
Supplementary Material of: Covered Information Disentanglement: Correcting Permutation Feature Importance in the Presence of Covariates

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We re-state theorem 0.1 here for clarity

Theorem 0.1. For a Markov Random Field, the covered information of a r.v. X_i by the set of random variables X_I , $I = \{1, \dots, N\} \setminus \{i\}$ w.r.t. Y is given by:

$$H_{X_i \cap Y}^{C(X_I)} = 1 + \frac{1}{H(X_i \cap Y)} \mathbf{E}_{\sim p(x_{\sim i, \sim y})} \left[\log \left(f \frac{\mathbf{d}^T \mathbf{F} \mathbf{e}}{\mathbf{d}^T \mathbf{F}_y \mathbf{F}_{x_i} \mathbf{e}} \right) \right] \quad (1)$$

where $p(x_{\sim i, \sim y})$ is the joint probability of r.v.s which are neighbors to either X_i or Y , \mathbf{F} is a matrix with the product of joint potential values ψ_{C_F} for set of cliques $F : \{X_i, Y \in F\}$; f , \mathbf{F}_y and \mathbf{F}_{x_i} are an entry, column and row of \mathbf{F} , respectively, while \mathbf{d} and \mathbf{e} are arrays with the product of potential values ψ_{C_D} , ψ_{C_E} for set of cliques $D : \{X_i \in D, Y \notin D\}$ and $E : \{X_i \notin E, Y \in E\}$ with fixed X_I .

Proof. Using definition 1, 2 and 3:

$$\frac{H(X_i \cap Y \cap \{\cup_{j \in I} X_j\})}{H(X_I \cap Y)} = 1 + \frac{\overset{\textcircled{1}}{H(X_i \cup Y \cup X_I)} - \overset{\textcircled{2}}{H(X_I \cup Y)} + \overset{\textcircled{3}}{H(X_I)} - \overset{\textcircled{4}}{H(X_i \cup X_I)}}{H(X_i \cap Y)} \quad (2)$$

Representing these terms with marginal distributions:

$$\textcircled{1} = - \sum_x p(x) \log p(x), \quad \textcircled{2} = - \sum_x p(x) \log \sum_{x_i} p(x), \quad \textcircled{3} = - \sum_x p(x) \log \sum_{x_i} \sum_y p(x), \quad \textcircled{4} = - \sum_x p(x) \log \sum_y p(x) \quad (3)$$

The probability density for Markov Random fields is equal to $p(x) = \prod_{c=1}^C \psi_c(x_c) / \mathbf{Z}$, where \mathbf{Z} is the partition function and c are cliques in the Markov network, C being the total number of cliques. Define two sets of cliques: $A : \{X_i \in A\}$ and $B : \{X_i \notin A\}$. In that case:

$$\textcircled{1} = - \sum_x p(x) \log \left[\log \prod_{C_B} \psi_{C_B}(x_{C_B}) + \log \prod_{C_A} \psi_{C_A}(x_{C_A}) \right] + \log(\mathbf{Z}), \quad (4)$$

$$\textcircled{2} = - \sum_x p(x) \log \left[\log \prod_{C_B} \psi_{C_B}(x_{C_B}) + \log \sum_{x_i} \prod_{C_A} \psi_{C_A}(x_{C_A}) \right] + \log(\mathbf{Z}) \quad (5)$$

$$\textcircled{1} - \textcircled{2} = - \sum_x p(x) \log \left(\frac{\prod_{C_A} \psi_{C_A}(x_{C_A})}{\sum_{x_i} \prod_{C_A} \psi_{C_A}(x_{C_A})} \right) \quad (6)$$

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To compute ③ – ④, define four sets of cliques: $C : \{X_i \notin C, Y \notin C\}$, $D : \{X_i \in D, Y \notin D\}$, $E : \{X_i \notin E, Y \in E\}$ and $F : \{X_i \in F, Y \in F\}$. In order to reduce the clutter, we will introduce the following functions: $d(x_i, x_I) = \prod_{j \in I, j \sim i} \psi(x_i, x_j)$, $e(y, x_I) = \prod_{j \in I, j \sim y} \psi(y, x_j)$, $f(x_i, y) = \psi(x_i, y)$, where we will abbreviate $d(x_i, x_I)$ into $d(x_i)$ and $e(y, x_I)$ into $e(y)$ when the value for random variable X_I is fixed. Then:

$$\textcircled{3} = - \sum_x p(x) \log \left[\log \prod_{C_C} \psi_{C_C}(x_{C_C}) + \log \sum_{x_i} \sum_y d(x_i) e(y) f(x_i, y) \right] + \log(\mathbf{Z}), \quad (7)$$

$$\textcircled{4} = - \sum_x p(x) \log \left[\log \prod_{C_C} \psi_{C_C}(x_{C_C}) + \log \sum_y d(x_i) e(y) f(x_i, y) \right] + \log(\mathbf{Z}) \quad (8)$$

$$\textcircled{3} - \textcircled{4} = - \sum_x p(x) \log \left(\frac{\sum_{x_i} \sum_y d(x_i) e(y) f(x_i, y)}{\sum_y d(x_i) e(y) f(x_i = X_i, y)} \right), \quad (9)$$

where $f(x_i = X_i, y)$ is the function f for a fixed value of the r.v. X_i . Since the set of cliques $A = \{D \cup F\}$, and denoting by $d(x_i = X_i)$, $f(x_i = X_i, Y = y)$ the functions d and f for fixed values of X_i and Y , then:

$$\begin{aligned} (\textcircled{1} - \textcircled{2}) + (\textcircled{3} - \textcircled{4}) &= - \sum_x p(x) \log \left(\frac{\sum_{x_i} \sum_y d(x_i = X_I) f(x_i = X_i, Y = y) e(y) f(x_i, y)}{\sum_{x_i} \sum_y d(x_i = X_I) d(x_i) f(x_i, Y = y) e(y) f(X_i, y)} \right) = \quad (10) \\ &\quad - \mathbf{E}_{x \sim p(x_{\sim i, \sim y})} \left[\log f(x_i = X_i, Y = y) + \log \left(\frac{\mathbf{d}^T \mathbf{F} \mathbf{e}}{\mathbf{d}^T \mathbf{F}_y \mathbf{F}_{x_i} \mathbf{e}} \right) \right], \end{aligned}$$

where $x_{\sim i, \sim y}$ is an instance of the set of r.v.s that are neighbors to X_i or Y , \mathbf{d} and \mathbf{e} are column arrays with the different values of $d(x_i)$ and $e(y)$ for fixed X_I , \mathbf{F} is a matrix with all the values $f(x_i, y)$ with varying values of X_i in the rows and Y in the columns, while \mathbf{F}_y and \mathbf{F}_{x_i} are row and column vectors of \mathbf{F} corresponding to fixed Y and fixed X_i , respectively. This yields the result of the theorem. □