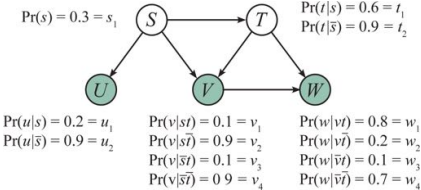


Distance measures

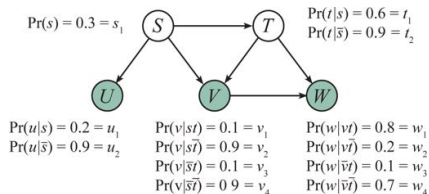
$$\text{KL} = \sum_{\mathbf{v} \in \mathbf{V}} \text{Pr}^o(\mathbf{v}) \cdot \ln \frac{\text{Pr}^o(\mathbf{v})}{\text{Pr}(\mathbf{v})}$$

$$\text{CD} = \ln \max_{\mathbf{v} \in \mathbf{V}} \frac{\text{Pr}(\mathbf{v})}{\text{Pr}^o(\mathbf{v})} - \ln \min_{\mathbf{v} \in \mathbf{V}} \frac{\text{Pr}(\mathbf{v})}{\text{Pr}^o(\mathbf{v})}$$

Example



Experiments



$$\text{set1} = \{v_1, u_2, w_2\}$$

$$\text{set2} = \{v_1, v_2, v_3, v_4\}$$

$$\text{set3} = \{v_1, v_2, u_1, u_2, w_1, w_2\}$$

	'uniform'			'biased'		
	set 1	set 2	set 3	set 1	set 2	set 3
$\ln(OR) = -2$	31	35	13	40	43	10
$\ln(OR) = -1$	19	14	6	30	34	5
$\ln(OR) = -0.5$	9	7	3	21	22	3
$\ln(OR) = 0.5$	9	9	6	22	35	9
$\ln(OR) = 1$	24	32	13	32	45	18
$\ln(OR) = 2$	50	68	35	53	58	35

Experiments

	CD-distance, 'uniform parameterisation'								
	L vs B			L vs C			B vs C		
	set 1	set 2	set 3	set 1	set 2	set 3	set 1	set 2	set 3
$\ln(OR) = -2$	L	L	L	C	C	L	C	C	C
$\ln(OR) = -1$	L	L	L	C	C	L	C	C	C
$\ln(OR) = -0.5$	L	L	L	C	C	L	C	C	C
$\ln(OR) = 0.5$	L	B	L	C	C	C	C	C	C
$\ln(OR) = 1$	L	B	L	C	C	C	C	C	C
$\ln(OR) = 2$	B	B	B	C	C	C	C	B	C

	CD-distance, 'biased parameterisation'								
	L vs B			L vs C			B vs C		
	set 1	set 2	set 3	set 1	set 2	set 3	set 1	set 2	set 3
$\ln(OR) = -2$	B	B	L	C	C	L	C	C	C
$\ln(OR) = -1$	L	L	L	C	C	L	C	C	C
$\ln(OR) = -0.5$	L	L	L	C	C	L	C	C	C
$\ln(OR) = 0.5$	L	B	L	C	C	C	C	C	C
$\ln(OR) = 1$	L	B	L	C	C	C	C	C	C
$\ln(OR) = 2$	B	B	L	C	C	C	C	C	C

Questions?