

Derivation

$$L = \sum_{n=1}^N \left\{ \frac{-\log(2\pi\sigma_u^2)}{2} - \frac{1}{2\sigma_u^2} * [x_{un} - (w_{u0} + \sum_{c \in \pi_u} w_{uc}x_{ucn})]^2 \right\} \quad (1. \text{from the slides})$$

$$\frac{\partial L}{\partial w_{u0}} = \sum_{n=1}^N (x_{un} - (w_{u1}x_{u1,n} + \dots + w_{uC}x_{uC,n} + w_{u0})) = 0$$

$$\frac{\partial L}{\partial w_{u1}} = \sum_{n=1}^N (x_{un} - (w_{u1}x_{u1,n} + \dots + w_{uC}x_{uC,n} + w_{u0})) x_{u1,n} = 0$$

$$\vdots$$

$$\frac{\partial L}{\partial w_{uC}} = \sum_{n=1}^N (x_{un} - (w_{u1}x_{u1,n} + \dots + w_{uC}x_{uC,n} + w_{u0})) x_{uC,n} = 0$$

(2. from the slides, use C+1 linear equations to solve for each of the C weights and the bias)

$$\mu_u = w_{u0} + \sum_{c \in \pi_u} w_{uc}x_{ucn} \quad (3. \text{calling this part as the mean for the } u\text{th RV})$$

$$L = -0.5N \log(2\pi) - 0.5N \log(\sigma_u^2) - \frac{0.5}{\sigma_u^2} \sum_{n=1}^N [x_{un} - \mu_u]^2 \quad (4. \text{Equation now changes like this})$$

$$\frac{\partial L}{\partial \sigma_u^2} = \frac{-N}{2\sigma_u^2} + \frac{1}{2\sigma_u^4} \sum_{n=1}^N [x_{un} - \mu_u]^2 = 0 \quad (5. \text{Taking partial derivative wrt variance and equating to 0 to find argmax})$$

$$\sigma_u^2 = \frac{\sum_{n=1}^N [x_{un} - \mu_u]^2}{N} \quad (6. \text{Re arranging terms we get this for optimal variance})$$

Implementation**1. get learned parameters**

- For each node in the given DGM we are trying to learn the following parameters: 1 bias term, C weight terms from its C parents, 1 variance term
- We first try to learn the C+1 weights by calling the `learn_node_parameter_w` and then use those weights to compute the mean μ_u using formula #3 above
- Using this mean μ_u for the x_u we can now compute variance using the formula #6 in the `learn_node_parameter_var` function

2. learn node parameter w

- We have to solve c+1 equations shown in figure #2. To do this we formulate that as $Ax = b$ which can then be fed into `np.linalg.solve(A,b)` to get the weights
- We take A as matrix of values corresponding to each w_{uc} and b as the values of the constants.
- $A = [\text{equation}_0, \text{equation}_1, \dots, \text{equation}_c]$, $b = [b_0, b_1, \dots, b_c]$
- Each $\text{equation}_i = [V_{u0}, V_{u1}, \dots, V_{uc}]$ (where V_{ui} is the value of the W_{uc} variable which can be found by using np by summing specific nodes across different axis)
- Each b_i can again be computed using numpy by summing across all observations based on the formula shown in figure 2
- Refer to code comments for more details on how each V_{uc} , b_i is computed

3. learn node parameter var

- Using this mean μ_u for the x_u we can now compute variance using the formula #6 in this function as per formula #6 (i.e. summing across all n observations of x_u)