Easy Factor Graph: the flexible and efficient tool for managing undirected graphical models

Casalino Andrea
andrecasa91@gmail.com

Chapter 1

What is EFG

Easy Factor Graph (EFG), is a simple and efficient C++ library for managing undirected graphical models.
EFG allows you to build step by step a graphical model made of unary or binary potentials, i.e. factors involving one or two variables. It contains several tools for exporting and importing graphs from textual file. EFG allows you to perform all the probabilistic queries described in Chapter 2, from marginal probabilities computation to learning the tunable parameters of a graph. All the theoretical computations described in the initial Sections of this guide are already implemented inside the library. However, you are strongly encouraged to read this guide to understand how to use such functionalities.
The rest of this guide is structured as follows. Chapter 2 will introduce the main theoretical concepts about factor graphs, with the aim of explaining the capabilities of EFG. Chapter 3 will explain the format of the xml files adopted to represent factor graphs, exploited when importing or exporting the models to or from textual files. Chapter 4 will present the examples adopted for showing how EFG works. All the remaining Chapters, will describe the structure of the classes constituting EFG [1].

[1] A similar guide, but in a html format, is also available at http://www.andreacasalino.altervista.org/__EFG_doxy_guide/index.html.

Chapter 2

Theoretical background on factor graphs

This Section will provide the basic concepts about probabilistic models. Moreover, a precise notation will be introduced and used for the rest of this document.

2.1 Preliminaries

This library is intended for managing network of categorical variables. Formally, the generic categorical variable V has a discrete domain Dom:

$$Dom(V) = \{v_0, \cdots, v_n\} \tag{2.1}$$

Essentially, $Dom(V)$ contains all the possible realizations of V. The above notation will be adopted for the rest of the guide: capital letters will refer to variable names, while non capital refer to their realizations. Group of categorical variables can be considered categorical variables too, having a domain that is the Cartesian product of the domains of the variables constituting the group. Suppose X is obtained as the union of variables $V_{1,2,3,4}$, i.e. $X = \bigcup_{i=1}^{4} V_i$, then:

$$Dom(X) = Dom(V_1) \times Dom(V_2) \times Dom(V_3) \times Dom(V_4) \tag{2.2}$$

The generic realization x of X is a set of realizations of the variables $V_{1,2,3,4}$, i.e. $x = \{v_1, v_2, v_3, v_4\}$. Suppose $V_{1,2,3}$ have the domains reported in the tables 2.1. The union $X = \bigcup_{i=1}^{3} V_i$ is a categoric variable whose domain is made by the combinations reported in table 2.2.

The entire population of variables contained in a model is a set denoted as $\mathcal{V} = \{V_1, \cdots, V_m\}$. As will be exposed in the following, the probability of $\bigcup_{V_i \in \mathcal{V}} V_i$ [1] is computed as the product of a certain number of components called factors.

Knowing the joint probability of $V_{1,\cdots,m}$, the probability distribution of a subset $S \subset \{V_1, \cdots, V_m\}$ can be in general (not only for graphical models) obtained through marginalization. Assume C is the complement of S:

$$C \cup S = \bigcup_{i=1}^{m} V_i \tag{2.3}$$

[1] Which is the joint probability distribution of all the variables in a model

$Dom(V_1)$
v_{10}
v_{11}

$Dom(V_2)$
v_{20}
v_{21}
v_{22}

$Dom(V_3)$
v_{30}
v_{31}

Table 2.1 Example of domains for the group of variables $V_{1,2,3}$.

$Dom(X) = Dom(V_1 \cup V_2 \cup V_3)$
$x_0 = \{v_{10}, v_{20}, v_{30}\}$
$x_1 = \{v_{10}, v_{20}, v_{31}\}$
$x_2 = \{v_{11}, v_{20}, v_{30}\}$
$x_3 = \{v_{11}, v_{20}, v_{31}\}$
$x_4 = \{v_{10}, v_{21}, v_{30}\}$
$x_5 = \{v_{10}, v_{21}, v_{31}\}$
$x_6 = \{v_{11}, v_{21}, v_{30}\}$
$x_7 = \{v_{11}, v_{21}, v_{31}\}$
$x_8 = \{v_{10}, v_{22}, v_{30}\}$
$x_9 = \{v_{10}, v_{22}, v_{31}\}$
$x_{10} = \{v_{11}, v_{22}, v_{30}\}$
$x_{11} = \{v_{11}, v_{22}, v_{31}\}$

Table 2.2 Example of domains for the group of variables $V_{1,2,3}$.

with $C \cap S = \emptyset$, then:

$$\mathbb{P}(S = s) = \sum_{\forall \hat{c} \in Dom(C)} \mathbb{P}(S = s, C = \hat{c}) \tag{2.4}$$

In the above computation, variables in C were marginalized. Indeed they were in a certain sense eliminated, since the probability of the sub set S was of interest, no matter the realizations of all the variables in C.

A factor, sometimes also called a potential, is a positive real function describing the correlation existing among a subset of variables $D^i \subset \mathcal{V}$. Suppose factor Φ_i involves $\{X, Y, Z\}$, i.e. $D^i = \{X, Y, Z\}$. Then, $\Phi_i(X, Y, Z)$ is a function defined over $Dom(D^i)$. More formally:

$$\Phi_i(D^i) = \Phi_i(X, Y, Z) : \text{DOMAIN}(X) \times \text{DOMAIN}(Y) \times \text{DOMAIN}(Z) \longrightarrow \mathbb{R}^+ \tag{2.5}$$

The aim of Φ_i is to assume 'high' values for those combinations $d^i = \{x, y, z\}$ that are probable to appear together and low values (at least a zero) for those being improbable. The entire population of factors $\{\Phi_1, \cdots \Phi_p\}$ correlating the variables of a model, is considered for computing $\mathbb{P}(V_{1,\cdots,m})$, i.e. the joint probability distribution of all the variables in the model. The energy function E of a graph is defined as the product of the factors:

$$E(V_{1,\cdots,m}) = \Phi_1(D^1) \cdot \cdots \cdot \Phi_p(D^p) = \prod_{i=1}^{p} \Phi_i(D^i) \tag{2.6}$$

E is addressed for computing the joint probability distribution of the variables in $\mathcal{V}$:

$$\mathbb{P}(V_{1,\cdots,m}) = \frac{E(V_{1,\cdots,m})}{\mathcal{Z}} \tag{2.7}$$

where $\mathcal{Z}$ is a normalization coefficient defined as follows:

$$\mathcal{Z} = \sum_{\forall \tilde{V}_{1,\cdots,m} \in Dom(\bigcup_{i=1,\cdots,m} V_i))} E(\tilde{V}_{1,\cdots,m}) \tag{2.8}$$

Although the general theory behind graphical models supports the existance of generic multivaried factors, this library will address only two possible types:

- Binary potentials: they involve a pair of variables.
- Unary potentials: they involve a single variable.

We can store the values in the image of a Binary potential in a two dimensional table. For instance, suppose Φ_b involves variables A and B, whose domains contains 3 and 5 possible values respectively:

$$\begin{aligned} \text{DOM}(A) &= \{a_1, a_2, a_3\} \\ \text{DOM}(B) &= \{b_1, b_2, b_3, b_4, b_5\} \end{aligned} \tag{2.9}$$

	b_0	b_1	b_2	b_3	b_4
a_0	1	4	0	0	0
a_1	0	1	0	0	0
a_2	0	0	5	0	1

Table 2.3 The values in the image of $\Phi_b(A, B)$.

a_0	a_1	a_2
0	2	0.5

Table 2.4 The values in the image of $\Phi_u(A)$.

The values assumed by $\Phi_b(A, B)$ are described by table 2.3. Essentially, $\Phi_b(A, B)$ tells us that the combinations $\{a_0, b_1\}$, $\{a_2, b_2\}$ are highly probable; while $\{a_0, b_0\}$, $\{a_1, b_1\}$ and $\{a_2, b_4\}$ are moderately probable. Let be $\Phi_u(A)$ a Unary potential involving variable A. The values characterizing Φ_u can be stored in a simple vector, see table 2.4. If $\Phi_b(A, B)$ would be the only potential in the model, the joint probability density of A and B will assume the following values [2]:

$$\mathbb{P}(a_0, b_1) = \frac{\Phi_b(a_0, b_1)}{\mathcal{Z}} = \frac{4}{\mathcal{Z}} = 0.3333 \tag{2.10}$$

$$\mathbb{P}(a_2, b_2) = \frac{\Phi_b(a_2, b_2)}{\mathcal{Z}} = \frac{5}{\mathcal{Z}} = 0.4167 \tag{2.11}$$

$$\mathbb{P}(a_0, b_0) = \frac{\Phi_b(a_0, b_0)}{\mathcal{Z}} = \mathbb{P}(a_1, b_1) = \mathbb{P}(a_2, b_4) = \frac{1}{\mathcal{Z}} = 0.0833 \tag{2.12}$$

since $\mathcal{Z}$ is equal to:

$$\mathcal{Z} = \sum_{\forall i=\{0,1,2\}, \forall j=\{0,1,2,3,4\}} \Phi_b(A = a_i, B = b_j) = 12 \tag{2.13}$$

Both Unary and Binary potentials, can be of two possible classes:

- Factors. The potential is simply described by a set of values characterizing the image of the factor. $\Phi_b(A, B)$ and $\Phi_u(A)$ of the previous example are both Simple shapes. Classes EFG::distribution::factor::cnst::Factor and EFG::distribution::factor::modif::Factor handles this kind of potentials.
- Exponential Factors. They are indicated with Ψ_i and their image set is defined as follows:

$$\Psi_i(X) = exp(w \cdot \Phi_i(X)) \tag{2.14}$$

  where Φ_i is a Simple shape. Classes EFG::distribution::factor::cnst::FactorExponential and EFG::distribution::factor::modif::Fact handles this kind of potentials. The weight w, can be tunable or not. In the first case, w is a free parameter whose value is decided after training the model (see Section 2.6), otherwise is a constant . Exponential factors with fixed weights will be denoted with $\overline{\Psi}_i$.

Figure 2.1 resumes all the possible categories of factors that can be present in the models handled by this library.

Figure 2.2 reports an example of undirected graph. Set $\mathcal{V}$ is made of 4 variables: A, B, C, D. There are 5 Binary potentials and 2 Unary ones. The graphical notation adopted for Fig. 2.2 will be adopted for the rest of this guide. Weights α, β, γ and δ are assumed for respectively $\Psi_{AC}, \Psi_{AB}, \Psi_{CD}, \Psi_B$. For the sake of clarity, the joint probability of the variables in Fig. 2.2 is computable as follows:

$$\begin{aligned} \mathbb{P}(A, B, C, D) &= \frac{E(A, B, C, D)}{\mathcal{Z}(\alpha, \beta, \gamma, \delta)} = \frac{E(A, B, CD)}{\sum_{\tilde{A}, \tilde{B}, \tilde{C}, \tilde{D}} E(\tilde{A}, \tilde{B}, \tilde{C}, \tilde{D})} \\ E(A, B, C, D) &= \Phi_A(A) \cdot exp(\alpha \Phi_{AC}(A, C)) \cdot exp(\beta \Phi_{AB}(A, B)) \cdots \\ \cdots & \quad \Phi_{BC}(B, C) \cdot exp(\gamma \Phi_{CD}(C, D)) \cdot \Phi_{BD}(B, D) \cdot exp(\delta \Phi_B(B)) \end{aligned} \tag{2.15}$$

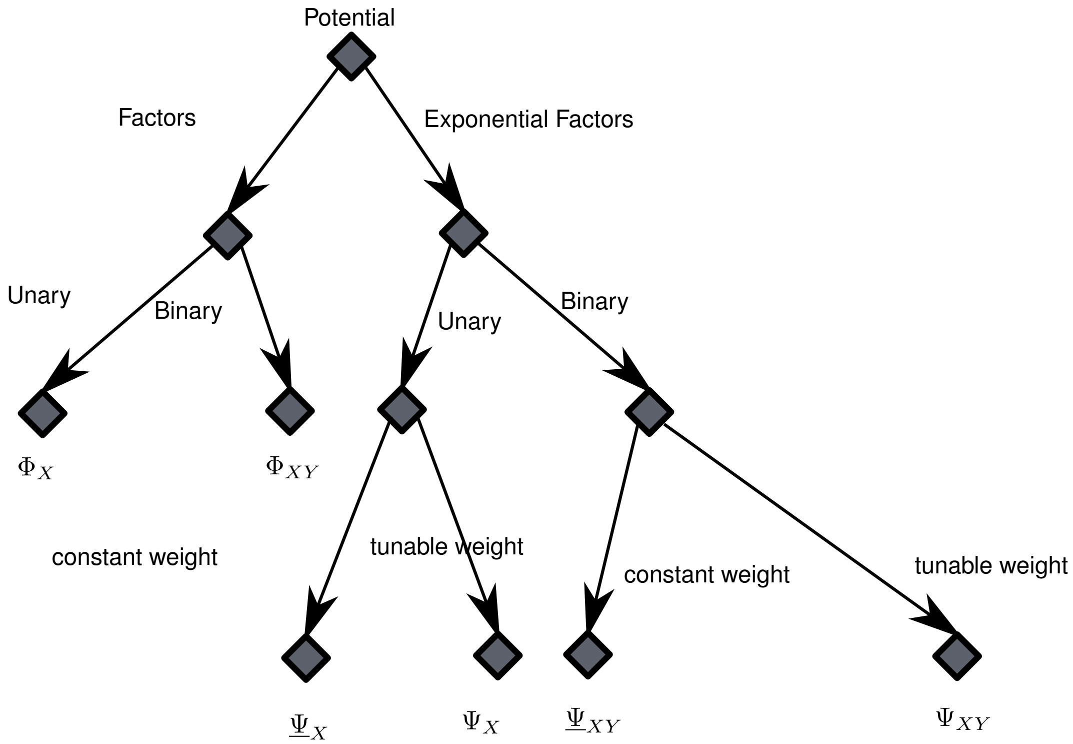


Figure 2.1 All the possible categories of factors, with the corresponding notation.

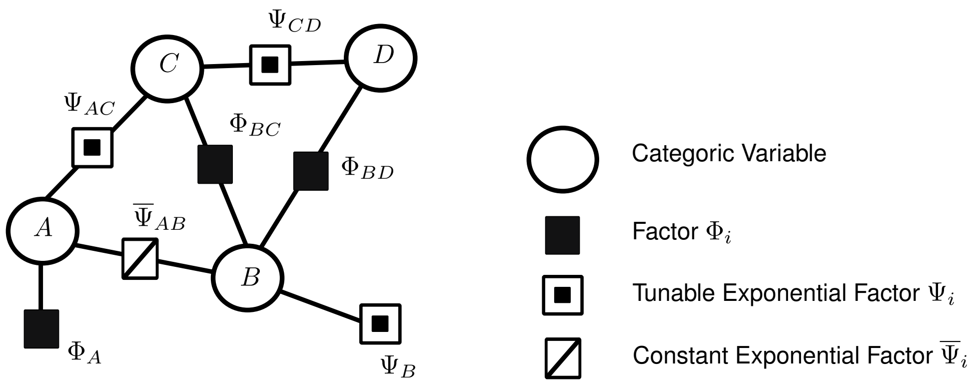


Figure 2.2 Example of graph: the legend of the right applies.

Graphical models are mainly used for performing belief propagation. Subset $\mathcal{O} = \{O_1, \cdots, O_f\} \subset \mathcal{V}$ is adopted for denoting the set of evidences: those variables in the net whose value become known. $\mathcal{O}$ can be dynamical or not. The hidden variables are contained in the complementary set $\mathcal{H} = \{H_1, \cdots, H_t\}$. Clearly $\mathcal{O} \cup \mathcal{H} = \mathcal{V}$ and $\mathcal{O} \cap \mathcal{H} = \emptyset$. H will be used for referring to the union of all the variables in the hidden set:

$$H = \bigcup_{i=1}^{t} H_i \tag{2.16}$$

while O is used for indicating the evidences:

$$O = \bigcup_{i=1}^{f} O_i \tag{2.17}$$

Knowing the joint probability distribution of variables in $\mathcal{V}$ (equation (2.7)) the conditional distribution of H w.r.t. O can be determined as follows:

$$\begin{aligned} \mathbb{P}(H = h|O = o) &= \frac{\mathbb{P}(H = h, O = o)}{\sum_{\forall \hat{h} \in Dom(H)} \mathbb{P}(H = \hat{h}, O = o)} \\ &= \frac{E(h, o)}{\sum_{\forall \hat{h} \in Dom(H)} E(\hat{h}, o)} = \frac{E(h, o)}{\mathcal{Z}(o)} \end{aligned} \tag{2.18}$$

The above computations are not actually done, since the number of combinations in the domain of $\mathcal{H}$ is huge also when considering a low-medium size graph. On the opposite, the marginal probability $\mathbb{P}(H_i = h_i|O = 0)$ of a single variable in $H_i \in \mathcal{H}$ is computationally tractable. Formally $\mathbb{P}(H_i = h_i|O = 0)$ is defined as follows:

$$\mathbb{P}(H_i = h_i|O = o) = \sum_{\forall \tilde{h} \in \{\mathcal{H} \setminus H_i\}} \mathbb{P}(H_i = h_i, \tilde{h}|O = o) \tag{2.19}$$

The above marginal distribution is essentially the conditional distribution of H_i w.r.t. O, no matter the other variables in $\mathcal{H}$.

A generic Random Field is a graphical model for which set $\mathcal{O}$ (and consequently $\mathcal{H}$) is dynamical: the set of observations as well the values assumed by the evidences may change during time. Random field are handled by class RandomField. Conditional Random Field are Random Field for which set $\mathcal{O}$ must be decided once and cannot change after. Only the values of the evidences during time may change. Class ConditionalRandomField is in charge of handling Conditional Random Field. Both Random Fields and Conditional Random Fields can be learnt knowing a training set, see Section 2.6. On the opposite, class Graph handles constant graphs: they are conceptually similar to Random Fields but learning is not possible. Indeed, all the Exponential Shape involved must be constant.

The rest of this Chapter is structured as follows. Section 2.2.2 will introduce the message passing algorithm, which is the pillar for performing belief propagation. Section 2.3 will expose the concept of maximum a posteriori estimation, useful when querying a graph, while Section 2.4 will address Gibbs sampling for producing a training set of a known model. Section 2.5 will present the concept of subgraph which is a useful way for computing the marginal probabilities of a sub group of variables in $\mathcal{H}$. Finally, 2.6 will discuss how the learning of a graphical model is done, with the aim of computing the weights of the Exponential shapes that are tunable.

2.2 Message Passing

Message passing is a powerful but conceptually simple algorithm adopted for propagating the belief across a net. Such a propagation is the starting point for performing many important operations, like computing the marginal distributions of single variables or obtaining sub graphs. Before detailing the steps involved in the message passing algorithm, let's start from an example of belief propagation. Without loss of generality we assume all the factors as simple Factors.

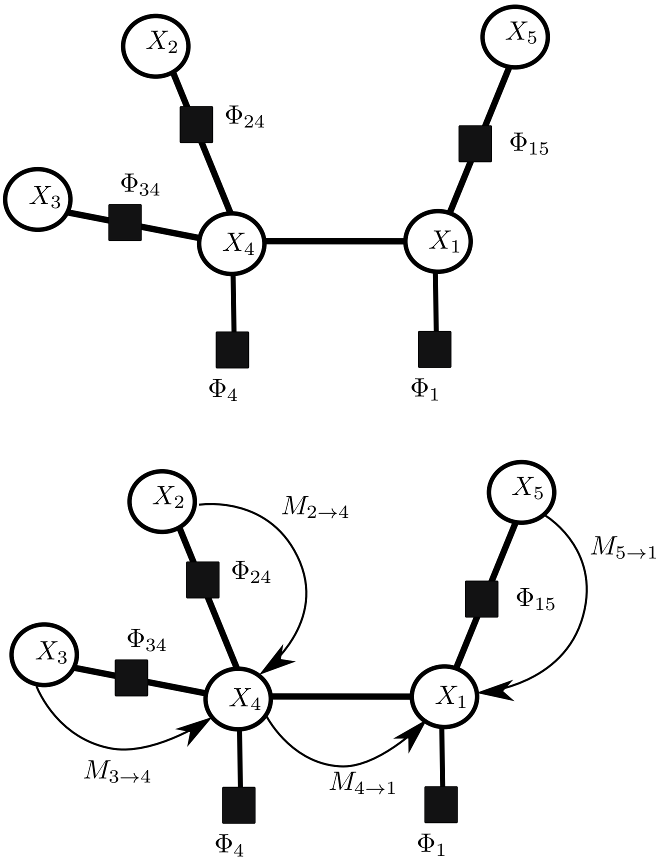


Figure 2.3 Example of graph adopted for explaining the message passing algorithm. Below are reported the messages to compute for obtaining the marginal probability of variable x_1

2.2.1 Belief propagation

Consider the graph reported in Figure 2.3. Supposing for the sake of simplicity that no evidences are available (i.e. $\mathcal{O} = \emptyset$). We are interested in computing $\mathbb{P}(X_1)$, i.e. the marginal probability of X_1. Recalling the definition introduced in the previous Section, the marginal probability is obtained by the following computation:

$$\mathbb{P}(x_1) = \sum_{\forall \tilde{x}_{2,3,4,5} \in \cup_{i=2}^{5} X_i} \mathbb{P}(x_1, \tilde{x}_{2,3,4,5}) \tag{2.20}$$

Simplifying the notation and getting rid of the normalization coefficient $\mathcal{Z}$ we can state the following:

$$\mathbb{P}(x_1) \propto \sum_{\tilde{x}_{2,3,4,5}} E(x_1, \tilde{x}_{2,3,4,5}) \tag{2.21}$$

Adopting the algebraic properties of the sums-products we can distribute the computations as follows:

$$\mathbb{P}(x_1) \propto \Phi_1(x_1) \sum_{\tilde{x}_5} \Phi_{15}(x_1, \tilde{x}_5) \sum_{\tilde{x}_4} \Phi_{14}(x_1, \tilde{x}_4) \Phi_4(\tilde{x}_4) \sum_{\tilde{x}_2} \Phi_{24}(\tilde{x}_{2,4}) \sum_{\tilde{x}_3} \Phi_{34}(\tilde{x}_{3,4}) \tag{2.22}$$

The first variable to marginalize can be $\tilde{x}_2$ or $\tilde{x}_3$, since they are involved in the last terms of the sums products. The 'messages' $M_{2\to4}$, $M_{3\to4}$ are defined as follows:

$$\begin{aligned} M_{2\to4}(\tilde{x}_4) &= \sum_{\tilde{x}_2} \Phi_{24}(\tilde{x}_{2,4}) \\ M_{3\to4}(\tilde{x}_4) &= \sum_{\tilde{x}_3} \Phi_{34}(\tilde{x}_{3,4}) \end{aligned} \tag{2.23}$$

[2]combinations having a null probability were omitted

Inserting $M_{2\to4}$ and $M_{3\to4}$ into equation (2.22) leads to:

$$\mathbb{P}(x_1) \propto \Phi_1(x_1)\sum_{\tilde{x}_5}\Phi_{15}(x_1,\tilde{x}_5)\sum_{\tilde{x}_4}\Phi_{14}(x_1,\tilde{x}_4)\Phi_4(\tilde{x}_4)M_{2\to4}(\tilde{x}_4)M_{3\to4}(\tilde{x}_4) \tag{2.24}$$

At this point the messages $M_{4\to1}$ and $M_{5\to1}$ can be computed in the following way:

$$\begin{aligned} M_{4\to1(x_1)} &= \sum_{\tilde{x}_4}\Phi_{14}(x_1,\tilde{x}_4)\Phi_4(\tilde{x}_4)M_{2\to4}(\tilde{x}_4)M_{3\to4}(\tilde{x}_4) \\ M_{5\to1}(x_1) &= \sum_{\tilde{x}_5}\Phi_{15}(x_1,\tilde{x}_5) \end{aligned} \tag{2.25}$$

After inserting $M_{4\to1}$ and $M_{5\to1}$ into equation (2.24) we obtain:

$$\begin{aligned} \mathbb{P}(x_1) &\propto \Phi_1(x_1)M_{4\to1}(x_1)M_{5\to1}(x_1) \\ \mathbb{P}(x_1) &= \frac{\Phi_1(x_1)M_{4\to1}(x_1)M_{5\to1}(x_1)}{\sum_{\tilde{x}_1}\Phi_1(\tilde{x}_1)M_{4\to1}(\tilde{x}_1)M_{5\to1}(\tilde{x}_1)} \end{aligned} \tag{2.26}$$

which ends the computations. Messages are, in a certain sense, able to simplify the graph sending some information from an area of the graph to another one. Indeed, variables can be replace by messages, which can be treated as additional factors. Figure 2.3 resumes the computations exposed. Notice that the computation of $M_{4\to1}$ must be done after computing the messages $M_{2\to4}$ and $M_{3\to4}$, while $M_{5\to1}$ can be computed independently from all the others.

2.2.2 Message Passing

The aforementioned considerations can be extended to a general structured graph. Look at Figure 2.4: the computation of Message $M_{B\to A}$ can be performed only after having computed all the messages $M_{V_{1,\cdots,m}\to B}$, i.e. the messages incoming from all the neighbours of B a part from A. Clearly $M_{B\to A}$ is computed as follows:

$$\begin{aligned} M_{B\to A}(a) &= \sum_{\tilde{b}}\Phi_{AB}(a,\tilde{b})M_{V1\to B}(\tilde{b})\cdot\dots\cdot M_{Vm\to B}(\tilde{b}) \\ &= \sum_{\tilde{b}}\Phi_{AB}(a,\tilde{b})\prod_{i=1}^{m}M_{V_i\to B}(\tilde{b}) \end{aligned} \tag{2.27}$$

Essentially, it's like having simplified the graph: we can append to A the message $M_{B\to A}(a)$ as it's a Factor, deleting factor Ψ_{AB} and all the other portions of the graph, see Figure 2.4. In turn, $M_{B\to A}(a)$ will be adopted for computing the message outgoing from A.
The above elimination is not actually done: all messages incoming to all nodes of a graph are computed and stored for using them in subsequent queries. This is partially not true when considering the evidences. Indeed, when the values of the evidences are retrieved, variables in $\mathcal{O}$ are temporary deleted and replaced with messages, see Figure 2.5. Suppose variable C is connected to a variable A through a binary potential $\Phi_{AC}(A,C)$ and to variable B through $\Phi_{B,C}$. Suppose also that variable C is an evidence assuming a value equal to $\hat{c}$, then the messages sent to A and B can be computed independently as follows:

$$\begin{aligned} M_{C\to A}(a) &= \Phi_{AC}(a,\hat{c}) \\ M_{C\to B}(b) &= \Phi_{BC}(b,\hat{c}) \end{aligned} \tag{2.28}$$

Therefore all the variables that become evidences can be considered as leaves of the graph, sending messages to all the neighbouring nodes, possibly splitting an initial compact graph into many subgraphs, refer to Figure 2.5. Such computations are automatically handled by the library.

All the above considerations are valid when considering politree, i.e. graph without loops. Indeed, for these kind of graphs the message passing algorithm is able in a finite number of iterations to compute all the messages, see Figure 2.6. The same is not true when having loopy graphs (see Figure 2.7), since deadlocking situations arise: no further messages can be computed since for every nodes some incoming ones are missing. In such cases a variant of the message passing called loopy belief propagation can be adopted. Loopy belief propagation initializes all the messages to basic shapes having the values of the image all equal to 1 and then recomputes all the messages of all the variables till convergence.
You don't have to handle the latter aspect: the belief propagation mechanism is automatically handled by the library, according to the connectivity of the model for which a query is asked.

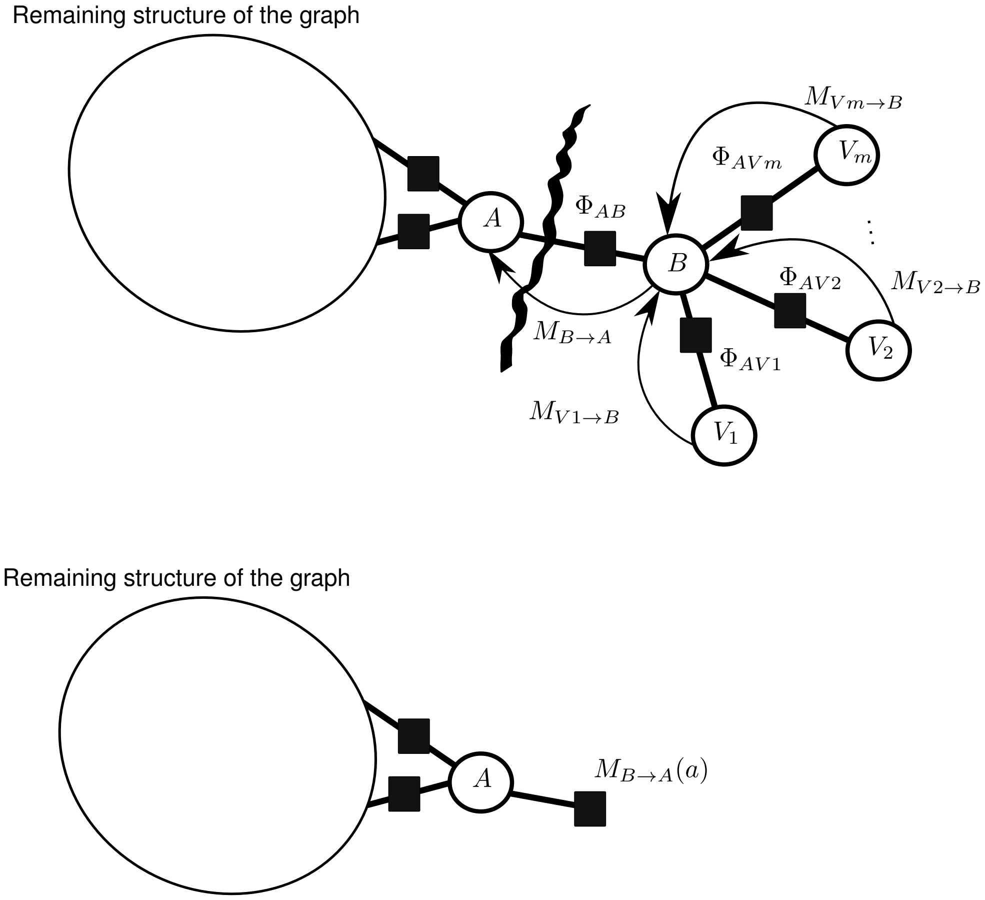


Figure 2.4 On the top the general mechanism involved in the message computation; on the bottom the simplification of the graph considering the computed message.

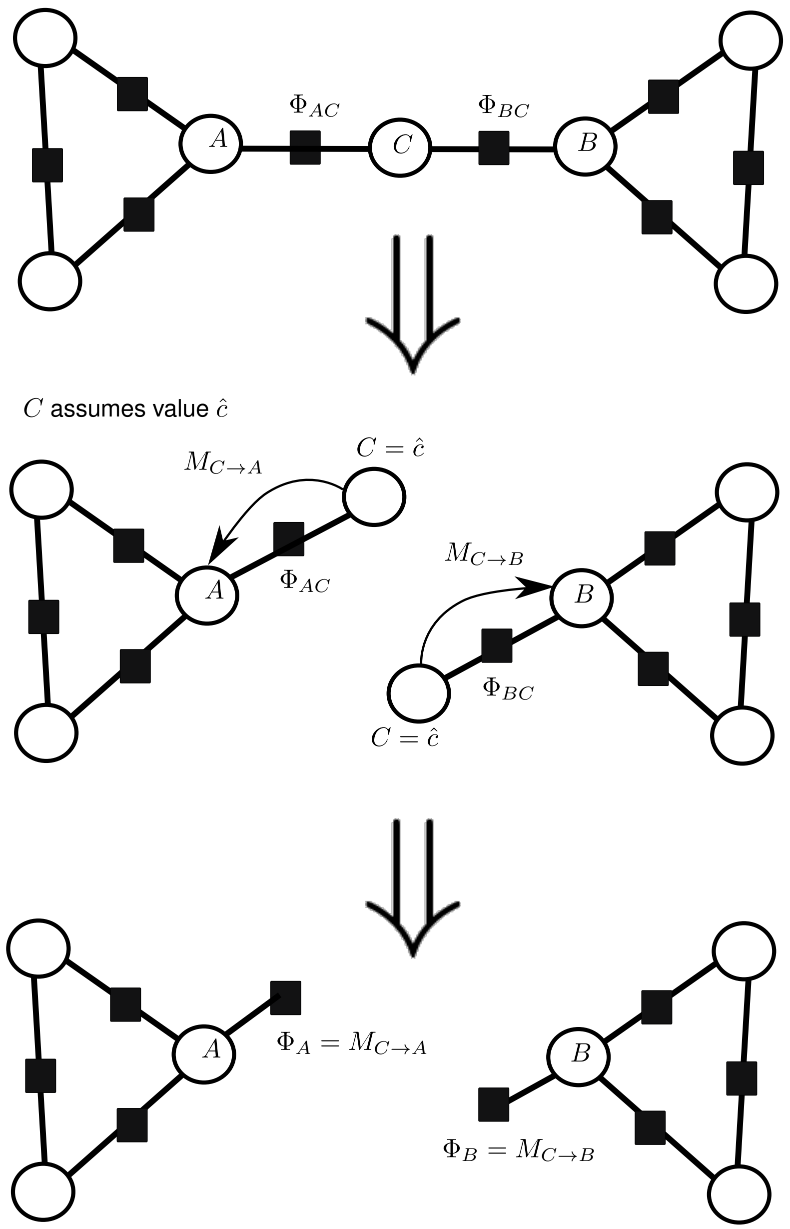


Figure 2.5 When variable C become an evidence, is temporary deleted from the graph, replaced by messages.

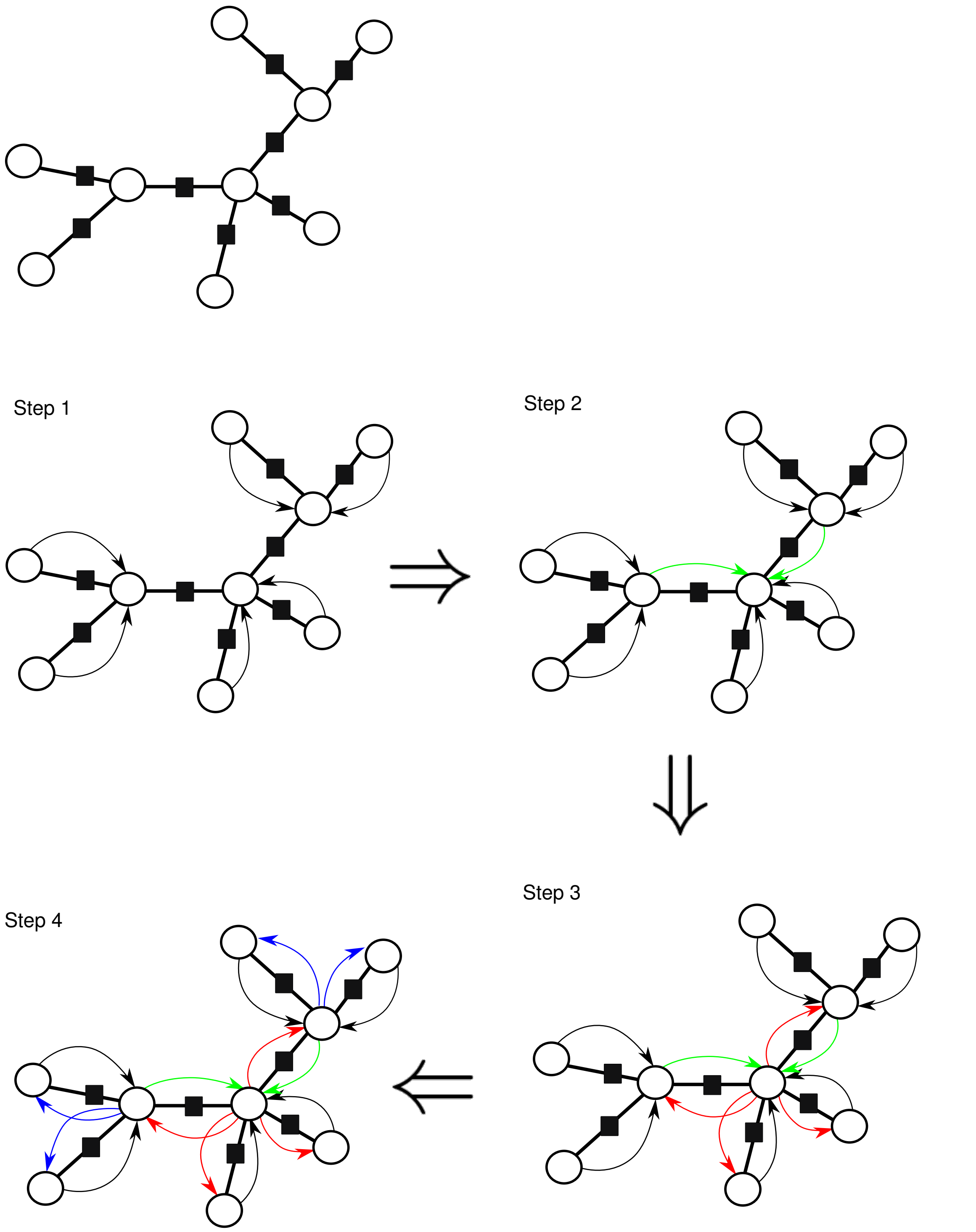


Figure 2.6 Steps involved for computing the messages of the politree represented at the top. The leaves are the first nodes for which the outgoing messages can be computed.

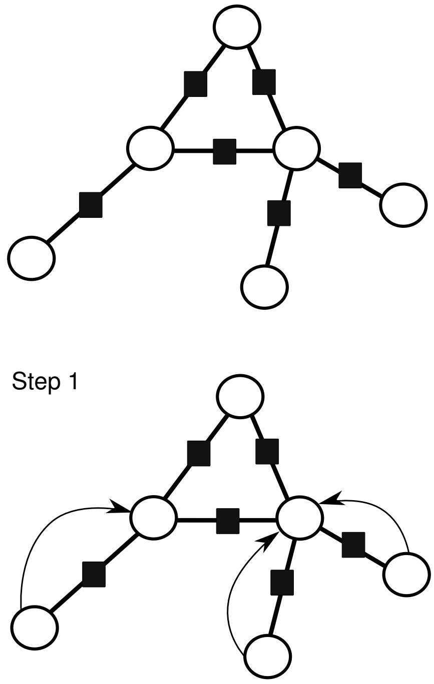


Figure 2.7 Steps involved for computing the messages on a loopy graph: after computing the messages outgoing from the leaves, a deadlock is reached since no further messages are computable.

2.3 Maximum a posteriori estimation

Suppose we are not interested in determining the marginal probability of a specific variable, but rather we want the combination in the hidden set $\mathcal{H}$ that maximises the probability $\mathbb{P}(H_{1,\cdots,n}|O)$. Clearly, we could try to compute the entire distribution $\mathbb{P}(H_{1,\cdots,n}|O)$ and then take the value of H maximising that distribution. However, this is not computationally possible since even for low medium size graphs the size of $Dom(\cup_{\forall H_i \in \mathcal{H}} H_i)$ can be huge.
Maximum a posteriori estimations solve this problem: the value maximising $\mathbb{P}(H_{1,\cdots,n}|O)$ is computed, without explicitly building the entire distribution $\mathbb{P}(H_{1,\cdots,n}|O)$. This is achieved by performing belief propagation with a slightly different version of the message passing algorithm presented in Section 2.2.2. Referring to Figure 2.4, the message to A is computed as follows when performing a maximum a posteriori estimation:

$$M_{B\to A}(a) = max_{\tilde{b}}\{\Phi_{AB}(a,\tilde{b})\prod_{i=1}^{m} M_{V_i\to B}(\tilde{b})\}\} \tag{2.29}$$

Essentially, the summation in equation (2.27) is replaced with the max operator. After all messages are computed, the estimation $h_{MAP} = \{h_{1MAP}, h_{2MAP}, \cdots\}$ is obtained by considering for every variable in $\mathcal{H}$ the value maximising:

$$h_{iMAP} = argmax\{\Phi_{Hi}(h_{iMAP})\prod_{k=1}^{L} M_k(h_{iMAP})\} \tag{2.30}$$

where $M_{1,\cdots,L}$ refer to all the messages incoming to H_i. To be precise, this procedure is not guaranteed to return the value actually maximising $\mathbb{P}(H_{1,\cdots,n}|O)$, but at least a strong local maximum is obtained.
At this point it is worthy to clarify that the combination $h_{MAP} = \{h_{1MAP}, h_{2MAP}, \cdots\}$ could not be obtained by simply assuming for every H_i the realization maximising the marginal distribution:

$$h_{MAP} \neq \{argmax(\mathbb{P}(h_1)), \cdots, argmax(\mathbb{P}(h_n))\} \tag{2.31}$$

This is due to the fact that $\mathbb{P}(H_{1,\cdots,n}|O)$ is a joint probability distribution, while the marginals $\mathbb{P}(H_i)$ are not. For better understanding this aspect consider the graph reported in Figure 2.8, with the potentials Φ_{XA}, Φ_{AB} and Φ_{YB} having the images defined in table 2.5. Suppose discovering that $X = 0$ and $Y = 1$. Then, performing the standard message passing algorithm explained in the previous Section we obtain the messages reported in Figure

	b_0	b_1
a_0	2	0
a_1	0	2

	x_0	x_1
a_0	1	0.1
a_1	0.1	1

	y_0	y_1
b_0	1	0.1
b_1	0.1	1

Table 2.5 Factors involved in the graph of Figure 2.8.

A	B	$E(A,B,X=0,Y=1)$
0	0	0.2
0	1	0
1	0	0
1	1	0.2

Table 2.6 Factors involved in the graph of Figure 2.8.

2.8. Clearly individual marginals for A and B would be equal to:

$$\mathbb{P}(A) = \begin{pmatrix} \mathbb{P}(A=0) \\ \mathbb{P}(A=1) \end{pmatrix} = \begin{pmatrix} 0.5 \\ 0.5 \end{pmatrix}$$
$$\mathbb{P}(B) = \begin{pmatrix} \mathbb{P}(B=0) \\ \mathbb{P}(B=1) \end{pmatrix} = \begin{pmatrix} 0.5 \\ 0.5 \end{pmatrix} \tag{2.32}$$

Therefore, all the combinations $\{A=0,B=0\}$, $\{A=0,B=1\}$, $\{A=1,B=0\}$, $\{A=1,B=1\}$ maximise $\mathbb{P}(A,B|O)$. However, it easy to prove that $E(A,B,X,Y)$ assumes the values reported in table 2.6. Therefore, the combinations actually maximising the joint distribution $\mathbb{P}(A,B|O)$ are $\{A=0,B=0\}$ and $\{A=1,B=1\}$, leading to a different result.

2.4 Gibbs sampling

Gibbs sampling is a Monte Carlo method for obtaining samples from a joint distribution of variables $X_{1,\cdots,m}$, without explicitly compute that distribution. Indeed, Gibbs sampling is an iterative method which requires every time to determine the conditional distribution of a single variable X_i w.r.t to all the others in the group.
More formally the algorithm starts with an initial combination of values $\{x^1_{1,\cdots,m}\}$ for the variable $\cup_{i=\{1,\cdots,m\}} X_i$. At every iteration, all the values of that combination are recomputed. At the j^{th} iteration the value of x^{j+1}_k for the subsequent iteration is obtaining by sampling from the following marginal distribution:

$$x^{j+1}_k \sim \mathbb{P}(x_k | x^j_{\{1,\cdots,m\}\setminus k}) \tag{2.33}$$

After an initial transient, the samples cumulated during the iterations can be considered as drawn from the joint distribution involving group $X_{1,\cdots,m}$.
This algorithm can be easily applied to graphical model. Indeed the methodologies exposed in Section 2.2.2 can be applied for determining the conditional distribution of a single variable $H_i \in \mathcal{H}$ w.r.t all the others (as well the evidences in $\mathcal{O}$), assuming all variables in $\mathcal{H} \setminus H_i$ as additional observations and computing the marginal probability of H_i.

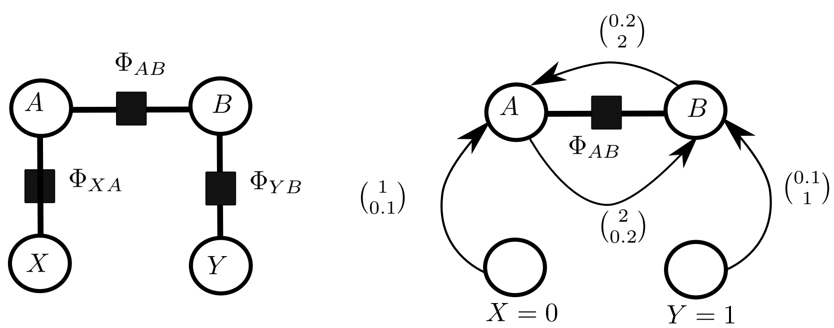


Figure 2.8 Example of graph adopted. When the evidences are retrieved, the messages computed by making use of the message passing algorithm are reported below.

2.5 Sub graphs

As explained in Section 2.2.2, the marginal probability of a variable $H_i \in \mathcal{H}$ can be efficiently computed by considering the messages produced by the message passing algorithm. The same messages can be also used for performing graph reduction, with the aim to model the joint probability distribution of a subset of variables $\{H_1, H_2, H_3\} \subset \mathcal{H}$, i.e. $\mathbb{P}(H_{1,2,3}|O)$. The latter quantity is the marginal probability of the subset of variables of interest.
The aim of message passing is essentially to simplify the graph, condensing all the belief information into the messages. Such property is exploited for computing sub graphs. Without loss of generality assume from now on $\mathcal{O} = \emptyset$. Consider the graph in Figure 2.9 and suppose we are interested in modelling $\mathbb{P}(A, B, C)$, no matter the values of the other variables. After computing all the messages exploiting message passing, the sub graph reported in Figure 2.9 is the one modelling $\mathbb{P}(A, B, C)$. Actually, that sub graph is a graphical model itself, for which all the properties exposed so far hold. For example the energy function E is computable as follows:

$$E(A = a, B = b, C = c) = \Phi_{AB}(a, b)\Phi_{BC}(b, c)\Phi_{AC}(a, c)M_{X\to A}(a)M_{Y\to B}(b) \tag{2.34}$$

while the joint probability of A, B and C can be computed in this way:

$$\mathbb{P}(A = a, B = b, C = c) = \frac{E(a, b, c)}{\sum_{\forall \tilde{a},\tilde{b},\mathbf{c}} E(\tilde{a}, \tilde{b}, \tilde{c})} \tag{2.35}$$

Notice that in this case the graph is significantly smaller than the originating one, implying that the above computations can be performed in an acceptable time.
Also Gibbs sampling can be applied to a reduced graph, producing samples drawn from the marginal probability $\mathbb{P}(A, B, C)$.
The reduction described so far is always possible when considering a subset of variables forming a connected subportion of the original graph, i.e. after reduction there must be a unique sub structure. For instance, variables X and Y of the graph in Figure 2.10 do not respect the latter specification, meaning that it is not possible to build a sub graph involving X and Y.

2.6 Learning

The aim of learning is to determine the optimal values for the w (equation (2.14)) of all the tunable potentials (see Section 2.1) Ψ. To this aim two cases must be distinguished:

- Learning must be performed for a RandomField: see Section 2.6.1
- Learning must be performed for a ConditionalRandomField: see Section 2.6.2

No matter the case, the population of tunable weights, i.e. the weights of the tunable Exponential Factors of the model, will be indicated with W:

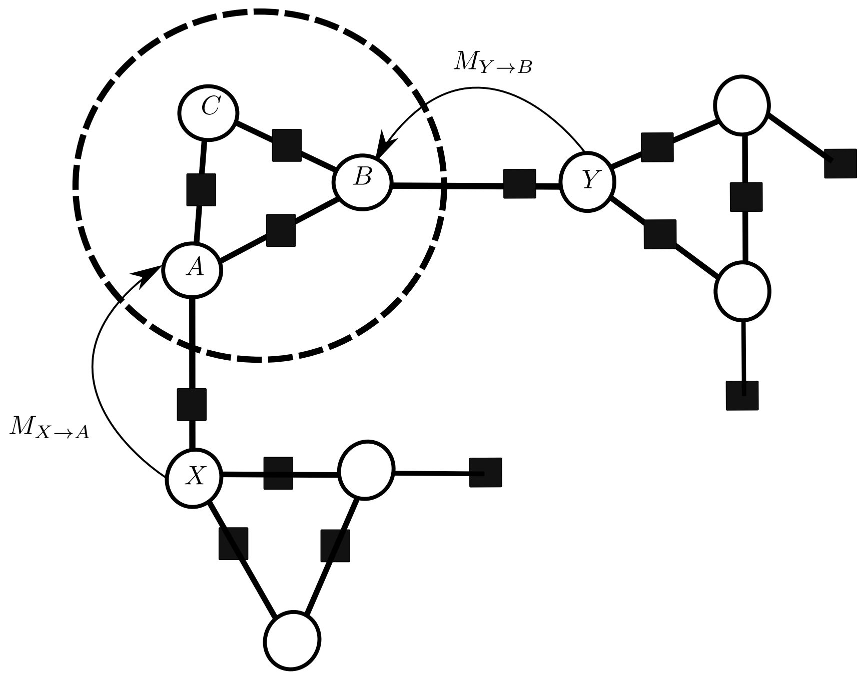
$$W = \{w_1, \cdots, w_D\} \tag{2.36}$$

w_i will refer to the i^{th} free parameter of the model. For the purpose of learning, we assume $\mathcal{O} = \emptyset$. Learning considers a training set $T = \{t_1, \cdots, t_N\}$ made of realizations of the joint distribution correlating all the variables in $\mathcal{V}$, no matter the fact that they are involved in tunable or non tunable potentials. As exposed in Section 2.1, if W is known, the probability of a combination t_j can be evaluated as follows:

$$\mathbb{P}(t_j) = \frac{E(t_j, W)}{\mathcal{Z}(W)} \tag{2.37}$$

At this point we can observe that the energy function is the product of two main factors: one depending from t_j and W and the other depending only upon t_j representing the contribution of all the non tunable potentials (Factors and Exponential Factors, see Section 2.1):

$$\begin{aligned} E(t_j, W) &= exp\big(w_1\Phi_1(t_j)\big)\cdot \cdots \cdot exp\big(w_D\Phi_D(t_j)\big)\cdot E_0(t_j) \\ &= exp\Big(\sum_{i=1}^{D} w_i\Phi_i(t_j)\Big)\cdot E_0(t_j) \end{aligned} \tag{2.38}$$



Sub graph involving A, B, C

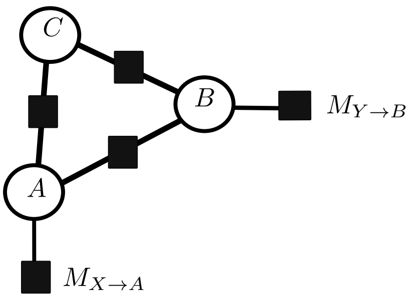


Figure 2.9 Example of graph reduction.

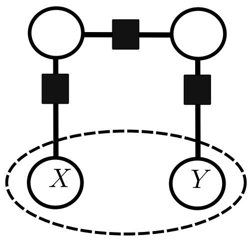


Figure 2.10 Example of a subset of variables for which the graph reduction is not possible.

The likelihood function L can be defined as follows:

$$L = \prod_{t_j \in T} \mathbb{P}(t_j) \tag{2.39}$$

passing to the logarithmic likelihood and dividing by the training set size N we obtain:

$$\begin{aligned} J = \frac{log(L)}{N} &= \sum_{t_j \in T} \frac{log(\mathbb{P}(t_j))}{N} \\ &= \sum_{t_j \in T} \frac{log(E(t_j, W)) - log(\mathcal{Z}(W)}{N} \\ &= \frac{1}{N} \sum_{t_j \in T} log(E(t_j, W)) - log(\mathcal{Z}(W)) \\ &= \frac{1}{N} \sum_{t_j \in T} \big(\sum_{i=1}^{D} w_i \Phi_i(t_j) \big) - log(\mathcal{Z}(W)) + \cdots \\ &+ \frac{1}{N} \sum_{t_j \in T} log(E_0(t_j)) \end{aligned} \tag{2.40}$$

The aim of learning become essentially to find the value of W maximising J. This is typically done iteratively, by searching at every iteration the optimum along a direction similar to the one given by the gradient $\frac{\partial J}{\partial W}$. The way the gradient is exploited to update the searching direction characterize the kind of aproach.
The basic gradient descend approach assumes the searching direction equal to the gradient, while Quasi Newton methods (`https://www.jstor.org/stable/2006193`) use an estimation of the hessian (computed using only the gradient variation) in order to correct the direction given by the gradient. Non linear conjugate approach (`https://www.caam.rice.edu/~yzhang/caam554/pdf/cgsurvey.pdf`) implements memory-based approaches that compute the new searching direction by considering both the actual value of the gradient as well as the old used direction.
The above methods are already implemented inside this library.

2.6.1 Learning of unconditioned model

The computations to perform for evaluating the gradient $\frac{\partial J}{\partial W}$ in case of unconditioned model will be exposed in this Section. Notice that in equation (2.40), term $\sum_{t_j \in T} log(E_0(t_j))$ is constant and consequently will be not considered for computing the gradient of J. Equation (2.40) can be rewritten as follows:

$$\begin{aligned} J &= \alpha(T, W) - \beta(W) \\ \alpha &= \frac{1}{N} \sum_{t_j \in T} \big(\sum_{i=1}^{D} w_i \Phi_i(t_j) \big) & (2.41) \\ \beta &= log(\mathcal{Z}(W)) & (2.42) \end{aligned}$$

α is influenced by T, while the same is not valid for β.

2.6.1.1 Gradient of α

By the analysis of the equation (2.41) it is clear that:

$$\frac{\partial \alpha}{\partial w_i} = \frac{1}{N} \sum_{t_j \in T} \Phi_i(t_j) \tag{2.43}$$

2.6.1.2 Gradient of β

The computation of $\frac{\partial \beta}{\partial w_i}$ requires to manipulate a little bit equation (2.42). Firstly the derivative of the logarithm must be computed:

$$\frac{\partial \beta}{\partial w_i} = \frac{1}{\mathcal{Z}} \frac{\partial \mathcal{Z}}{\partial w_i} \tag{2.44}$$

The normalizing coefficient $\mathcal{Z}$ is made of the following terms (see also equation (2.7)):

$$\mathcal{Z}(W) = \sum_{\tilde{V} \in \bigcup_{i=1}^{p} V_i} \left(exp(\sum_{i=1}^{D} w_i \Phi_i(\tilde{V})) \cdot E_0(\tilde{V}) \right) \tag{2.45}$$

Introducing equation (2.45) into (2.44) leads to:

$$\begin{aligned}
\frac{\partial \beta}{\partial w_i} &= \frac{1}{\mathcal{Z}} \frac{\partial}{\partial w_i} \left(\sum_{\tilde{V}} exp(\sum_{i=1}^{D} w_i \Phi_i(\tilde{V})) E_0(\tilde{V}) \right) \\
&= \frac{1}{\mathcal{Z}} \sum_{\tilde{V}} \frac{\partial}{\partial w_i} \left(exp(\sum_{i=1}^{D} w_i \Phi_i(\tilde{V})) \right) E_0(\tilde{V}) \\
&= \frac{1}{\mathcal{Z}} \sum_{\tilde{V}} exp(\sum_{i=1}^{D} w_i \Phi_i(\tilde{V})) E_0(\tilde{V}) \Phi_i(\tilde{V}) \\
&= \sum_{\tilde{V}} \frac{exp(\sum_{i=1}^{D} w_i \Phi_i(\tilde{V})) E_0(\tilde{V})}{\mathcal{Z}} \Phi_i(\tilde{V}) \\
&= \sum_{\tilde{V}} \frac{E(\tilde{V})}{\mathcal{Z}} \Phi_i(\tilde{V}) \\
&= \sum_{\tilde{V}} \mathbb{P}(\tilde{V}) \Phi_i(\tilde{V})
\end{aligned} \tag{2.46}$$

Last term in the above equations can be further elaborated. Assume that the variables involved in potential Φ_j are $V_{1,2}$, then:

$$\begin{aligned}
\frac{\partial \beta}{\partial w_i} &= \sum_{\tilde{V}} \mathbb{P}(\tilde{V}) \Phi_i(\tilde{V}) \\
&= \sum_{\tilde{V}_{1,2}} \Phi_i(\tilde{V}_{1,2}) \sum_{\tilde{V}_{3,4,\dots}} \mathbb{P}(\tilde{V}_{1,2,3,4,\dots}) \\
&= \sum_{\tilde{V}_{1,2}} \Phi_i(\tilde{V}_{1,2}) \mathbb{P}(\tilde{V}_{1,2})
\end{aligned} \tag{2.47}$$

where $\mathbb{P}(\tilde{V}_{1,2})$ is the marginal probability (see the initial part of Section 2.1) of the variables involved in the potential Φ_i, which can be easily computable by considering the sub graph containing only V_1 and V_2 as variables (see Section 2.5). Notice that in case Φ_i is a unary potential the same holds, considering the marginal distribution of the single variable involved by Φ_i:

$$\frac{\partial \beta}{\partial w_i} = \sum_{\forall \tilde{V}_1} \Phi_i(\tilde{V}_1) \mathbb{P}(\tilde{V}_1) \tag{2.48}$$

which can be easily obtained through the message passing algorithm (Section 2.2.2).

After all the manipulations performed, the gradient $\frac{\partial J}{\partial w_i}$ has the following compact expression:

$$\frac{\partial J}{\partial w_i} = \frac{1}{N} \sum_{j=1}^{N} \Phi_i(D_j^i) - \sum_{\tilde{D}^i} \mathbb{P}(\tilde{D}^i) \Phi_i(\tilde{D}^i) \tag{2.49}$$

2.6.2 Learning of conditioned model

For such models leaning is more demanding as will be exposed. Recalling the definition provided in the final part of Section 2.1, Conditional Random Fields are graphs for which the set of observations $\mathcal{O}$ is fixed. The training set T is made of realizations of both $\mathcal{H}$ and $\mathcal{O}$:

$$\begin{aligned} T &= \{t_1, \cdots, t_N\} \\ &= \{\{h_1, o_1\}, \cdots, \{h_N, o_N\}\} \end{aligned} \tag{2.50}$$

We recall , equation (2.18), that the conditional probability of the hidden variables w.r.t. the observed ones is defined as follows:

$$\begin{aligned} \mathbb{P}(h_j, o_j) &= \frac{E(h_j, o_j, W)}{\mathcal{Z}(o_j, W)} \\ E(h_j, o_j, W) &= exp(\sum_{i=1}^{D} w_i \Phi_i(h_j, o_j)) E_0(h_j, o_j) \\ \mathcal{Z}(o_j, W) &= \sum_{\tilde{h}} E(\tilde{h}, o_j, W) \end{aligned} \tag{2.51}$$

The aim of learning is to maximise a likelihood unction L defined in this case as follows:

$$L = \prod_{h_j \in T} \mathbb{P}(h_j | o_j) \tag{2.52}$$

Passing to the logarithms and dividing by the training set size we obtain the following objective function J:

$$\begin{aligned} J &= \frac{log(L)}{N} \\ &= \frac{1}{N} \sum_{h_j, o_j \in T} log(E(h_j, o_j, W)) - \frac{1}{N} \sum_{h_j, o_j \in T} log(Z(o_j, W)) \\ &= \frac{1}{N} \sum_{h_j, o_j \in T} (\sum_{i=1}^{D} w_i \Phi_i(h_j, o_j)) - \frac{1}{N} \sum_{h_j, o_j \in T} log(Z(o_j, W)) \\ &+ \frac{1}{N} \sum_{h_j, o_j \in T} log(E_0(h_j, o_j)) \end{aligned} \tag{2.53}$$

Neglecting E_0 which not depends upon W, equation (2.53) can be rewritten as follows:

$$\begin{aligned} J &= \alpha(T, W) - \beta(T, W) \\ \alpha(T, W) &= \frac{1}{N} \sum_{h_j, o_j} (\sum_{i=1}^{D} w_i \Phi_i(h_j, o_j)) \\ \beta(T, W) &= \frac{1}{N} \sum_{o_j} log(\mathcal{Z}(o_j, W)) \end{aligned} \tag{2.54}$$

At this point, an important remark must be done: differently from the β defined in equation (2.42), $\beta(T, W)$ of conditioned model is a function of the training set. The latter observation has an important consequence: when performing learning of unconditioned model, belief propagation (i.e. the computation of the messages through message passing with the aim of computing the marginal probabilities of the groups of variables involved in the factor of the model) must be performed once for every iteration of the gradient descend; on the opposite when considering conditioned model, belief propagation must be performed at every iteration for every element of the training set, see equation (2.58). This makes the learning of conditioned models much more computationally demanding. This price is paid in order to not model the correlation among the observations [3], which can be interesting for many applications. The computation of $\frac{\partial \alpha}{\partial w_i}$ is analogous to the one of non conditioned model, equation (2.43).

[3]that can be highly correlated

2.6.2.1 Gradient of β

Following the same approach in Section 2.6.1.2, the gradient of β can be computed as follows:

$$\begin{aligned}
\frac{\partial \beta}{\partial w_i} &= \frac{1}{N}\sum_{j=1}^{N}\frac{\partial log(\mathcal{Z}(o_j, W))}{\partial w_i} \\
&= \frac{1}{N}\sum_{j=1}^{N}\frac{1}{\mathcal{Z}(o_j)}\frac{\partial \mathcal{Z}(o_j, W)}{\partial w_i} \\
&= \frac{1}{N}\sum_{j=1}^{N}\frac{\partial}{\partial w_i}\Big(\sum_{\tilde{h}} exp(\sum_{i=1}^{D} w_i \Phi_i(\tilde{h}, o_j)) E_0(\tilde{h}, o_j)\Big) \\
&= \frac{1}{N}\sum_{j=1}^{N}\sum_{\tilde{h}}\Big(exp(\sum_{i=1}^{D} w_i \Phi_j(\tilde{h}, o_j)) E_0(\tilde{h}, o_j)\Phi_i(\tilde{h}, o_j)\Big) \\
&= \frac{1}{N}\sum_{j=1}^{N}\sum_{\tilde{h}}\frac{E(\tilde{h}, o_j, W)}{\mathcal{Z}(o_1)}\Phi_i(\tilde{h}, o_j) \\
&= \frac{1}{N}\sum_{j=1}^{N}\sum_{\tilde{h}}\mathbb{P}(\tilde{h}|o_j)\Phi_i(\tilde{h}, o_j)
\end{aligned} \tag{2.55}$$

Suppose the variables involved in the factor Φ_j are $\tilde{h}_{1,2}$, then:

$$\begin{aligned}
\frac{\partial \beta}{\partial w_i} &= \frac{1}{N}\sum_{j=1}^{N}\sum_{\tilde{h}}\mathbb{P}(\tilde{h}|o_j)\Phi_i(\tilde{h}, o_j) \\
&= \frac{1}{N}\sum_{j=1}^{N}\sum_{\tilde{h}_{1,2}}\Phi_i(\tilde{h}_{1,2})\sum_{\tilde{h}_{3,4,\dots}}\mathbb{P}(\tilde{h}_{1,2,3,4,\dots}|o_j) \\
&= \frac{1}{N}\sum_{j=1}^{N}\sum_{\tilde{h}_{1,2}}\Phi_i(\tilde{h}_{1,2})\mathbb{P}(\tilde{h}_{1,2}|o_j)
\end{aligned} \tag{2.56}$$

where $\mathbb{P}(\tilde{h}_{1,2}|o_j)$ is the conditioned marginal probability of group $\tilde{h}_{1,2}$ w.r.t. the observations o_j.

Grouping all the simplifications we obtain:

$$\frac{\partial J}{\partial w_i} = \frac{1}{N}\sum_{j=1}^{N}\Phi_i(h_j, o_j) - \frac{1}{N}\sum_{j=1}^{N}\Big(\sum_{\tilde{h}_{1,2}}\mathbb{P}(\tilde{h}_{1,2}|o_j)\Phi_i(\tilde{h}_{1,2})\Big) \tag{2.57}$$

Generalizing:

$$\frac{\partial J}{\partial w_i} = \frac{1}{N}\sum_{j=1}^{N}\Phi_i(D_j^i, o_j) - \frac{1}{N}\sum_{j=1}^{N}\Big(\sum_{\tilde{D}^i}\mathbb{P}(\tilde{D}^i|o_j)\Phi_i(\tilde{D}^i, o_j)\Big) \tag{2.58}$$

2.6.3 Learning of modular structure

Suppose to have a modular structure made of repeating units as for example the graph in Figure 2.11. Every single unit has the same population of potentials and we would like to enforce this fact when performing learning. In particular we'll have some sets of Exponential shape sharing the same weight w_1 (see Figure 2.11). Motivated by this example, we included in the library the possibility to specify that a potential must share its weight with another one. Then, learning is done consistently with the aforementioned specification.

2.6.3.1 Gradient of α

Considering the model in Figure 2.11, the α part of J (equation (2.41)) can be computed as follows:

$$\alpha = \frac{1}{N} \sum_{t_j} \big(w_1 \Phi_1(a_{1j}, b_{1j}) + w_1 \Phi_2(a_{2j}, b_{2j}) + w_1 \Phi_3(a_{3j}, b_{3j}) + \cdots + \\ \cdots + \sum_{i=2}^{D} w_i \Phi_i(t_j) \big) \tag{2.59}$$

which leads to:

$$\frac{\partial \alpha}{\partial w_1} = \frac{1}{N} \sum_{t_j} \big(\Phi_1(a_{1j}, b_{1j}) + \Phi_2(a_{2j}, b_{2j}) + \Phi_3(a_{3j}, b_{3j}) \big) \tag{2.60}$$

2.6.3.2 Gradient of β

Regarding the β part of J we can write what follows:

$$\begin{aligned}
\frac{\partial \beta}{\partial w_1} &= \frac{1}{Z} \frac{\partial Z}{\partial w_1} \\
&= \frac{1}{Z} \frac{\partial}{\partial w_1} \big(\sum_{\tilde{V}} \Big(exp\big(w_1 (\Psi_1(a_{1j}, b_{1j}) + \cdots \\
\cdots &+ \Psi_2(a_{2j}, b_{2j}) + \Psi_3(a_{3j}, b_{3j})) + \sum_{i=2}^{D} w_i \Phi_i(\tilde{V}) \big) E_0(\tilde{V})) \big) \Big) \\
&= \sum_{\tilde{V}} \mathbb{P}(\tilde{V}) (\Phi_1(\tilde{a}_1, \tilde{b}_1) + \Phi_2(\tilde{a}_2, \tilde{b}_2) + \Phi_3(\tilde{a}_3, \tilde{b}_3)) \\
&= \sum_{\tilde{V}} \mathbb{P}(\tilde{V}) \Phi_1(\tilde{a}_1, \tilde{b}_1) + \sum_{\tilde{V}} \mathbb{P}(\tilde{V}) \Phi_2(\tilde{a}_2, \tilde{b}_2) + \sum_{\tilde{V}} \mathbb{P}(\tilde{V}) \Phi_3(\tilde{a}_3, \tilde{b}_3) \\
&= \sum_{\tilde{A}_1, \tilde{B}_1} \mathbb{P}(\tilde{A}_1, \tilde{B}_1) \Phi_1(\tilde{A}_1, \tilde{B}_1) + \sum_{\tilde{A}_2, \tilde{B}_2} \mathbb{P}(\tilde{A}_2, \tilde{B}_2) \Phi_2(\tilde{A}_2, \tilde{B}_2) + \cdots \\
\cdots &+ \sum_{\tilde{A}_3, \tilde{B}_3} \mathbb{P}(\tilde{A}_3, \tilde{B}_3) \Phi_3(\tilde{A}_3, \tilde{B}_3)
\end{aligned} \tag{2.61}$$

Notice that the gradient $\frac{\partial J}{\partial w_1}$ is the summation of three terms: the ones that would have been obtained considering separately the three potentials in which w_1 is involved (equation (2.49)):

$$\begin{aligned}
\frac{\partial J}{\partial w_1} &= \frac{1}{N} \sum_{j=1}^{N} \Phi_1(a_i^1, b_i^1) - \sum_{\tilde{a}^1, \tilde{b}^1} \mathbb{P}(\tilde{a}^1, \tilde{b}^1) \Phi_1(\tilde{a}^1, \tilde{b}^1) + \cdots \\
&+ \frac{1}{N} \sum_{j=1}^{N} \Phi_2(a_i^2, b_i^2) - \sum_{\tilde{a}^2, \tilde{b}^2} \mathbb{P}(\tilde{a}^2, \tilde{b}^2) \Phi_2(\tilde{a}^2, \tilde{b}^2) + \cdots \\
&+ \frac{1}{N} \sum_{j=1}^{N} \Phi_3(a_i^3, b_i^3) - \sum_{\tilde{a}^3, \tilde{b}^3} \mathbb{P}(\tilde{a}^3, \tilde{b}^3) \Phi_3(\tilde{a}^3, \tilde{b}^3) +
\end{aligned} \tag{2.62}$$

The above result has a general validity, also considering conditioned graphs.

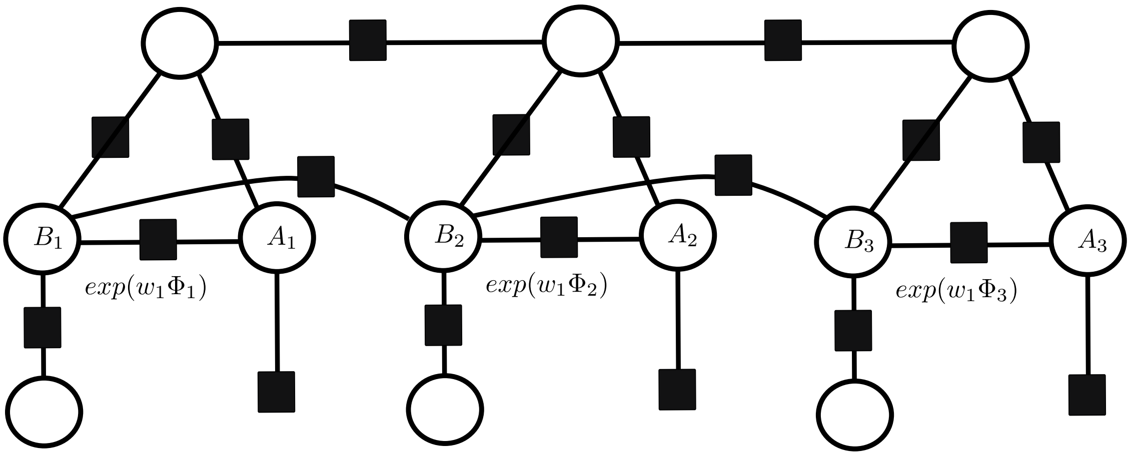


Figure 2.11 Example of modular structure: weight w_1 is simultaneously involved into potentials Φ_1, Φ_2 and Φ_3.

Chapter 3

Import models from xml files

The aim of this Section is to expose how to build graphical models from XML files describing their structures. In particular, the syntax of such an XML will be clarified. Figure 3.1 visually explains the structure of a valid XML. Essentially two kind of tags must be incorporated:

- Variable: describes the information related to a variable present in the graph. There must a tag of this kind for every variable constituting the model. Fields description:
  - name: is a string indicating the name of this variable.
  - Size: is the size of the variable, i.e. the size of Dom, see Section 2.1.
  - flag[optional] : is a flag that can assume two possible values, 'O' or 'H' according to the fact that this variable is in set $\mathcal{O}$ (Section 2.1) or not respectively. When non specifying this flag 'H' is assumed.
- Potential: describes the information related to a unary or a binary potential present in the graph (see Section 2.1). Fields description:
  - var: the name of the first variable involved.
  - var[optional]: the name of the second variable involved. Is omitted when considering unary potentials, while is mandatory when a binary potentials is described by this tag.
  - weight[optional]: when specifying an Exponential Factors (Section 2.1) it must be present for indicating the value of the weight w (equation (2.14)). When omitting, the potential is assumed to be a simple Factor.
  - tunability[optional]: it is a flag for specifying whether the weight of this Exponential Factor is tunable or not (see Section 2.1). Is ignored in case weight is omitted. It can assumes two possible values, 'Y' or 'N' according to the fact that the weight involved is tunable or not respectively. When weight is specified and tunability is omitted, a value equal to 'Y' is assumed.
- Share[optional]: you must specify this sub tag when the containing Exponential Factor shares its weight with another potential in the model. Sub fields var are exploited for specifying the variables involved by the potential whose weight is to share. If weight is omitted in the containing Potential tag, this sub tag is ignored, even though the value assigned to weight is ignored since it is shared with another potential. The potential sharing its weight must be clearly an Exponential shape, otherwise the sharing directive is ignored.

  The following components are exclusive: only one of them can be specified in a Potential tag and at the same time at least one must be present.

  - Correlation: it can assume two possible values, 'T' or 'F'. When 'T' is passed, this potential is assumed to be a correlating potential (see sample 4.1.2.2), otherwise when passing 'F' a simple anti correlating factor is assumed. It is invalid in case this Potential is a unary one. In case weight was specified, an Exponential Factor is built, passing as input the correlating or anti-correlating Factor described by this tag.

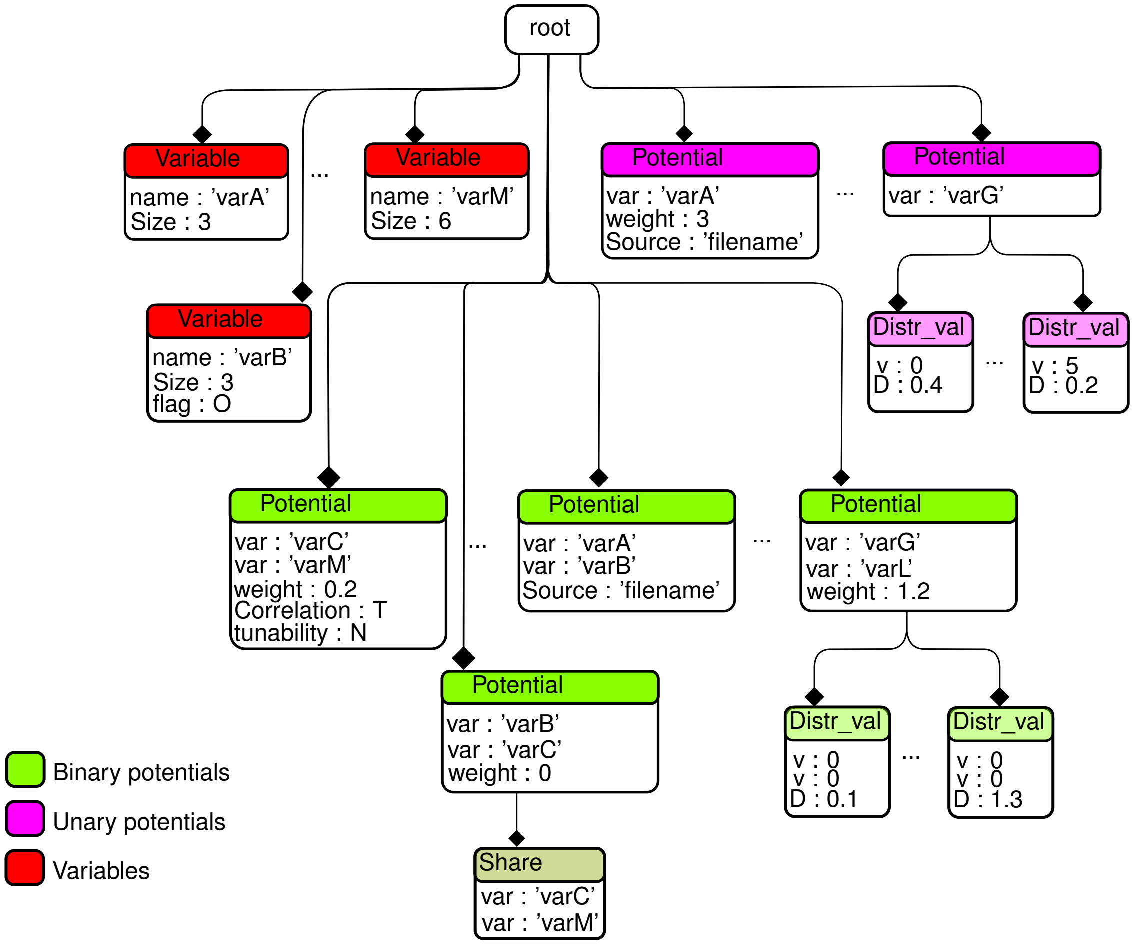


Figure 3.1 The structure of the XML describing a graphical model.

– Source: it is the location of a textual file describing the values of the distribution characterizing this potential. Rows of this file contain the values charactering the image of the potential. Combinations not specified are assumed to have an image value equal to 0. Clearly the number of values charactering the distribution must be consistent with the number of specified var fields. In case weight was specified, an Exponential Factor is built, starting from the Factor described by the values specified in the aforementioned file. For instance, the potential Φ_b of Section 2.1 would have been described by a file containing the following rows:

$$\begin{matrix} 0 & 0 & 1 \\ 0 & 1 & 4 \\ 1 & 1 & 1 \\ 2 & 2 & 5 \\ 2 & 4 & 1 \end{matrix} \tag{3.1}$$

– Set of sub tags Distr_val: is a set of nested tags describing the distribution of the this potential. Similarly to Source, every element use fields v for describing the combination, while D is used for specifying the value assumed by the distribution. For example the potential Φ_b of Section 2.1 would have been described by the syntax reported in Figure 3.2. In case weight was specified, an Exponential Factor is built, starting from the Factor whose distribution is specified by the aforementioned sub tags.

```
<Potential ···>
    <Distr_val "v"=0 "v"=0 "D"=1>
    <Distr_val "v"=0 "v"=1 "D"=4>
    <Distr_val "v"=1 "v"=1 "D"=1>
    <Distr_val "v"=2 "v"=2 "D"=5>
    <Distr_val "v"=2 "v"=4 "D"=1>
</Potential>
```

Figure 3.2 Syntax to adopt for describing the potential Φ_b of Section 2.1, using a population of Distr_val sub tags.

Chapter 4

Samples

4.1 Sample 01: Potential handling

The aim of this series of examples is mainly to show how to handle the creation of variables and factors.

4.1.1 Variables creation

4.1.1.1 part 01

This example creates a tow initial variables A and B with a domain size equal to 2 and places them into a group storing them. Later, it adds variables C and D, with the same domain size. Finally, tries to add again C, showing the this further addition is correctly refused.

4.1.1.2 part 02

This example considers 3 variables A, B and C with a domain sizes equal to, respectively, 2,4 and 3, i.e:

$$\begin{aligned} Dom(A) &= \{a_1 = 0, a_2 = 1\} \\ Dom(B) &= \{b_1 = 0, b_2 = 1, b_3 = 2, b_4 = 3\} \\ Dom(C) &= \{c_1 = 0, c_2 = 1, c_3 = 2\} \end{aligned} \tag{4.1}$$

Then, evaluates the joint domain of: $A \cup B$, $A \cup C$ and $A \cup B \cup C$, which should results in the following combinations reported in, respectively, tables 4.1, 4.2 and 4.3.

4.1.2 Factors creation

4.1.2.1 part 01

Part 01 creates a shape factor Φ_{AB}, involving the pair of variables A and B. Both that variables have a domain size equal to 4, i.e. $Dom(A) = \{a_0 = 0, a_1 = 1, a_2 = 2, a_3 = 3\}$ and $Dom(B) = \{b_0 = 0, b_1 = 1, b_2 = 2, b_3 = 3\}$. The generic value in the image Φ_{AB} is equal to:

$$\Phi_{AB}(A = a, B = b) = a + 2 \cdot b \tag{4.2}$$

Table 4.4 reports the entire image of Φ_{AB}.

$Dom(AB) = Dom(A \cup B)$
$\{a_1, b_1\}$
$\{a_1, b_2\}$
$\{a_1, b_3\}$
$\{a_1, b_4\}$
$\{a_2, b_1\}$
$\{a_2, b_2\}$
$\{a_2, b_3\}$
$\{a_2, b_4\}$

Table 4.1 Domain of AB.

$Dom(AC) = Dom(A \cup C)$
$\{a_1, c_1\}$
$\{a_1, c_2\}$
$\{a_1, c_3\}$
$\{a_2, c_1\}$
$\{a_2, c_2\}$
$\{a_2, c_3\}$

Table 4.2 Domain of AC.

$Dom(ABC) = Dom(A \cup B \cup C)$
$\{a_1, b_1, c_1\}$
$\{a_1, b_1, c_2\}$
$\{a_1, b_1, c_3\}$
$\{a_1, b_2, c_1\}$
$\{a_1, b_2, c_2\}$
$\{a_1, b_2, c_3\}$
$\{a_1, b_3, c_1\}$
$\{a_1, b_3, c_2\}$
$\{a_1, b_3, c_3\}$
$\{a_1, b_4, c_1\}$
$\{a_1, b_4, c_2\}$
$\{a_1, b_4, c_3\}$
$\{a_2, b_1, c_1\}$
$\{a_2, b_1, c_2\}$
$\{a_2, b_1, c_3\}$
$\{a_2, b_2, c_1\}$
$\{a_2, b_2, c_2\}$
$\{a_2, b_2, c_3\}$
$\{a_2, b_3, c_1\}$
$\{a_2, b_3, c_2\}$
$\{a_2, b_3, c_3\}$
$\{a_2, b_4, c_1\}$
$\{a_2, b_4, c_2\}$
$\{a_2, b_4, c_3\}$

Table 4.3 Domain of ABC.

	$b_0 = 0$	$b_1 = 1$	$b_2 = 2$	$b_3 = 3$
$a_0 = 0$	0	2	4	6
$a_1 = 1$	1	3	5	7
$a_2 = 2$	2	4	6	8
$a_3 = 3$	3	5	7	9

Table 4.4 The values in the image of Φ_{AB}.

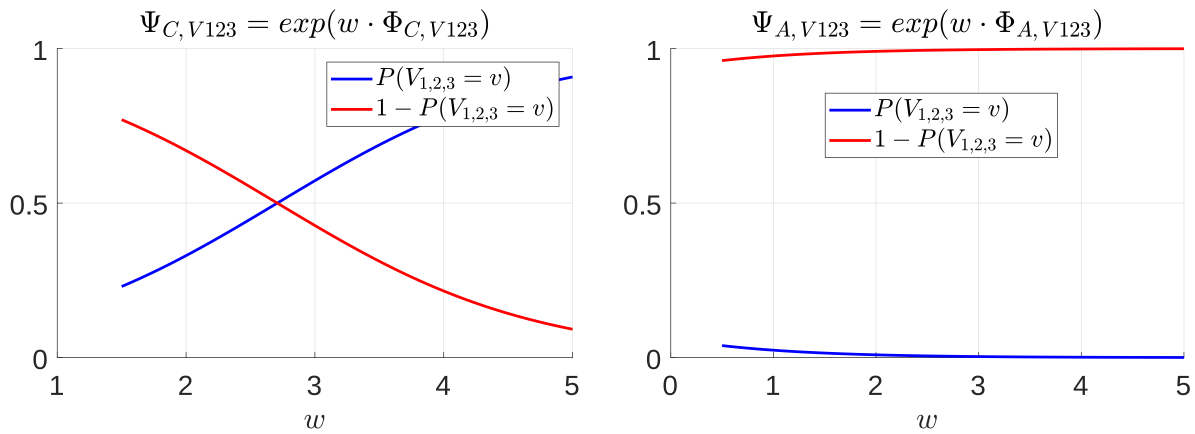


Figure 4.1 The probability $\mathbb{P}(V_1 = v, V_2 = v, V_3 = v|w)$ and its complement, when considering a ternary correlating factor, on the left, and an anti-correlating one, on the right.

4.1.2.2 part 02

Part 02 considers a ternary correlating factor $\Phi_{C\ V123}$, involving variables V_1, V_2 and V_3, each having a domain size equal to 3. Ternary factors cannot be part of a graph, but it is anyway possible to build them as distribution object. The values in the image of $\Phi_{C\ V123}$ are all 0, except for those combination for which V_1, V_2 and V_3 assume the same value $(0, 1$ or $2)$ and in such cases, the image is equal to 1.
The same example builds at a second stage a ternary anti-correlating factor $\Phi_{A\ V123}$. The values in the image of $\Phi_{A\ V123}$ are all 1, except for those combination for which V_1, V_2 and V_3 assume the same value $(0, 1$ or $2)$ and in such cases the image is equal to 1.
When considering a graph having only $\Psi_{C,\ V123} = exp(\Phi_{C\ V123} \cdot w)$ as a factor, the ripartition function Z is equal to:

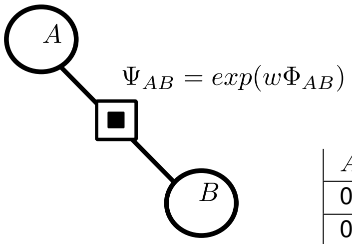
$$Z = (4^3 - 4) + 4 \cdot exp(w) \tag{4.3}$$

The probability to have as a realization a combination with the same values is equal to:

$$\begin{aligned}
\mathbb{P}(V_1 = v, V_2 = v, V_3 = v) &= \sum_{i=0}^{3} \mathbb{P}(V_1 = i, V_2 = i, V_3 = i) && (4.4)\\
&= \sum_{i=0}^{3} \frac{\Psi_{C\ V123}(i,i,i)}{Z} && (4.5)\\
&= 4 \cdot \frac{\Psi_{C\ V123}(0,0,0)}{Z} && (4.6)\\
&= \frac{4 \cdot exp(w)}{(4^3 - 4) + 4 \cdot exp(w)} && (4.7)
\end{aligned}$$

The value assumed by $\mathbb{P}(V_1 = v, V_2 = v, V_3 = v|w)$ is reported in Figure 4.1, together with the complementary probability $1 - \mathbb{P}(V_1 = v, V_2 = v, V_3 = v|w)$.
When considering a graph having only $\Psi_{A,\ V123} = exp(\Phi_{A\ V123} \cdot w)$ as factor, the ripartition function Z is equal to:

$$Z = (4^3 - 4) \cdot exp(w) + 4 \tag{4.8}$$



A	B	$\Psi_{AB}(A,B) = E(A,B)$
0	0	exp(w)
0	1	1
1	0	1
1	1	exp(w)

Figure 4.2 On the left the graph considered in this example, while on the right the image of factor Ψ_{AB}. Since that potential is the only one present in the graph, the values in the image of Ψ_{AB} are also the ones assume by the energy function E.

The probability to have as a realization a combination with the same values is equal to:

$$\begin{aligned}
\mathbb{P}(V_1 = v, V_2 = v, V_3 = v) &= \sum_{i=0}^{3} \mathbb{P}(V_1 = i, V_2 = i, V_3 = i) && (4.9)\\
&= \sum_{i=0}^{3} \frac{\Psi_{A\ V123}(i,i,i)}{Z} && (4.10)\\
&= 4 \cdot \frac{\Psi_{A\ V123}(0,0,0)}{Z} && (4.11)\\
&= \frac{4}{(4^3-4)\cdot exp(w) + 4} && (4.12)
\end{aligned}$$

The value assumed by $\mathbb{P}(V_1 = v, V_2 = v, V_3 = v|w)$ is reported in Figure 4.1, together with its complement $1 - \mathbb{P}(V_1 = v, V_2 = v, V_3 = v|w)$. Indeed, when the variables are correlated, i.e. they share $\Psi_{C\ V123}$, the probability $\mathbb{P}(V_1 = v, V_2 = v, V_3 = v|w)$ is big. Moreover, the more w is high (i.e. the more the variables are correlated), the more the latter probability is big. On the opposite, when the variables are anti-correlated, the opposite situation arises.

4.2 Sample 02: Belief propagation, part A

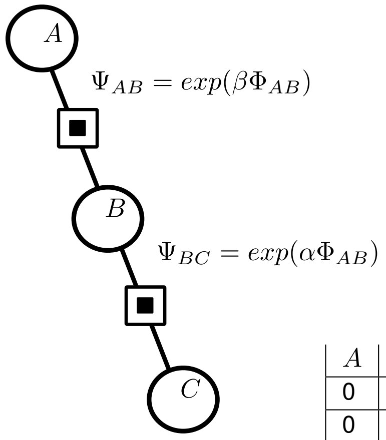
The aim of this series of examples is to show how to perform probabilistic queries on factor graphs.

4.2.1 part 01

This example creates a graph having a single binary exponential shape Ψ_{AB}, see Figure 4.2, with a A and B having a Dom size equal to 2. $\Psi_{AB} = exp(w\Phi_{AB})$, where Φ_{AB} is a simple correlating factor. The image of Ψ_{AB} is reported in the right part of Figure 4.2.
Variable B is considered as an evidence, whose value is equal, for the first part of the example, to 0, while a value of 1 is assumed in the second part. The probability of A conditioned to B, is equal to (see equation (2.18)):

$$\mathbb{P}(A = a|B = 0) = \frac{E(A = a, B = 0)}{E(A = 0, B = 0) + E(A = 1, B = 0)} \Rightarrow \begin{bmatrix} \mathbb{P}(A = 0|B = 0) = \frac{exp(w)}{1+exp(w)} \\ \mathbb{P}(A = 1|B = 0) = \frac{1}{1+exp(w)} \end{bmatrix} \quad (4.13)$$

$$\mathbb{P}(A = a|B = 1) = \frac{E(A = a, B = 1)}{E(A = 0, B = 1) + E(A = 1, B = 1)} \Rightarrow \begin{bmatrix} \mathbb{P}(A = 0|B = 1) = \frac{1}{1+exp(w)} \\ \mathbb{P}(A = 1|B = 1) = \frac{exp(w)}{1+exp(w)} \end{bmatrix} \quad (4.14)$$



A	B	$\Psi_{AB}(A,B)$
0	0	exp(β)
0	1	1
1	0	1
1	1	exp(β)

B	C	$\Psi_{BC}(B,C)$
0	0	exp(α)
0	1	1
1	0	1
1	1	exp(α)

Figure 4.3 On the left the graph considered in this example, while on the right the images of factor Ψ_{AB} and Ψ_{BC} having, respectively, a weight equal to β and α.

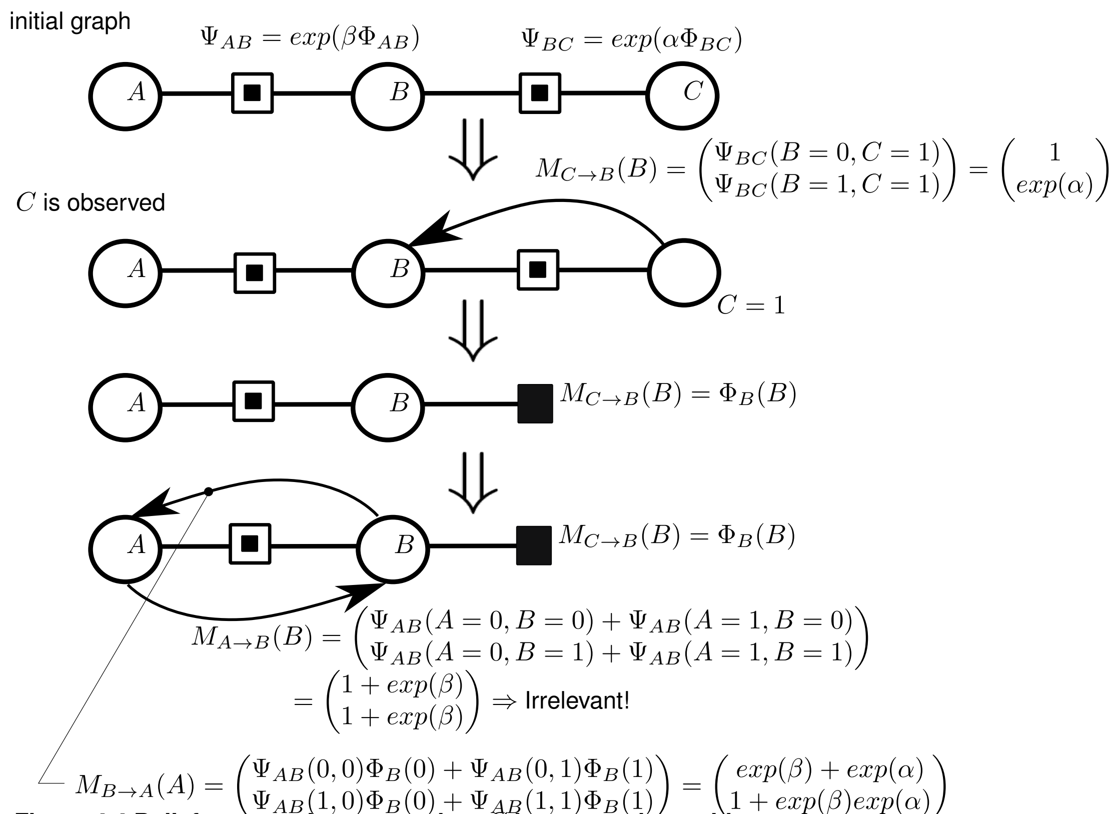


Figure 4.4 Belief propagation steps when C is assumed as evidence.

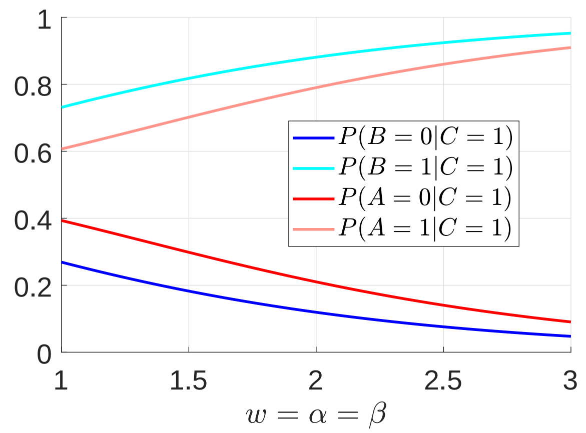


Figure 4.5 The marginals of variables B and A, when having a $C = 1$ as evidence of the graph reported in Figure 4.4.

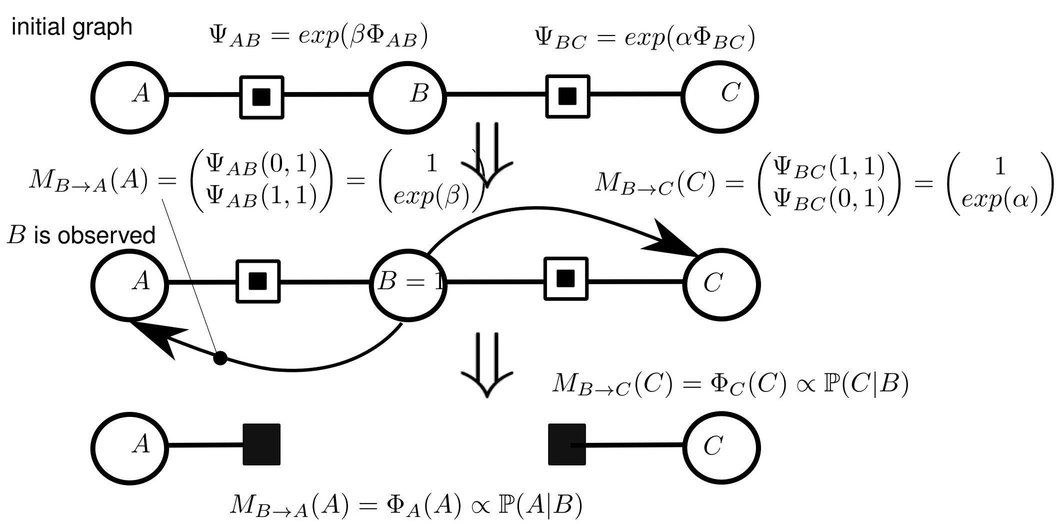
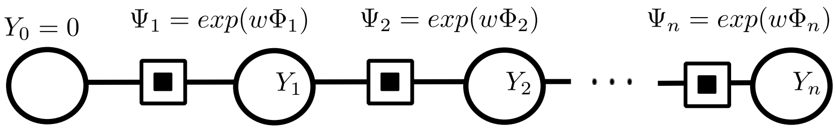


Figure 4.6 Belief propagation steps when B is assumed as evidence.



$\Psi_i(Y_{i-1}, Y_i)$	$Y_i = 0$	$Y_i = 1$	$\cdots$	$Y_i = m$
$Y_{i-1} = 0$	$exp(w)$	1	$\cdots$	1
$Y_{i-1} = 1$	1	$exp(w)$	$\cdots$	1
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
$Y_{i-1} = m$	1	1	$\cdots$	$exp(w)$

Figure 4.7 On the top the chain considered in this example, while on the bottom the image of the generic factor $\Psi_i(Y_{i-1}, Y_i)$.

4.2.2 part 02

A slightly more complex graph, made of two exponential correlating factors Ψ_{BC} and Ψ_{AB}, is built in this sample. The considered graph is reported in Figure 4.3. The two involved factors have two different weights, α and β: the resulting image sets are reported in the right part of Figure 4.3.
In the first part, $C = 1$ is assumed as evidence and the marginal probabilities of A and B conditioned to C are computed. They are compared with the theoretical results, obtained by applying the message passing algorithm (Section 2.2.2), whose steps are here detailed [1]. The message passing steps are summarized in Figure 4.4. After having computed all the messages, it is clear that the marginal probabilities are equal to:

$$\mathbb{P}(A|C=1) = \frac{1}{Z} M_{B\rightarrow A}(A) = \frac{1}{Z} \begin{bmatrix} exp(\alpha) + exp(\beta) \\ 1 + exp(\alpha) \cdot exp(\beta) \end{bmatrix} \tag{4.15}$$

$$\mathbb{P}(B|C=1) = \frac{1}{Z} \Phi_B(B) \cdot M_{A\rightarrow B}(B) = \frac{1}{Z} \Phi_B(B) = \frac{1}{Z} \begin{bmatrix} 1 \\ exp(\alpha) \end{bmatrix} \tag{4.16}$$

Figure 4.5 shows the values assumed by the marginals when varying the coefficients α and β. As can be seen, the more A, B and C are correlated (i.e. the more α and β are big) the more $\mathbb{P}(B=1|C=1)$ and $\mathbb{P}(A=1|C=1)$ are big. Notice also that when assuming $\alpha = \beta$, $\mathbb{P}(B=1|C=1)$ is always bigger than $\mathbb{P}(A=1|C=1)$. This is intuitively explained by the fact that C is directly connected to B, while A is indirectly connected to C, through B.
In the second part, $B = 1$ is assumed as evidence and the marginal probabilities of A and C conditioned to B are computed. The theoretical results can be computed again considering the message passing, whoe steps are reported in Figure 4.6. The marginal probabilities are in this case equal to:

$$\mathbb{P}(A|B=1) = \frac{1}{Z} \Phi_A(A) = \frac{1}{Z} \begin{bmatrix} 1 \\ exp(\beta) \end{bmatrix} \tag{4.17}$$

$$\mathbb{P}(C|B=1) = \frac{1}{Z} \Phi_C(C) = \frac{1}{Z} \begin{bmatrix} 1 \\ exp(\alpha) \end{bmatrix} \tag{4.18}$$

4.2.3 part 03

In this sample, a linear chain of variables $Y_{0,1,2,\cdots,n}$ is considered. All variables in the chain have the same Dom size and all the factors $\Psi_{1,\cdots,n}$, Figure 4.7, are simple exponential correlating factors. The image of the generic factor Ψ_i is reported in the right part of Figure 4.7.
The evidence $Y_0 = 0$ is assumed and the marginals of the last variable in the chain Y_n, i.e. the one furthest to Y_0, are computed. Figure 4.8 reports the probability $\mathbb{P}(Y_n = 0|Y_0 = 0)$, when varying the chain size, as well the domain size of the variables. As can be seen, the more the chain is longer, the lower is the aforementioned probability, as Y_n is more and more indirectly correlated to Y_0. Similar considerations hold for the domain size.

[1] The same steps are internally execute by Node_factory.

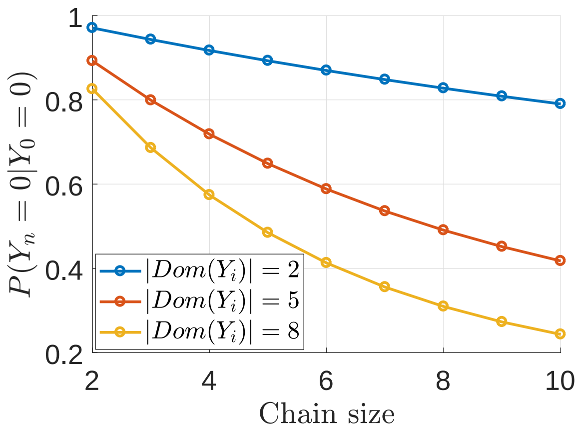


Figure 4.8 Marginal probability of Y_n when varying the chain size of the structure presented in Figure 4.7. w is assumed equal to 3.5.

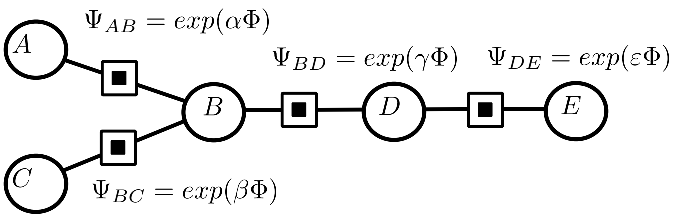


Figure 4.9 The factor graph considered by part 01.

4.3 Sample 03: Belief propagation, part B

The aim of this series of examples is to show how to perform probabilistic queries on articulated complex graphs.

4.3.1 part 01

Part 01 considers a graph made of 5 variables with a Dom size equal to 2 and some simple exponential correlating factors, having different weights. The graph is reported in Figure 4.9, together with the weights of factor $\alpha, \beta, \gamma, \varepsilon$.
At first stage, the evidence $E = 1$ is assumed and the marginal probabilities of the other variables are computed with the message passing, whose steps are summarized in Figure 4.10. After the convergence of the message passing, the marginals of the variables are computed as similarly done for the previous examples. In a second phase, the evidence $E = 0$ is assumed. The computation of the marginals is omitted since it is specular to the previous case.
Finally, $D = 1$ is assumed and a new belief propagation is done, whose computations are reported in Figure 4.11.

4.3.2 part 02

Part 02 considers the graph reported in Figure 4.12. All the variables in Figure 4.12 have a domain size equal to 2, and all the factors are simply correlating exponential shape, having a unitary weight. Variables v_1, v_2 and v_3 are treated as evidences and the belief is propagated across the other ones, leading to the computation of the individual marginal probabilities. Since, the addressed structure is a politree (refer to Figure 2.6), the message passing algorithm converges within a finite number of steps.
In principle, the same approach followed in the previous examples can be followed to compute some theoretical results, with the aim of performing the comparisons. Anyway, for this kind of graph such an approach would be too complex. For this reason, results are compared with a Gibbs sampling approach: a series of samples $\mathcal{T} = \{T_1, \cdots, T_N\}$ are taken from the joint conditioned distribution $\mathbb{P}(T = v_{4,5,6,7,8,9,10,11,12,13}|v_{1,2,3})$. Then, to

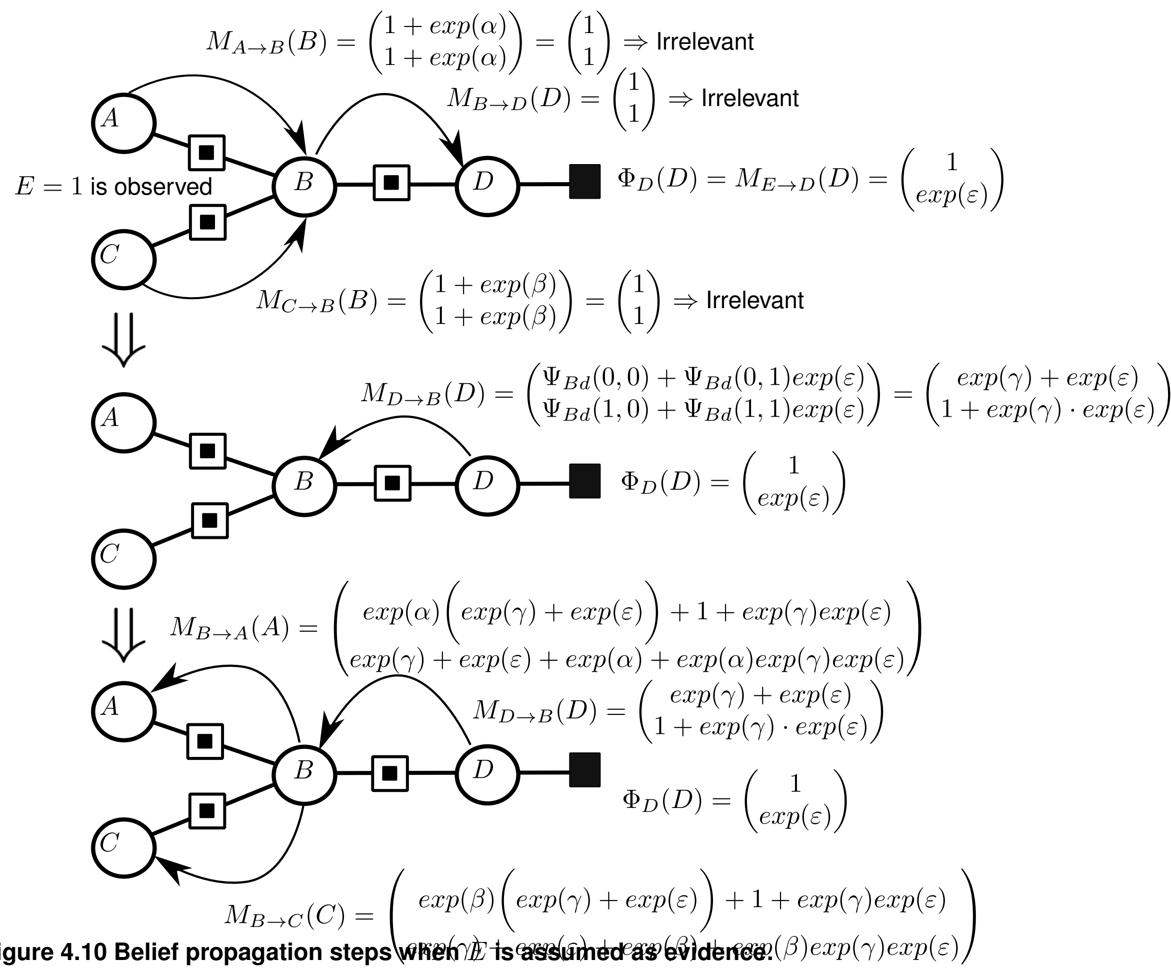


Figure 4.10 Belief propagation steps when E is assumed as evidence.

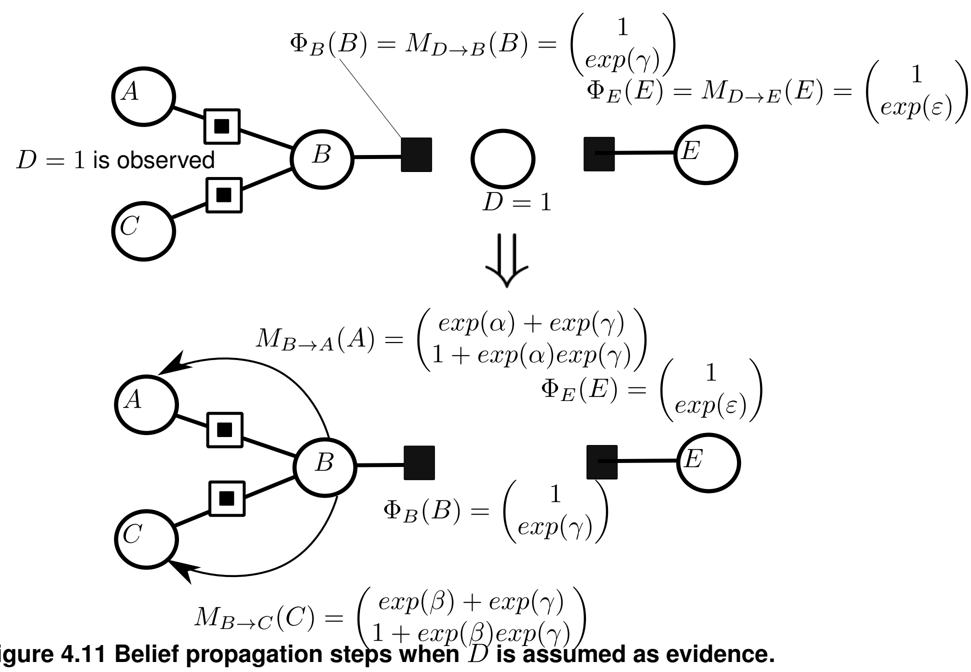


Figure 4.11 Belief propagation steps when D is assumed as evidence.

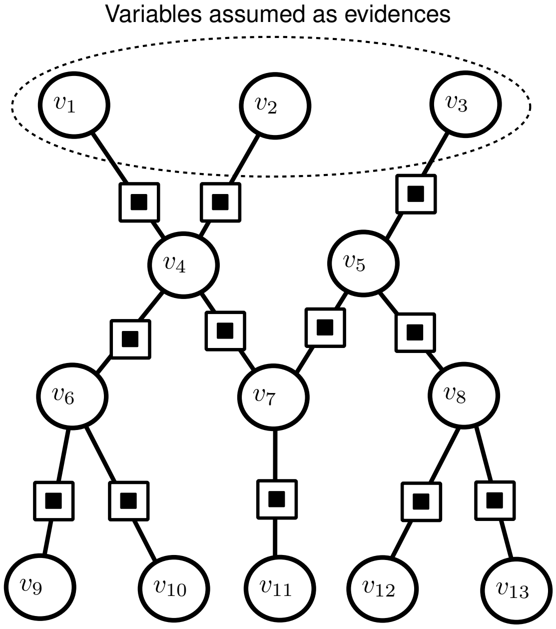


Figure 4.12 The factor graph considered by part 02.

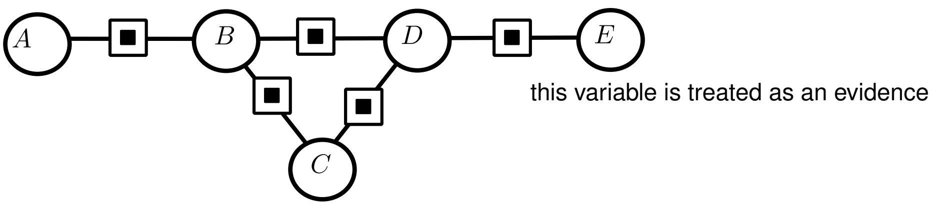


Figure 4.13 The factor graph considered by part 03.

evaluate the marginal probability $\mathbb{P}(v_i|v_{1,2,3})$ of a generic hidden variable v_i, the following empirical frequency is computed:

$$\mathbb{P}(v_i = v|v_{1,2,3}) = \frac{\sum_{T_j \in \mathcal{T}} L_{Ti}(T_j, v)}{N} \tag{4.19}$$

where $L_{Ti}(T_j, v)$ is an indicator function equal to 1 only for those samples for which v_i assumed a value equal to v.

4.3.3 part 03

Part 03 considers the graph reported in Figure 4.13. As for the example in the previous part, all variables are binary, and the potentials are simply exponential correlating with a unitary weight. However, this structure is loopy. E is treated as an evidence and the belief propagation is performed considering the loopy version of the message passing discussed in Section 2.2.2.

4.3.4 part 04

The last example in this series, considers a complex loopy graph, represented in Figure 4.14. As for other examples, all the variables are binary and the factors are exponential simply correlating with unitary weights. v_1 is assumed as evidence and the belief is propagated with the loopy version of message passing. Results are compared to the empirical frequencies obtained with a Gibbs sampler, as similarly done for the example of part 02.

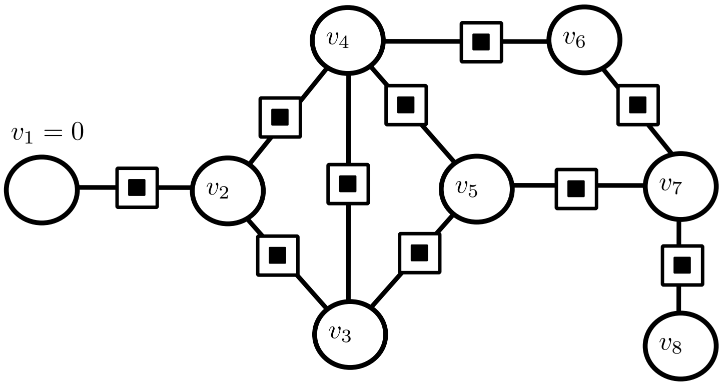


Figure 4.14 The factor graph considered by part 04.

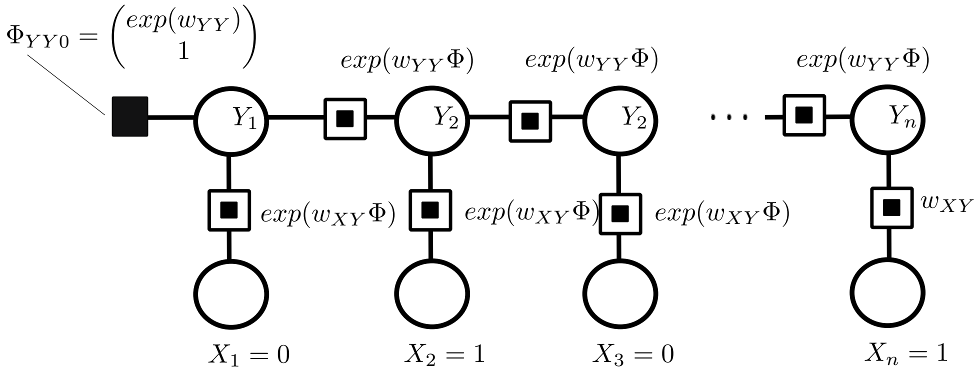


Figure 4.15 The chain structure considered by Sample 04.

4.4 Sample 04: Hidden Markov model like structure

The structure reported in Figure 4.15 is considered in this example. The reported chain is similar to those considered in Hidden Markov models, for which the chain of hidden variables $Y_{1,2,\dots}$ are connected to the chain of evidences $X_{1,2,\dots}$. The potential Φ_{YY0}, represents an a-priori knowledge about variable Y_1. All the variables are binary and the potentials are simply correlating exponential potentials. In particular, the ones connecting the hidden variables have a weight equal to w_{YY}, while the ones connecting the evidences to the hidden set share a weight equal to w_{XY}. The evidences are set as indicated in Figure 4.15, i.e. 0 and 1 are alternated in the chain represented by $X_{1,2,\dots}$. The MAP estimation [2] of the hidden set (Section 2.3) is computed into two different situations:

- case a): $w_{XY} >> w_{YY}$
- case b): $w_{XY} << w_{YY}$

Here the point is that when considering case a), the information about the evidences and the correlations between $Y_{1,2,\dots}$ and $X_{1,2,\dots}$ is predominant. On the opposite, when dealing with case b), the correlations among the hidden variables as well as the prior knowledge about Y_0 is predominant. For this reason, for case a) the MAP estimation of the hidden variables is equal to $h^a_{MAP} = \{0, 1, 0, 1, \cdots\}$, while for case b) the MAP estimation is equal to $h^b_{MAP} = \{0, 0, 0, 0, \cdots\}$.

4.5 Sample 05: Matricial structure

The matrix-like structure reported in Figure 4.16 is considered in this example. The variables in the matrix have all the same domain size and the are correlated by the potentials populating the matrix, which are all simple exponential

[2] The Node_factory class is in charge of invoking the proper version of the message passing algorithm that leads to the MAP estimation computation.

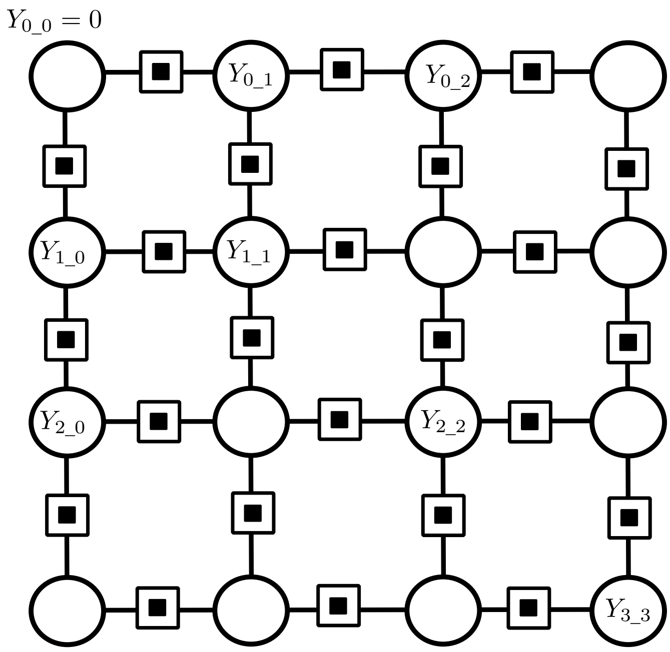


Figure 4.16 The matricial structure considered by Sample 05.

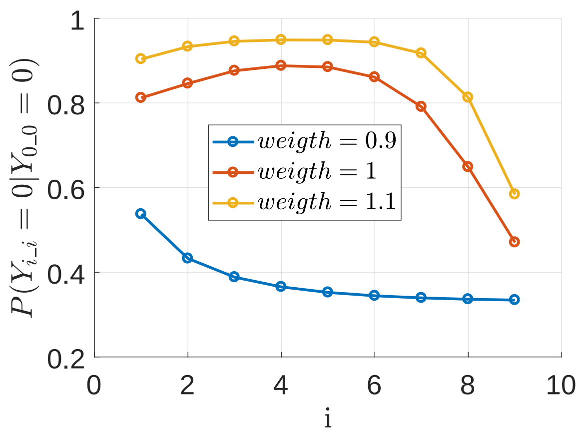


Figure 4.17 The marginals of variables Y_{i_i}, conditioned to $Y_{0\_0} = 0$ as evidence of the graph reported in Figure 4.16, when varying the weight of the correlating exponential factors involved in the structure.

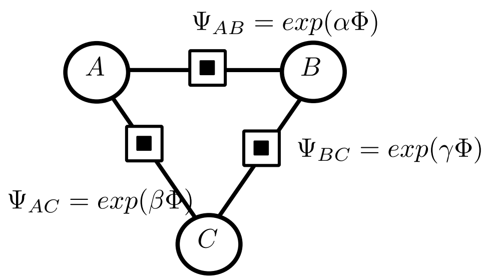


Figure 4.18 The graph considered by part 01.

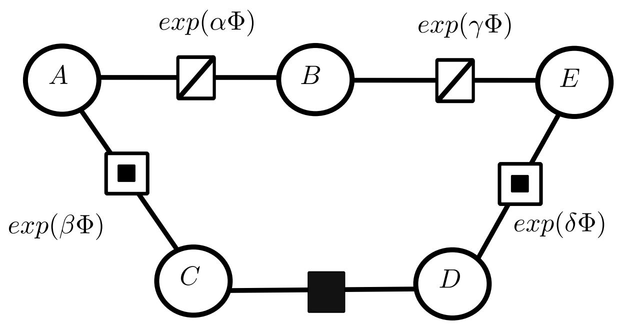


Figure 4.19 The graph considered by part 02.

correlating factors sharing the same weight. The example builds the matrix and then assumes $Y_{0\_0} = 0$ as an evidence. Then, the marginals of the variables along the diagonal of the matrix, i.e. Y_{i_i}, are evaluated. As can be seen, the marginal probability $\mathbb{P}(Y_{i\_i} = 0|Y_{0\_0})$ decreases descending the diagonal. Figure 4.17 reports the results obtained when varying the weight of the correlating factors, on a matrix made of $10x10$ variables having a Dom size equal to 3.

4.6 Sample 06: Learning, part A

The aim of this series of examples is to show how to perform the learning of factor graphs. In all the examples contained in this Section, learning is done with the following methodology. A Gibbs sampler is used to take samples from the joint distribution correlating all the variables in a model A. Model A is actually the model to learn. The training set obtained from model A, is used to train a model B. Model B has the same variables and factors of model A, but with different values for the free parameters $w_{1,2,\dots}$ (Section 2.6). In this way, after having performed the learning, the value of the free parameters in model B will assume similar values to the ones in model A, showing the effectiveness of the functionalities contained in EFG. Clearly, this is not the approach followed in real applications, were the real coefficient of the model are unknown and only a training set of examples are available.

4.6.1 part 01

Part 01 considers the loopy graph reported in Figure 4.18. A, B and C are all binary variables, while Ψ_{AB}, Ψ_{AC} and Ψ_{BC} are simple correlating exponential distributions having as weights, respectively, α, β and γ.
Some samples are generated from the model with a Gibbs sampling, in order to use it later as a training set. All the weigths in the model are set to 1, and tuned using a quasi newton trainer that consider the previously generated training set. The aim is to show that after training the values of the weights are similar to the initial ones.

4.6.2 part 02

Part 02 considers a structure made of both tunable and non-tunable factors. The considered structure is reported in Figure 4.19. Weights β and δ must be tuned through learning, as similarly described in Section 4.6.1, while α and γ are constant and known (refer also to the formalism described in Figure 2.2).

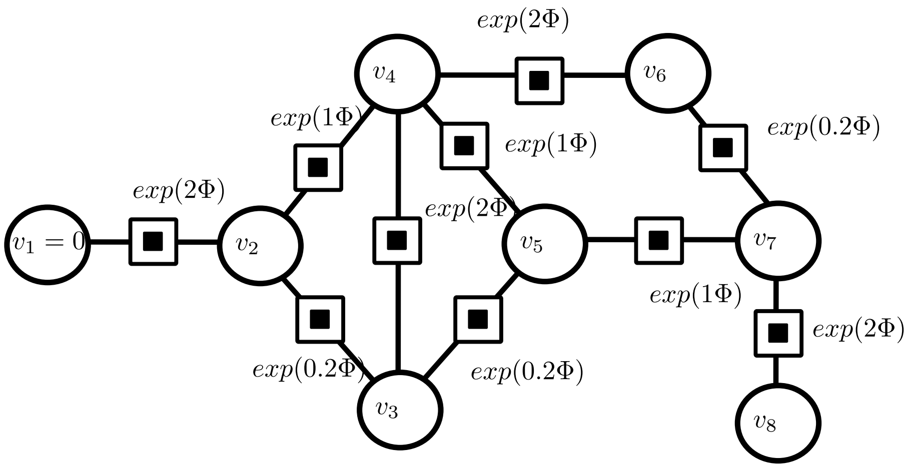


Figure 4.20 The graph considered by part 03.

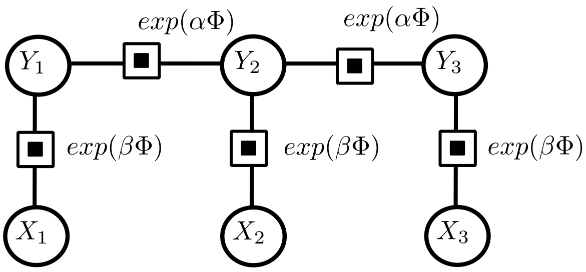


Figure 4.21 The graph considered by part 04.

4.6.3 part 03

Part 03 considers the loopy structure reported in Section 4.3.4. However, here instead of having constant exponential shapes, all the factors are made of tunable exponentials. The value assumed by the weight of model A (see the introduction of this Section) are showed in Figure 4.20. Weights are tuned through learning as similarly described in Section 4.6.1.

4.6.4 part 04

Part 04 considers the structure reported in Figure 4.21, for which all the potentials connecting pairs Y_{i-1}, Y_i share the same weight α, while the factors connecting pairs X_i, Y_i share the weight β. The approach described Weights are tuned through learning as similarly described in Section 4.6.1.

4.7 Sample 07: Learning, part B

The aim of this example is to show how the learning process can be done when dealing with Conditional random fields. In particular, the structure reported in Figure 4.22 is considered (values of the free parameters are not indicated, since the reader may refer to the sources provided).
The approach adopted is similar to the one followed in the previous series of example, considering a couple of model A and B (see the initial part of the previous Section). However, in this case we cannot simply draw samples from the joint distribution correlating the variables in the model, since such a distribution does not exists. Indeed, the conditional random field of Figure 4.22, models the conditional distribution of variables $Y_{1,2,\dots}$ w.r.t the evidences $X_{1,2,\dots}$. For this reason, all the possible combination of evidences are determined, considering all $x \in \{Dom(X_1) \cup Dom(X_2) \cup \cdots\}$. For each x, samples from the conditioned distribution $\mathbb{P}(Y_{1,2,\dots}|x)$ are taken with a Gibbs sampler. The entire population of samples determined is actually the training set adopted fro training the conditional random field in Figure 4.22.

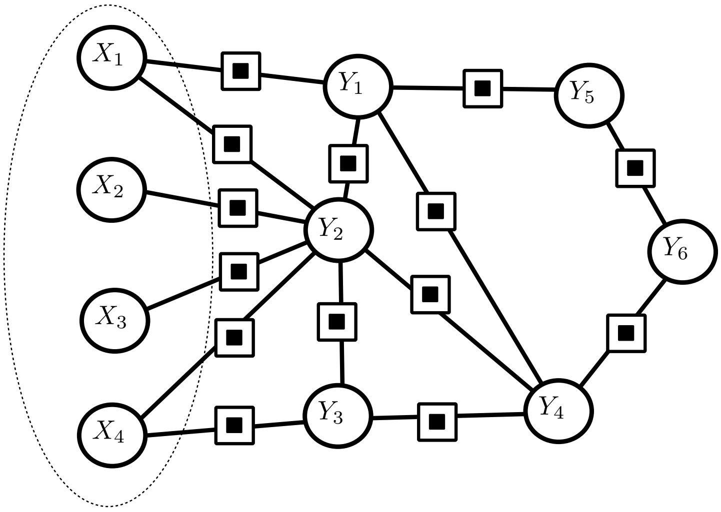


Figure 4.22 The conditional random field considered in Sample 07.

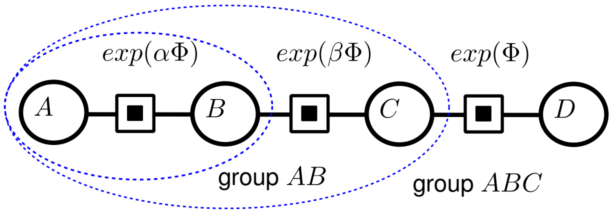


Figure 4.23 The chain considered in the example. All the underlying simple shapes are simple correlating.

4.8 Sample 08: Sub-graphing

4.8.1 part 01

The chain structure described in Figure 4.23 is addressed in this example. The sub-graphs containing variables A, B, C and A, B are built, in order to compute the joint marginal probability distributions of that two groups of variables.
The values are compared to the real ones, obtained by considering the joint distribution [3] of all the variables in the chain, which can be obtained by computing the energy function E, equation (2.6) (computations are here omitted for brevity). Knowing the joint distribution of a group of variables, the marginal distribution of a sub-group can be obtained by marginalization, equation (2.4):

$$\begin{aligned} \mathbb{P}(A = a, B = b, C = c) &= \sum_{\tilde{d} \in Dom(D)} \mathbb{P}(A = a, B = b, C = c, D = \tilde{d}) \\ \mathbb{P}(A = a, B = b) &= \sum_{\tilde{c} \in Dom(C), \tilde{d} \in Dom(D)} \mathbb{P}(A = a, B = b, C = \tilde{c}, D = \tilde{d}) \end{aligned} \tag{4.20}$$

Applying the above rules to the chain of Figure 4.23 leads to obtain the theoretical marginal distributions indicated in Figure 4.24.

4.8.2 part 02

The aim of this example is to show how sub-graphs (see Section 2.5) can be computed using SubGraph. The example starts building the structure described in Figure 4.25 (refer to the sources for the details regarding the

[3]Which is significantly time consuming to compute. For this reason, the SubGraph class is able to compute the marginals without explicitly compute the entire joint distribution of the variables in the model. Here we want just to compare the theoretical result with the one obtained by the SubGraph class.

A	B	$\mathbb{P}(A,B)$
0	0	$\frac{exp(\alpha)}{1+exp(\alpha)}$
0	1	$\frac{1}{1+exp(\alpha)}$
1	0	$\frac{1}{1+exp(\alpha)}$
1	1	$\frac{exp(\alpha)}{1+exp(\alpha)}$

A	B	C	$\mathbb{P}(A,B,C)$
0	0	0	$\frac{1}{Z_{ABC}} \cdot exp(\alpha)exp(\beta)$
0	1	0	$\frac{1}{Z_{ABC}}$
1	0	0	$\frac{1}{Z_{ABC}} \cdot exp(\beta)$
1	1	0	$\frac{1}{Z_{ABC}} \cdot exp(\alpha)$
0	0	1	$\frac{1}{Z_{ABC}} \cdot exp(\alpha)$
0	1	1	$\frac{1}{Z_{ABC}} \cdot exp(\beta)$
1	0	1	$\frac{1}{Z_{ABC}}$
1	1	1	$\frac{1}{Z_{ABC}} \cdot exp(\alpha)exp(\beta)$

Figure 4.24 Marginal probabilities of the sub-groups $\{A,B,C\}$ and $\{A,B\}$. The normalization coefficient Z_{ABC} is equal to $Z_{ABC} = 2\Big(1 + exp(\alpha) + exp(\beta) + exp(\alpha)exp(\beta)\Big)$.

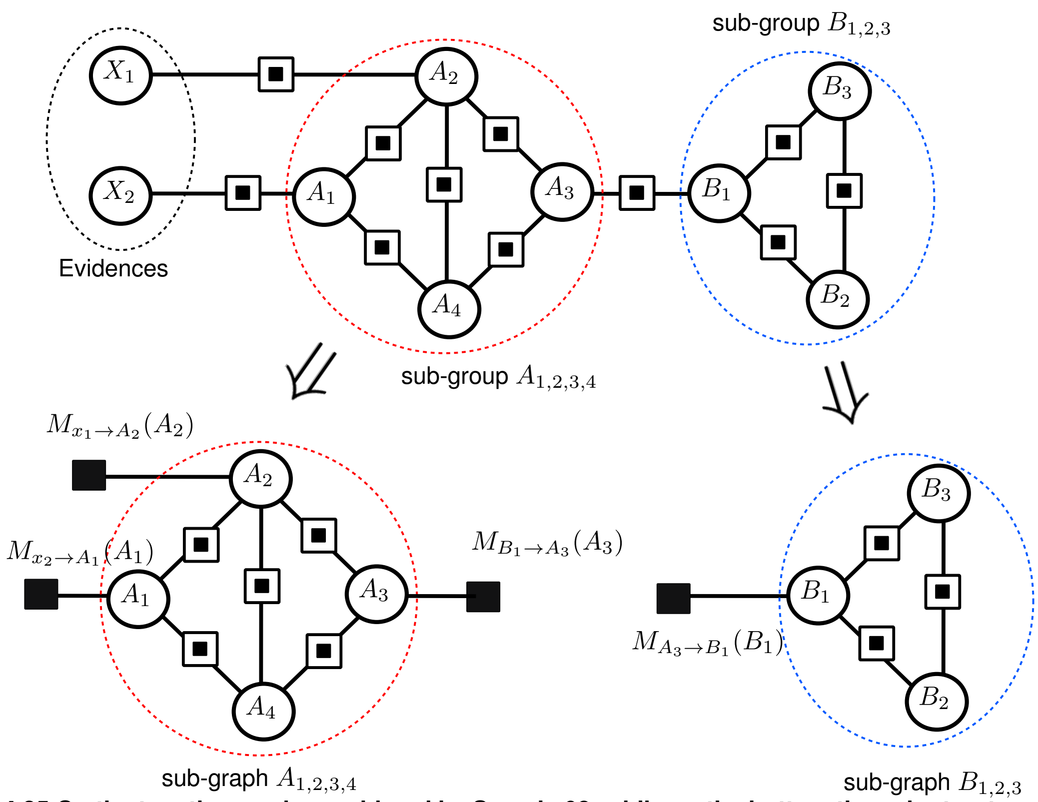


Figure 4.25 On the top, the graph considered by Sample 08, while on the bottom the sub-structures of the two groups $A_{1,2,3,4}$ ad $B_{1,2,3}$.

variables and factors involved in the structure) and assumes the following evidences: $X_1 = 0$ and $X_2 = 0$. Then, the two sub-graphs considering the sub-group of variables $A_{1,2,3,4}$ and $B_{1,2,3}$ are computed, refer to Figure 4.25. The marginal probabilities of some combinations for $A_{1,2,3,4}$ conditioned to the evidences $X_{1,2}$ are computed and compared with the empirical frequencies computed considering a samples set produced by a Gibb sampler on the entire graph: samples for $t = A_{1,2,3,4}, B_{1,23}$ are drawn and the empirical frequencies of specific combinations of $A_{1,2,3,4}$ are computed as similarly done in 4.3.2. The same thing is done for the sub-graph $B_{1,2,3}$.
At a second stage, the evidences $X_{1,2}$ are changed and the sub-graphs, as well as the marginal probabilities, are consequently recomputed.

Chapter 5

Namespace Index

5.1 Namespace List

Here is a list of all documented namespaces with brief descriptions:

Chapter 6

Hierarchical Index

6.1 Class Hierarchy

This inheritance list is sorted roughly, but not completely, alphabetically:

Chapter 7

Class Index

7.1 Class List

Here are the classes, structs, unions and interfaces with brief descriptions:

Chapter 8

Namespace Documentation

8.1 EFG Namespace Reference

Namespaces

- categoric
- distribution
- io
- model
- strct
- train

Classes

- class Cache
- struct Comparator
- class Error
- struct Hasher
- class MessagesMerger

Typedefs

- template<typename K , typename V >
  using SmartMap = std::unordered_map< std::shared_ptr< K >, V, Hasher< K >, Comparator< K > >

  An unordered_map that stores as keys shared pointers that can't be null.
- template<typename T >
  using SmartSet = std::unordered_set< std::shared_ptr< T >, Hasher< T >, Comparator< T > >

  An unordered_set that stores shared pointers that can't be null.

Functions

- template<typename T , typename M , typename Predicate >
  void **dynamic_const_predicate** (const M &subject, const Predicate &predicate)
- template<typename T , typename M , typename Predicate >
  void **dynamic_predicate** (M &subject, const Predicate &predicate)
- template<typename K , typename V , typename Predicate >
  void **for_each** (SmartMap< K, V > &subject, const Predicate &pred)
- template<typename K , typename V , typename Predicate >
  void **for_each** (const SmartMap< K, V > &subject, const Predicate &pred)
- template<typename T , typename Predicate >
  void **for_each** (const SmartSet< T > &subject, const Predicate &pred)

8.1.1 Detailed Description

Author: Andrea Casalino Created: 01.01.2021

report any bug to andrecasa91@gmail.com.

Author: Andrea Casalino Created: 31.03.2022

report any bug to andrecasa91@gmail.com.

8.1.2 Typedef Documentation

8.1.2.1 SmartMap

```
template<typename K , typename V >
using EFG::SmartMap = typedef std::unordered_map<std::shared_ptr<K>, V, Hasher<K>, Comparator<K>
>
```

An unordered_map that stores as keys shared pointers that can't be null.

Keys are hashed by hashing the elements wrapped inside the shared pointer.

Keys are compared by comparing the elements wrapped inside the shared pointer.

8.1.2.2 SmartSet

```
template<typename T >
using EFG::SmartSet = typedef std::unordered_set<std::shared_ptr<T>, Hasher<T>, Comparator<T>
>
```

An unordered_set that stores shared pointers that can't be null.

Elements are hashed by hashing the elements wrapped inside the shared pointer.

Elements are compared by comparing the elements wrapped inside the shared pointer.

8.2 EFG::categoric Namespace Reference

Classes

- class Combination

  An immutable combination of discrete values.
- class Group

  An ensemble of categoric variables. Each variable in the ensemble should have its own unique name.
- class GroupRange

  This object allows to iterate all the elements in the joint domain of a group of variables, without precomputing all the elements in such domain. For example when having a domain made by variables = { A (size = 2), B (size = 3), C (size = 2) }, the elements in the joint domain that will be iterated are: <0,0,0> <0,0,1> <0,1,0> <0,1,1> <0,2,0> <0,2,1> <1,0,0> <1,0,1> <1,1,0> <1,1,1> <1,2,0> <1,2,1> After construction, the Range object starts to point to the first element in the joint domain <0,0,...>. Then, when incrementing the object, the following element is pointed. When calling get() the current pointed element can be accessed.
- class Variable

  An object representing an immutable categoric variable.

Typedefs

- using **VariablesSoup** = std::vector< VariablePtr >
- using **VariablesSet** = SmartSet< Variable >
- using **VariablePtr** = std::shared_ptr< Variable >

Functions

- bool **operator==** (const Combination &a, const Combination &b)
- bool **operator!=** (const Combination &a, const Combination &b)
- VariablesSet **to_vars_set** (const VariablesSoup &soup)
- VariablesSet & operator-= (VariablesSet &subject, const VariablesSet &to_remove)

  removes the second set from the first
- VariablesSet get_complementary (const VariablesSet &entire_set, const VariablesSet &subset)
- bool **operator==** (const GroupRange &a, const GroupRange &b)
- bool **operator!=** (const GroupRange &a, const GroupRange &b)
- template<typename Predicate >
  void for_each_combination (GroupRange &range, const Predicate &predicate)

  Applies the passed predicate to all the elements that can be ranged using the passed range.
- VariablePtr **make_variable** (const std::size_t &size, const std::string &name)

8.2.1 Detailed Description

Author: Andrea Casalino Created: 01.01.2021

report any bug to andrecasa91@gmail.com.

8.2.2 Function Documentation

8.2.2.1 get_complementary()

```
VariablesSet EFG::categoric::get_complementary (
            const VariablesSet & entire_set,
            const VariablesSet & subset )
```

Returns

the complementary group of the entire_set, i.e. returns entire_set \ subset

8.3 EFG::distribution Namespace Reference

Classes

- class CombinationFinder

  An object used to search for the images associated to sub combinations that are part of a bigger one.
- class Distribution

  Base object for any kind of distribution. Any kind of distribution has:
- class DistributionConcrete
- class DistributionSetter
- class Evaluator
- class Evidence
- class Factor
- class FactorExponential

  An exponential factor applies an exponential function to map the raw values inside the combination map to the actual images. More precisely, given the weight w characterizing the factor the image value is obtained in this way: image = exp(w ∗ raw_value)
- struct GenericCopyTag
- class Indicator
- class MessageMAP
- class MessageSUM
- class UnaryFactor
- struct UseSimpleAntiCorrelation
- struct UseSimpleCorrelation

Typedefs

- using **CombinationRawValuesMap** = std::map< categoric::Combination, float >
- using **DistributionPtr** = std::shared_ptr< Distribution >
- using **DistributionCnstPtr** = std::shared_ptr< const Distribution >
- using **CombinationRawValuesMapPtr** = std::shared_ptr< CombinationRawValuesMap >
- using **EvaluatorPtr** = std::shared_ptr< Evaluator >

8.3.1 Detailed Description

Author: Andrea Casalino Created: 01.01.2021

report any bug to `andrecasa91@gmail.com`.

8.4 EFG::io Namespace Reference

Namespaces

- json
- xml

Classes

- struct AdderPtrs
- struct AwarePtrs
- class File

Typedefs

- using **IStream** = std::unique_ptr< std::ifstream >
- using **OStream** = std::unique_ptr< std::ofstream >

Functions

- void import_values (distribution::Factor &recipient, const std::string &file_name)

  Fill the passed factor with the combinations found in the passed file. The file should be a matrix of raw values. Each row represent a combination and a raw image (as last element) to add to the combination map of the passed distribution.
- train::TrainSet import_train_set (const std::string &file_name)

  Imports the training set from a file. The file should be a matrix of raw values. Each row represent a combination, i.e. a element of the training set to import.
- template<typename Model >
  AwarePtrs **getAwareComponents** (Model &model)
- template<typename Model >
  AdderPtrs **getAdderComponents** (Model &model)
- IStream **make_in_stream** (const std::string &file_name)
- OStream **make_out_stream** (const std::string &file_name)
- template<typename Predicate >
  void **for_each_line** (IStream &stream, const Predicate &pred)
- categoric::Combination **parse_combination** (const std::vector< std::string > &values)

8.4.1 Detailed Description

Author: Andrea Casalino Created: 01.01.2021

report any bug to andrecasa91@gmail.com.

8.4.2 Function Documentation

8.4.2.1 import_train_set()

```
train::TrainSet EFG::io::import_train_set (
            const std::string & file_name )
```

Imports the training set from a file. The file should be a matrix of raw values. Each row represent a combination, i.e. a element of the training set to import.

Exceptions

in	case the passed file is inexistent
in	case not all the combinations in file have the same size.

8.4.2.2 import_values()

```
void EFG::io::import_values (
            distribution::Factor & recipient,
            const std::string & file_name )
```

Fill the passed factor with the combinations found in the passed file. The file should be a matrix of raw values. Each row represent a combination and a raw image (as last element) to add to the combination map of the passed distribution.

Exceptions

in	case the passed file is inexistent
in	case the parsed combination is inconsitent for the passed distribution

8.5 EFG::io::json Namespace Reference

Classes

- class Exporter
- class Importer

8.5.1 Detailed Description

Author: Andrea Casalino Created: 01.01.2021

report any bug to andrecasa91@gmail.com.

8.6 EFG::io::xml Namespace Reference

Classes

- class Exporter
- struct ExportInfo
- class Importer

8.6.1 Detailed Description

Author: Andrea Casalino Created: 01.01.2021

report any bug to andrecasa91@gmail.com.

8.7 EFG::model Namespace Reference

Classes

- class ConditionalRandomField

  Similar to RandomField, with the difference that the model structure is immutable after construction. This applies also to the evidence set, which can't be changed over the time.
- class Graph

  A simple graph object, that stores only const factors. Evidences may be changed over the time.
- class RandomField

  A complete undurected factor graph storing both constant and tunable factors. Evidences may be changed over the time.

8.7.1 Detailed Description

Author: Andrea Casalino Created: 01.01.2021

report any bug to andrecasa91@gmail.com.

8.8 EFG::strct Namespace Reference

Classes

- class BaselineLoopyPropagator
- class BeliefAware

  The propagation relies on a concrete implementation of a BeliePropagationStrategy. In case no other is specified, a default one, BaselineBeliefPropagator, is instantiated and used internally. You can override this default propagator using setPropagationStrategy(...).
- struct ClusterInfo
- struct Connection
- struct ConnectionAndDependencies
- class ConnectionsManager
- struct EvidenceNodeLocation
- class EvidenceRemover
- class EvidenceSetter
- class FactorsAdder
- class FactorsAware
- class GibbsSampler

  Refer also to https://en.wikipedia.org/wiki/Gibbs_sampling.
- struct GraphState
- struct HiddenCluster

Clusters of hidden node. Each cluster is a group of connected hidden nodes. Nodes in different clusters are not currently connected, due to the model structure or the kind of evidences currently applied.

- struct HiddenNodeLocation
- class LoopyBeliefPropagationStrategy
- struct Node
- class Pool
- class PoolAware
- struct PropagationContext
- struct PropagationResult

  a structure that can be exposed after having propagated the belief, providing info on the encountered structure.
- class QueryManager
- class StateAware
- class UniformSampler

Typedefs

- using **LoopyBeliefPropagationStrategyPtr** = std::unique_ptr< LoopyBeliefPropagationStrategy >
- using **Task** = std::function< void(const std::size_t)>
- using **Tasks** = std::vector< Task >
- using **Nodes** = SmartMap< categoric::Variable, std::unique_ptr< Node > >
- using **Evidences** = SmartMap< categoric::Variable, std::size_t >
- using **HiddenClusters** = std::list< HiddenCluster >
- using **NodeLocation** = std::variant< HiddenNodeLocation, EvidenceNodeLocation >

Enumerations

- enum **PropagationKind** { **SUM**, **MAP** }

Functions

- template<typename... Args>
  std::unique_ptr< distribution::UnaryFactor > **make_unary** (Args &&...args)
- template<typename MessageT >
  std::unique_ptr< MessageT > **make_message** (const distribution::UnaryFactor &merged_unaries, const distribution::Distribution &binary_factor)
- std::unique_ptr< distribution::Evidence > **make_evidence** (const distribution::Distribution &binary_factor, const categoric::VariablePtr &evidence_var, const std::size_t evidence)

8.8.1 Detailed Description

Author: Andrea Casalino Created: 01.01.2021

report any bug to `andrecasa91@gmail.com`.

Author: Andrea Casalino Created: 28.03.2022

report any bug to `andrecasa91@gmail.com`.

8.9 EFG::train Namespace Reference

Classes

- class BaseTuner
- class BinaryTuner
- class CompositeTuner
- class FactorsTunableAdder
- class FactorsTunableAware
- struct TrainInfo
- class TrainSet
- class Tuner
- class UnaryTuner

Typedefs

- using **FactorExponentialPtr** = std::shared_ptr< distribution::FactorExponential >
- using **TunerPtr** = std::unique_ptr< Tuner >
- using **Tuners** = std::vector< TunerPtr >

Functions

- void set_ones (FactorsTunableAware &subject)
- void train_model (FactorsTunableAware &subject, ::train::Trainer &trainer, const TrainSet &train_set, const TrainInfo &info=TrainInfo{})
- void **visit_tuner** (const TunerPtr &to_visit, const std::function< void(const BaseTuner &)> &base_case, const std::function< void(const CompositeTuner &)> &composite_case)
- void **visit_tuner** (TunerPtr &to_visit, const std::function< void(BaseTuner &)> &base_case, const std↩ ::function< void(CompositeTuner &)> &composite_case)

8.9.1 Detailed Description

Author: Andrea Casalino Created: 01.01.2021

report any bug to andrecasa91@gmail.com.

8.9.2 Function Documentation

8.9.2.1 set_ones()

```
void EFG::train::set_ones (
            FactorsTunableAware & subject )
```

Parameters

sets	equal to 1 the weight of all the tunable clusters

8.9.2.2 train_model()

```
void EFG::train::train_model (
            FactorsTunableAware & subject,
            ::train::Trainer & trainer,
            const TrainSet & train_set,
            const TrainInfo & info = TrainInfo{} )
```

Parameters

the	model to tune
the	training approach to adopt
the	train set to use

Chapter 9

Class Documentation

9.1 EFG::io::AdderPtrs Struct Reference

Public Attributes

- strct::FactorsAdder * **as_factors_const_adder**
- train::FactorsTunableAdder * **as_factors_tunable_adder**

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/io/Utils.h

9.2 EFG::io::AwarePtrs Struct Reference

Public Attributes

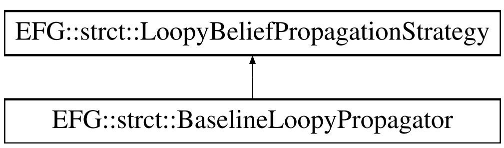
- const strct::StateAware * **as_structure_aware**
- const strct::FactorsAware * **as_factors_const_aware**
- const train::FactorsTunableAware * **as_factors_tunable_aware**

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/io/Utils.h

9.3 EFG::strct::BaselineLoopyPropagator Class Reference

Inheritance diagram for EFG::strct::BaselineLoopyPropagator:



Public Member Functions

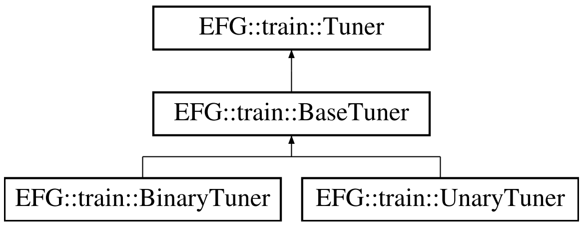
- bool **propagateBelief** (HiddenCluster &subject, const PropagationKind &kind, const PropagationContext &context, Pool &pool) final

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/BaselineLoopy↩ Propagator.h

9.4 EFG::train::BaseTuner Class Reference

Inheritance diagram for EFG::train::BaseTuner:



Public Member Functions

- FactorExponentialPtr **getFactorPtr** () const
- const distribution::FactorExponential & **getFactor** () const
- float **getGradientAlpha** (const TrainSet::Iterator &iter) final
- void **setWeight** (const float &w) final
- float **getWeight** () const final

Protected Member Functions

- **BaseTuner** (const FactorExponentialPtr &factor, const categoric::VariablesSoup &variables_in_model)
- float **dotProduct** (const std::vector< float > &prob) const

The documentation for this class was generated from the following file:

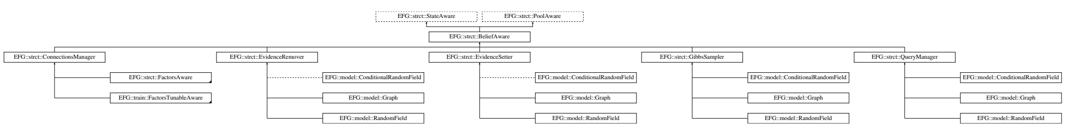
- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/trainable/tuners/Base↩ Tuner.h

9.5 EFG::strct::BeliefAware Class Reference

The propagation relies on a concrete implementation of a BeliePropagationStrategy. In case no other is specified, a default one, BaselineBeliefPropagator, is instantiated and used internally. You can override this default propagator using setPropagationStrategy(...).

`#include <BeliefAware.h>`

Inheritance diagram for EFG::strct::BeliefAware:



Public Member Functions

- const PropagationContext & **getPropagationContext** () const
- void **setPropagationContext** (const PropagationContext &ctxt)
- bool **hasPropagationResult** () const
- const PropagationResult & **getLastPropagationResult** () const
- void **setLoopyPropagationStrategy** (LoopyBeliefPropagationStrategyPtr strategy)

Protected Member Functions

- void **resetBelief** ()
- void **propagateBelief** (const PropagationKind &kind)
- bool **wouldNeedPropagation** (const PropagationKind &kind) const

9.5.1 Detailed Description

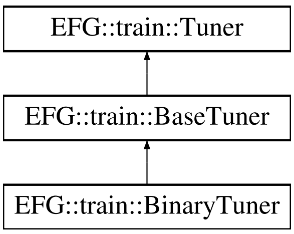
The propagation relies on a concrete implementation of a BeliePropagationStrategy. In case no other is specified, a default one, BaselineBeliefPropagator, is instantiated and used internally. You can override this default propagator using setPropagationStrategy(...).

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/components/Belief↩ Aware.h

9.6 EFG::train::BinaryTuner Class Reference

Inheritance diagram for EFG::train::BinaryTuner:



Public Member Functions

- **BinaryTuner** (strct::Node &nodeA, strct::Node &nodeB, const std::shared_ptr< distribution::FactorExponential > &factor, const categoric::VariablesSoup &variables_in_model)
- float **getGradientBeta** () final

Protected Attributes

- strct::Node & **nodeA**
- strct::Node & **nodeB**

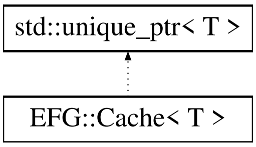
Additional Inherited Members

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/trainable/tuners/Binary↩
Tuner.h

9.7 EFG::Cache< T > Class Template Reference

Inheritance diagram for EFG::Cache< T >:



Public Member Functions

- T & **reset** (std::unique_ptr< T > new_value=nullptr)
- bool **empty** () const
- T ∗ **get** ()
- const T ∗ **get** () const

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/misc/Cache.h

9.8 EFG::strct::ClusterInfo Struct Reference

Public Attributes

- bool **tree_or_loopy_graph**
- std::size_t size

  number of nodes that constitutes the graph.

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/components/Belief↩
Aware.h

9.9 EFG::categoric::Combination Class Reference

An immutable combination of discrete values.

```
#include <Combination.h>
```

Public Member Functions

- Combination (const std::size_t bufferSize)
  A buffer of zeros with the passed size is created.
- Combination (std::vector< std::size_t > &&buffer)
- **Combination** (const Combination &o)
- bool operator< (const Combination &o) const
  compare two equally sized combination. Examples of ordering: <0,0,0> < <0,1,0> <0,1> < <1,0>
- std::size_t **size** () const
- const std::vector< std::size_t > & **data** () const

9.9.1 Detailed Description

An immutable combination of discrete values.

9.9.2 Constructor & Destructor Documentation

9.9.2.1 Combination() [1/2]

```
EFG::categoric::Combination::Combination (
            const std::size_t bufferSize )
```

A buffer of zeros with the passed size is created.

Parameters

the	size of the combination to build

Exceptions

if	bufferSize is 0

9.9.2.2 Combination() [2/2]

```
EFG::categoric::Combination::Combination (
            std::vector< std::size_t > && buffer )
```

Parameters

the	values that will characterize the Combination

Exceptions

if	buffer is empty

9.9.3 Member Function Documentation

9.9.3.1 operator<()

```
bool EFG::categoric::Combination::operator< (
            const Combination & o ) const
```

compare two equally sized combination. Examples of ordering: <0,0,0> < <0,1,0> <0,1> < <1,0>

Exceptions

when	the passed combination has a different size

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/categoric/Combination.h

9.10 EFG::distribution::CombinationFinder Class Reference

An object used to search for the images associated to sub combinations that are part of a bigger one.

```
#include <CombinationFinder.h>
```

Classes

- struct Result

    Searches for matches. For example assume having built this object with a bigger_group equal to <A,B,C,D> while the variables describing the distribution this finder refers to is equal to <B,D>. When passing a comb equal to <0,1,2,0>, this object searches for the immage associated to the sub combination <B,D> = <1,0>.

Public Member Functions

- Result **find** (const categoric::Combination &comb) const

Friends

- class **DistributionConcrete**

9.10.1 Detailed Description

An object used to search for the images associated to sub combinations that are part of a bigger one.

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/distribution/Combination↩
Finder.h

9.11 EFG::Comparator< T > Struct Template Reference

Public Member Functions

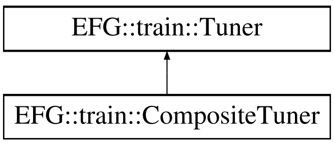
- bool **operator()** (const std::shared_ptr< T > &a, const std::shared_ptr< T > &b) const

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/misc/SmartPointerUtils.h

9.12 EFG::train::CompositeTuner Class Reference

Inheritance diagram for EFG::train::CompositeTuner:



Public Member Functions

- Tuners & **getElements** ()
- const Tuners & **getElements** () const
- **CompositeTuner** (TunerPtr elementA, TunerPtr elementB)
- float **getGradientAlpha** (const TrainSet::Iterator &iter) final
- float **getGradientBeta** () final
- void **setWeight** (const float &w) final
- float **getWeight** () const final
- void **addElement** (TunerPtr element)

The documentation for this class was generated from the following file:

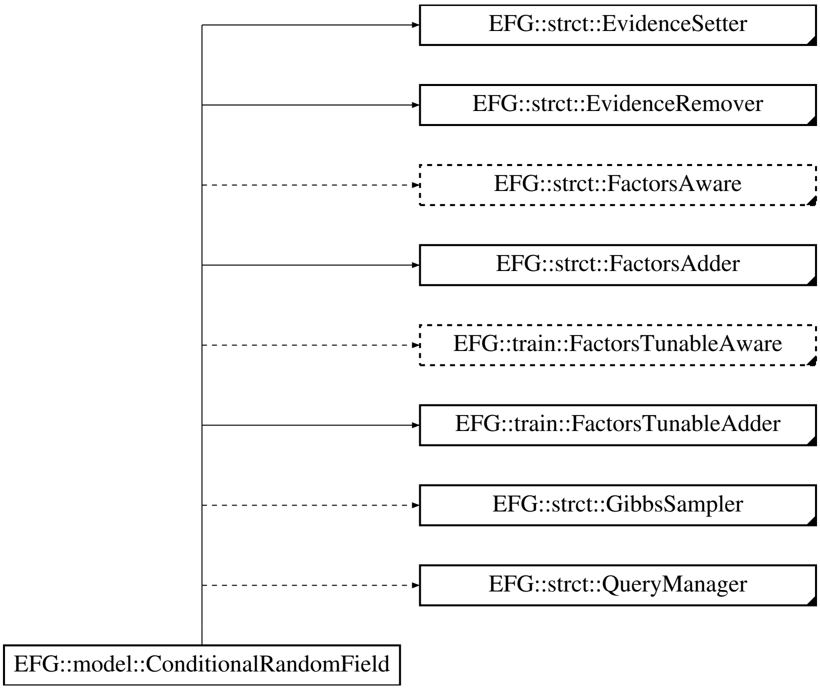
- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/trainable/tuners/Composite↩
Tuner.h

9.13 EFG::model::ConditionalRandomField Class Reference

Similar to RandomField, with the difference that the model structure is immutable after construction. This applies also to the evidence set, which can't be changed over the time.

```
#include <ConditionalRandomField.h>
```

Inheritance diagram for EFG::model::ConditionalRandomField:



Public Member Functions

- **ConditionalRandomField** (const ConditionalRandomField &o)
- ConditionalRandomField & **operator=** (const ConditionalRandomField &)=delete
- ConditionalRandomField (const RandomField &source, const bool copy)

  All the factors of the passed source are inserted/copied. The evidence set is deduced by the passed source.
- void setEvidences (const std::vector< std::size_t > &values)

  Sets the new set of evidences.
- std::vector< categoric::Combination > makeTrainSet (const GibbsSampler::SamplesGenerationContext &context, const float range_percentage=1.f, const std::size_t threads=1)

  Builds a training set for the conditioned model. Instead of using Gibbs sampler for a single combination of evidence, it tries to span all the possible combination of evidences and generate some samples conditioned to each of this evidences value. Then, gather results to build the training set. Actually, not ALL possible evidence are spwan if that would be too much computationally demanding. In such cases, simply pass a number lower than 1 as range_↩ percentage.

Protected Member Functions

- std::vector< float > **getWeightsGradient_** (const train::TrainSet::Iterator &train_set_combinations) final

Additional Inherited Members

9.13.1 Detailed Description

Similar to RandomField, with the difference that the model structure is immutable after construction. This applies also to the evidence set, which can't be changed over the time.

9.13.2 Constructor & Destructor Documentation

9.13.2.1 ConditionalRandomField()

```
EFG::model::ConditionalRandomField::ConditionalRandomField (
            const RandomField & source,
            const bool copy )
```

All the factors of the passed source are inserted/copied. The evidence set is deduced by the passed source.

Parameters

the	model to emulate for building the structure of this one.
then	passing true the factors are deep copied, while in the contrary case the smart pointers storing the factors of the source are copied and inserted.

Exceptions

in	case the passed source has no evidences

9.13.3 Member Function Documentation

9.13.3.1 makeTrainSet()

```
std::vector<categoric::Combination> EFG::model::ConditionalRandomField::makeTrainSet (
            const GibbsSampler::SamplesGenerationContext & context,
            const float range_percentage = 1.f,
            const std::size_t threads = 1 )
```

Builds a training set for the conditioned model. Instead of using Gibbs sampler for a single combination of evidence, it tries to span all the possible combination of evidences and generate some samples conditioned to each of this evidences value. Then, gather results to build the training set. Actually, not ALL possible evidence are spwan if that would be too much computationally demanding. In such cases, simply pass a number lower than 1 as range_↩ percentage.

Parameters

information	used for samples generation
parameter	handling how many evidence values are accounted for the samples generation
the	number of threads to use for speeding up the process

9.13.3.2 setEvidences()

```
void EFG::model::ConditionalRandomField::setEvidences (
            const std::vector< std::size_t > & values )
```

Sets the new set of evidences.

Parameters

the	new set of evidence values. The variables order is the same of the set obtained using getObservedVariables().

Exceptions

the	number of passed values does not match the number of evidences.
in	case some evidence values are inconsistent

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/model/ConditionalRandom↩ Field.h

9.14 EFG::strct::Connection Struct Reference

Public Attributes

- distribution::DistributionCnstPtr **factor**
- std::unique_ptr< const distribution::UnaryFactor > **message**

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/components/State↩ Aware.h

9.15 EFG::strct::ConnectionAndDependencies Struct Reference

Public Attributes

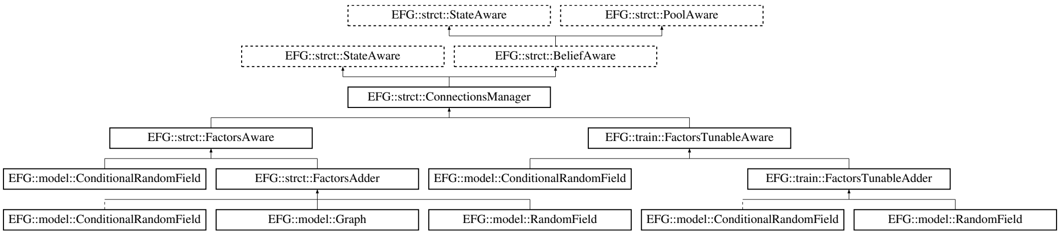
- Connection ∗ **connection**
- Node ∗ **sender**
- std::vector< const Connection ∗ > **dependencies**

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/components/State←
Aware.h

9.16 EFG::strct::ConnectionsManager Class Reference

Inheritance diagram for EFG::strct::ConnectionsManager:



Public Member Functions

- const std::set< distribution::DistributionCnstPtr > & getAllFactors () const

Protected Member Functions

- void **addDistribution** (const EFG::distribution::DistributionCnstPtr &distribution)

9.16.1 Member Function Documentation

9.16.1.1 getAllFactors()

```
const std::set<distribution::DistributionCnstPtr>& EFG::strct::ConnectionsManager::getAll←
Factors ( ) const  [inline]
```

Returns

all the factors in the model, tunable and constant.

The documentation for this class was generated from the following file:

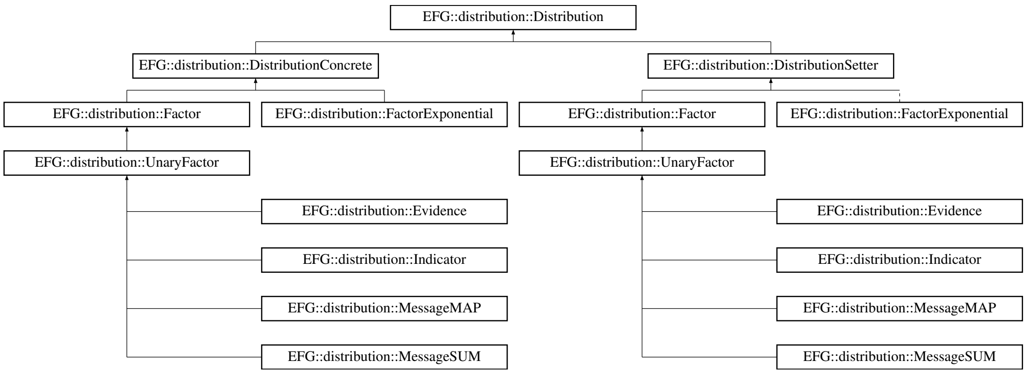
- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/Connections←
Manager.h

9.17 EFG::distribution::Distribution Class Reference

Base object for any kind of distribution. Any kind of distribution has:

`#include <Distribution.h>`

Inheritance diagram for EFG::distribution::Distribution:



Public Member Functions

- virtual const Evaluator & getEvaluator () const =0
- virtual const categoric::Group & **getGroup** () const =0
- virtual const CombinationRawValuesMap & **getCombinationsMap** () const =0
- virtual CombinationFinder **makeFinder** (const categoric::VariablesSoup &bigger_group) const =0
- float evaluate (const categoric::Combination &comb) const

  searches for the image associated to the passed combination
- std::vector< float > getProbabilities () const

Protected Member Functions

- virtual CombinationRawValuesMap & **getCombinationsMap_** ()=0
- virtual Evaluator & **getEvaluator_** ()=0

9.17.1 Detailed Description

Base object for any kind of distribution. Any kind of distribution has:

- A group of variables the distribution refer to
- A domain, represented by the combinations map. To each key in the map, a raw image value (a float number) is associated.
- Images set, which are the image values associated to each element in the combinations map. They can be obtained by applying a certain function f(x) to the raw images. In order to save memory, the combinations having an image equal to 0 are not explicitly instanciated in the combinations map, even if they are accounted when calling evaluate(...)

9.17.2 Member Function Documentation

9.17.2.1 evaluate()

```
float EFG::distribution::Distribution::evaluate (
            const categoric::Combination & comb ) const
```

searches for the image associated to the passed combination

Returns

the value of the image.

9.17.2.2 getEvaluator()

```
virtual const Evaluator& EFG::distribution::Distribution::getEvaluator ( ) const  [pure virtual]
```

Returns

the evaluator used to compute the images

Implemented in EFG::distribution::DistributionConcrete.

9.17.2.3 getProbabilities()

```
std::vector<float> EFG::distribution::Distribution::getProbabilities ( ) const
```

Returns

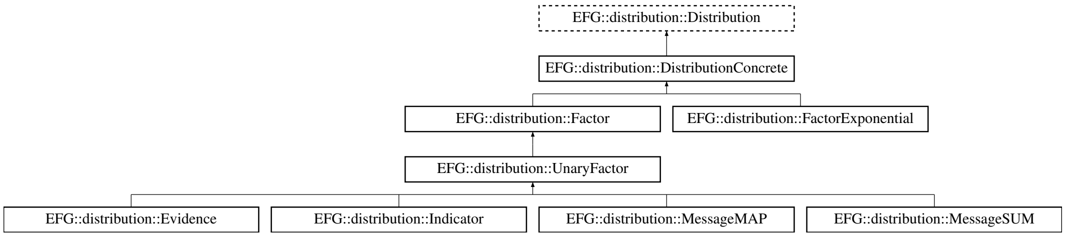
the probabilities associated to each combination in the domain, when assuming only the existance of this distribution. Such probabilities are actually the normalized images. The order of returned values, refer to the combinations that can be iterated by categoric::GroupRange on the variables representing this distribution.

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/distribution/Distribution.h

9.18 EFG::distribution::DistributionConcrete Class Reference

Inheritance diagram for EFG::distribution::DistributionConcrete:



Public Member Functions

- **DistributionConcrete** (const DistributionConcrete &o)=delete
- DistributionConcrete & **operator==** (const DistributionConcrete &)=delete
- **DistributionConcrete** (DistributionConcrete &&o)=delete
- DistributionConcrete & **operator==** (DistributionConcrete &&)=delete
- CombinationFinder **makeFinder** (const categoric::VariablesSoup &bigger_group) const final
- const Evaluator & getEvaluator () const final
- const categoric::Group & **getGroup** () const final
- const CombinationRawValuesMap & **getCombinationsMap** () const final
- void replaceVariables (const categoric::VariablesSoup &new_variables)

  Replaces the variables this distribution should refer to.

Protected Member Functions

- **DistributionConcrete** (const EvaluatorPtr &evaluator, const categoric::Group &vars)
- **DistributionConcrete** (const EvaluatorPtr &evaluator, const categoric::Group &vars, const CombinationRawValuesMapPtr &map)
- CombinationRawValuesMap & **getCombinationsMap_** () final
- Evaluator & **getEvaluator_** () final

9.18.1 Member Function Documentation

9.18.1.1 getEvaluator()

```
const Evaluator& EFG::distribution::DistributionConcrete::getEvaluator ( ) const  [inline],
[final], [virtual]
```

Returns

the evaluator used to compute the images

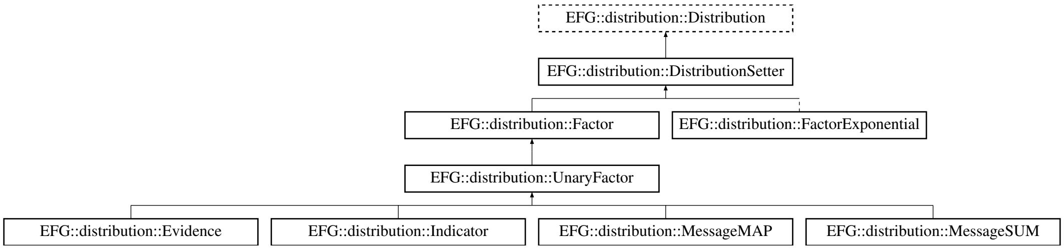
Implements EFG::distribution::Distribution.

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/distribution/DistributionConcrete.h

9.19 EFG::distribution::DistributionSetter Class Reference

Inheritance diagram for EFG::distribution::DistributionSetter:



Public Member Functions

- void setImageRaw (const categoric::Combination &comb, const float &value)

  sets the raw value of the image related to the passed combination. In case the combination is currently not part of the distribution, it is added to the combinations map, with the passed raw image value.
- void setAllImagesRaw (const float &value)

  sets the raw images of all the combinations (which are actually instanciated in the combinations map) equal to the passed value
- void clear ()

  Removes all the combinations from the combinations map.

Additional Inherited Members

9.19.1 Member Function Documentation

9.19.1.1 setAllImagesRaw()

```
void EFG::distribution::DistributionSetter::setAllImagesRaw (
            const float & value )
```

sets the raw images of all the combinations (which are actually instanciated in the combinations map) equal to the passed value

Exceptions

passing	a negative number for value

9.19.1.2 setImageRaw()

```
void EFG::distribution::DistributionSetter::setImageRaw (
```

```
const categoric::Combination & comb,
const float & value )
```

sets the raw value of the image related to the passed combination. In case the combination is currently not part of the distribution, it is added to the combinations map, with the passed raw image value.

Parameters

the	combination whose raw image must be set
the	raw image value to assume

Exceptions

passing	a negative number for value

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/distribution/Distribution↩ Setter.h

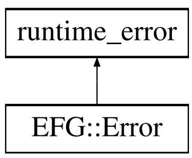
9.20 EFG::distribution::UnaryFactor::DontFillDomainTag Struct Reference

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/SpecialFactors.h

9.21 EFG::Error Class Reference

Inheritance diagram for EFG::Error:



Public Member Functions

- **Error** (const std::string &what)
- template<typename T1 , typename T2 , typename... Slices>
  Error (const T1 &first, const T2 &second, const Slices &...args)

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/Error.h

9.22 EFG::distribution::Evaluator Class Reference

Public Member Functions

- virtual float evaluate (const float &input) const =0

  applies a specific function to obtain the image from the passed rwa value

9.22.1 Member Function Documentation

9.22.1.1 evaluate()

```
virtual float EFG::distribution::Evaluator::evaluate (
            const float & input ) const  [pure virtual]
```

applies a specific function to obtain the image from the passed rwa value

Parameters

the	raw value to convert

Returns

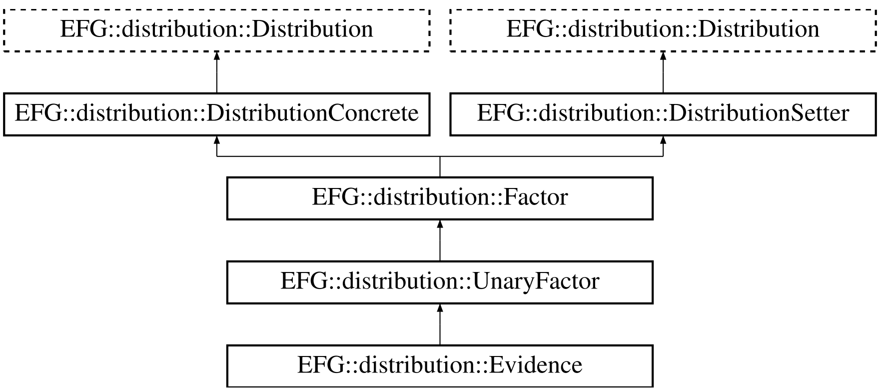
the converted image

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/distribution/Evaluator.h

9.23 EFG::distribution::Evidence Class Reference

Inheritance diagram for EFG::distribution::Evidence:



Public Member Functions

- **Evidence** (const Distribution &binary_factor, const categoric::VariablePtr &evidence_var, const std::size_t evidence)

Additional Inherited Members

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/SpecialFactors.h

9.24 EFG::strct::EvidenceNodeLocation Struct Reference

Public Attributes

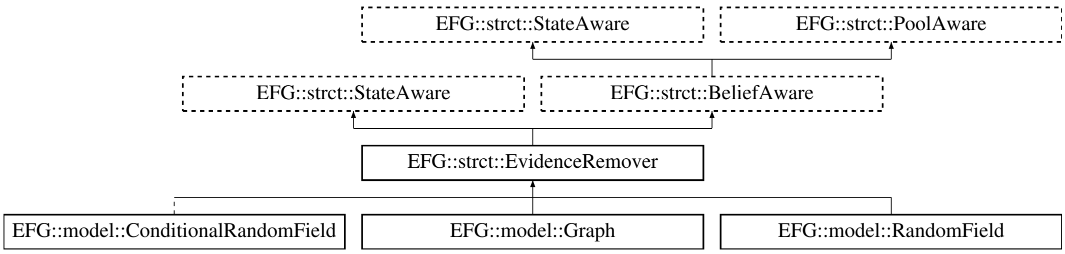
- Evidences::iterator **evidence**
- Node $*$ **node**

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/components/State←
Aware.h

9.25 EFG::strct::EvidenceRemover Class Reference

Inheritance diagram for EFG::strct::EvidenceRemover:



Public Member Functions

- void removeEvidence (const categoric::VariablePtr &variable)

  update the evidence set by removing the specified variable.
- void removeEvidence (const std::string &variable)

  similar to removeEvidence(const categoric::VariablePtr &), but passing the variable name, which is internally searched.
- void removeEvidences (const categoric::VariablesSet &variables)

  update the evidence set by removing all the specified variables.
- void removeEvidences (const std::unordered_set< std::string > &variables)

  similar to removeEvidences(const categoric::VariablesSet &), but passing the variable names, which are internally searched.
- void removeAllEvidences ()

  removes all the evidences currently set for this model.

Additional Inherited Members

9.25.1 Member Function Documentation

9.25.1.1 removeEvidence()

```
void EFG::strct::EvidenceRemover::removeEvidence (
            const categoric::VariablePtr & variable )
```

update the evidence set by removing the specified variable.

Parameters

the	involved variable

Exceptions

in	case the passed variable is not part of the model.
in	case the passed variable is not part of the current evidence set.

9.25.1.2 removeEvidences()

```
void EFG::strct::EvidenceRemover::removeEvidences (
            const categoric::VariablesSet & variables )
```

update the evidence set by removing all the specified variables.

Parameters

the	involved variables

Exceptions

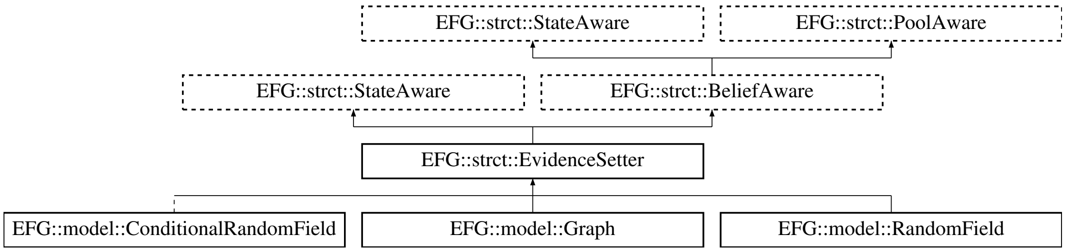
in	case one of the passed variable is not part of the model.
in	case one of the passed variable is not part of the current evidence set.

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/Evidence↩ Manager.h

9.26 EFG::strct::EvidenceSetter Class Reference

Inheritance diagram for EFG::strct::EvidenceSetter:



Public Member Functions

- void setEvidence (const categoric::VariablePtr &variable, const std::size_t value)

  update the evidence set with the specified new evidence. In case the involved variable was already part of the evidence set, the evidence value is simply updated. On the contrary case, the involved variable is moved into the evidence set, with the specified value.
- void setEvidence (const std::string &variable, const std::size_t value)

  Similar to setEvidence(const categoric::VariablePtr &, const std::size_t) , but passing the variable name, which is interally searched.

Additional Inherited Members

9.26.1 Member Function Documentation

9.26.1.1 setEvidence()

```
void EFG::strct::EvidenceSetter::setEvidence (
            const categoric::VariablePtr & variable,
            const std::size_t value )
```

update the evidence set with the specified new evidence. In case the involved variable was already part of the evidence set, the evidence value is simply updated. On the contrary case, the involved variable is moved into the evidence set, with the specified value.

Parameters

the	involved variable
the	evidence value

Exceptions

in	case the passed variable is not part of the model.

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/Evidence↩ Manager.h

9.27 EFG::io::xml::Exporter Class Reference

Static Public Member Functions

- template<typename Model >
  static std::string exportToString (const Model &model, const std::string &model_name)

  exports the model (variables and factors) into a string, describing an xml.
- template<typename Model >
  static void exportToFile (const Model &model, const ExportInfo &info)

  exports the model (variables and factors) into an xml file

9.27.1 Member Function Documentation

9.27.1.1 exportToFile()

```
template<typename Model >
static void EFG::io::xml::Exporter::exportToFile (
            const Model & model,
            const ExportInfo & info )  [inline], [static]
```

exports the model (variables and factors) into an xml file

Parameters

the	model to export
info	describing the xml to generate.

9.27.1.2 exportToString()

```
template<typename Model >
static std::string EFG::io::xml::Exporter::exportToString (
            const Model & model,
            const std::string & model_name )  [inline], [static]
```

exports the model (variables and factors) into a string, describing an xml.

Parameters

the	model to export
the	model name to report in the xml

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/io/xml/Exporter.h

9.28 EFG::io::json::Exporter Class Reference

Static Public Member Functions

- template<typename Model >
  static nlohmann::json exportToJson (const Model &model)

  exports the model (variables and factors) into a json.
- template<typename Model >
  static void exportToFile (const Model &model, const std::string &file_path)

  exports the model (variables and factors) into an json file

9.28.1 Member Function Documentation

9.28.1.1 exportToFile()

```
template<typename Model >
static void EFG::io::json::Exporter::exportToFile (
            const Model & model,
            const std::string & file_path )  [inline], [static]
```

exports the model (variables and factors) into an json file

Parameters

the	model to export
the	file to generate storing the exported json

9.28.1.2 exportToJson()

```
template<typename Model >
static nlohmann::json EFG::io::json::Exporter::exportToJson (
            const Model & model )  [inline], [static]
```

exports the model (variables and factors) into a json.

Parameters

the	model to export

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/io/json/Exporter.h

9.29 EFG::io::xml::ExportInfo Struct Reference

Public Attributes

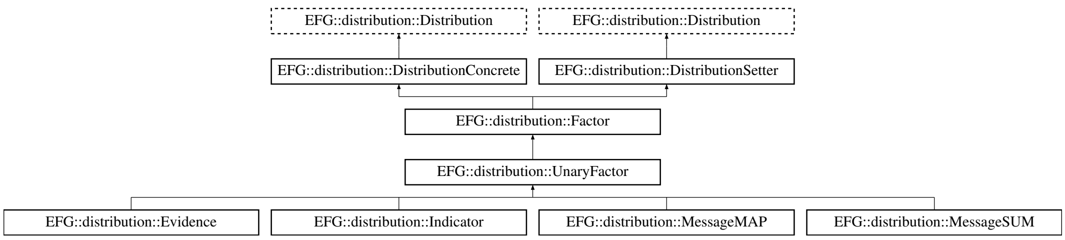
- std::string **file_path**
- std::string **model_name** = "Model"

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/io/xml/Exporter.h

9.30 EFG::distribution::Factor Class Reference

Inheritance diagram for EFG::distribution::Factor:



Public Member Functions

- Factor (const Distribution &to_clone, const GenericCopyTag &GENERIC_COPY_TAG)

  The variables set representing this factor is copied from the passed one. All the combinations instanciated in the passed factor, are copied in the combinations map of the factor to build, assigning the images values obtained by evaluating the passed factor.
- **Factor** (const Factor &o)
- Factor (const categoric::Group &vars)

  The variables set representing this factor is assumed equal to the passed one. No combinations is instanciated, implicitly assuming all the images equal to 0.
- Factor (const categoric::Group &vars, const UseSimpleCorrelation &)

  A simply correlating factor is built. All the variables in the passed group should have the same size. The images pertaining to the combinations having all values equal, are assumed equal to 1, all the others to 0. For instance assume to pass a variable set equal to: {<A: size 3>, <B: size 3>, <C: size 3>}. Then, the following combinations map is built: <0,0,0> -> 1 <0,0,1> -> 0 <0,0,2> -> 0.
- Factor (const categoric::Group &vars, const UseSimpleAntiCorrelation &)

Similar to Factor(const categoric::Group &, const UseSimpleCorrelation &), but considering a simple anti-correlation. Therefore, to all combinations having all equal values, an image equal to 0 is assigned. All the other ones, are assigned a value equal to 1. For instance assume to pass a variable set equal to: {<A: size 2>, <B: size 2>}. Then, the following combinations map is built: <0,0,0> -> 0 <0,0,1> -> 1 <0,0,2> -> 1.

- template<typename... Distributions>
  Factor (const Distribution &first, const Distribution &second, const Distributions &...others)

  Builds the factor by merging all the passed factors. The variables set representing this factor is obtained as the union of the all the variables sets of the passed distribution.
- Factor cloneWithPermutedGroup (const categoric::Group &new_order) const

  Generates a Factor similar to this one, permuting the group of variables.

Protected Member Functions

- **Factor** (const categoric::Group &vars, const CombinationRawValuesMapPtr &map)
- **Factor** (const std::vector< const Distribution ∗ > &factors)

9.30.1 Constructor & Destructor Documentation

9.30.1.1 Factor() [1/2]

```
EFG::distribution::Factor::Factor (
            const categoric::Group & vars,
            const UseSimpleCorrelation &   )
```

A simply correlating factor is built. All the variables in the passed group should have the same size. The images pertaining to the combinations having all values equal, are assumed equal to 1, all the others to 0. For instance assume to pass a variable set equal to: {<A: size 3>, <B: size 3>, <C: size 3>}. Then, the following combinations map is built: <0,0,0> -> 1 <0,0,1> -> 0 <0,0,2> -> 0.

<0,1,0> -> 0 <0,1,1> -> 0 <0,1,2> -> 0

<0,2,0> -> 0 <0,2,1> -> 0 <0,2,2> -> 0

<1,0,0> -> 0 <1,0,1> -> 0 <1,0,2> -> 0

<1,1,0> -> 0 <1,1,1> -> 1 <1,1,2> -> 0

<1,2,0> -> 0 <1,2,1> -> 0 <1,2,2> -> 0

<2,0,0> -> 0 <2,0,1> -> 0 <2,0,2> -> 0

<2,1,0> -> 0 <2,1,1> -> 0 <2,1,2> -> 0

<2,2,0> -> 0 <2,2,1> -> 0 <2,2,2> -> 1

9.30.1.2 Factor() [2/2]

```
EFG::distribution::Factor::Factor (
            const categoric::Group & vars,
            const UseSimpleAntiCorrelation &  )
```

Similar to Factor(const categoric::Group &, const UseSimpleCorrelation &), but considering a simple anti-correlation. Therefore, to all combinations having all equal values, an image equal to 0 is assigned. All the other ones, are assigned a value equal to 1. For instance assume to pass a variable set equal to: {<A: size 2>, <B: size 2>}. Then, the following combinations map is built: <0,0,0> -> 0 <0,0,1> -> 1 <0,0,2> -> 1.

<0,1,0> -> 1 <0,1,1> -> 1 <0,1,2> -> 1

<0,2,0> -> 1 <0,2,1> -> 1 <0,2,2> -> 1

<1,0,0> -> 1 <1,0,1> -> 1 <1,0,2> -> 1

<1,1,0> -> 1 <1,1,1> -> 0 <1,1,2> -> 1

<1,2,0> -> 1 <1,2,1> -> 1 <1,2,2> -> 1

<2,0,0> -> 1 <2,0,1> -> 1 <2,0,2> -> 1

<2,1,0> -> 1 <2,1,1> -> 1 <2,1,2> -> 1

<2,2,0> -> 1 <2,2,1> -> 1 <2,2,2> -> 0

9.30.2 Member Function Documentation

9.30.2.1 cloneWithPermutedGroup()

```
Factor EFG::distribution::Factor::cloneWithPermutedGroup (
            const categoric::Group & new_order ) const
```

Generates a Factor similar to this one, permuting the group of variables.

Parameters

the	new variables group order to assume

Returns

the permuted variables factor

Exceptions

in	case new_order.getVariablesSet() != this->getVariables().getVariablesSet()

The documentation for this class was generated from the following file:

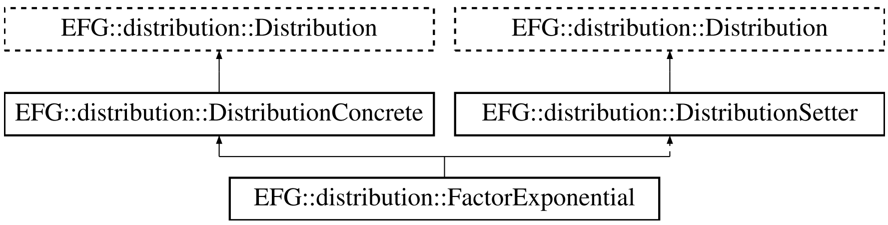
- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/distribution/Factor.h

9.31 EFG::distribution::FactorExponential Class Reference

An exponential factor applies an exponential function to map the raw values inside the combination map to the actual images. More precisely, given the weight w characterizing the factor the image value is obtained in this way: image = exp(w * raw_value)

```
#include <FactorExponential.h>
```

Inheritance diagram for EFG::distribution::FactorExponential:



Public Member Functions

- FactorExponential (const Factor &factor, const float weigth)

  The same variables describing the passed factor are assumed for the object to build. The map of combinations is built by iterating all the possible ones of the group of variables describing the passed factor. The raw values are computed by evaluating the passed factor over each possible combination.
- FactorExponential (const Factor &factor)

  Same as FactorExponential(const Factor &, const float), assuming weigth = 1.
- **FactorExponential** (const FactorExponential &o)
- void setWeight (const float w)

  sets the weight used by the exponential evaluator.
- float getWeight () const

Additional Inherited Members

9.31.1 Detailed Description

An exponential factor applies an exponential function to map the raw values inside the combination map to the actual images. More precisely, given the weight w characterizing the factor the image value is obtained in this way: image = exp(w * raw_value)

All the combinations are instanciated in the combinations map when building this object.

9.31.2 Constructor & Destructor Documentation

9.31.2.1 FactorExponential()

```
EFG::distribution::FactorExponential::FactorExponential (
            const Factor & factor,
            const float weigth )
```

The same variables describing the passed factor are assumed for the object to build. The map of combinations is built by iterating all the possible ones of the group of variables describing the passed factor. The raw values are computed by evaluating the passed factor over each possible combination.

Parameters

the	baseline factor
the	weight that will be considered by the exponential evaluator

9.31.3 Member Function Documentation

9.31.3.1 getWeight()

```
float EFG::distribution::FactorExponential::getWeight ( ) const
```

Returns

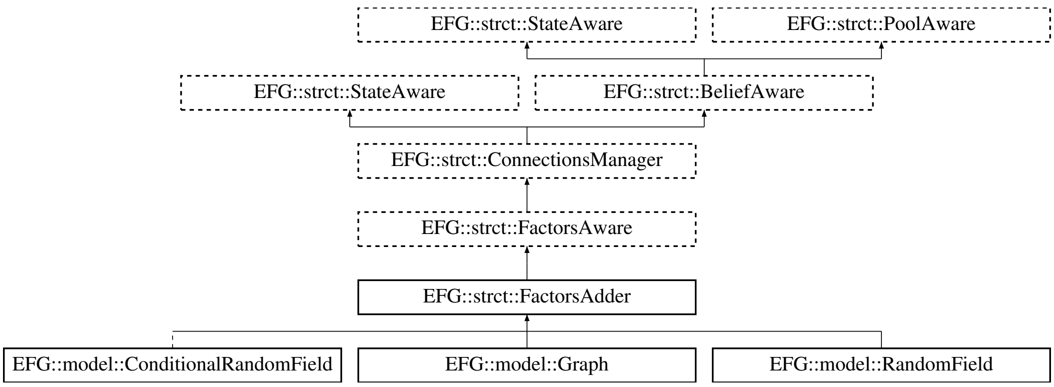
the weight used by the exponential evaluator.

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/distribution/FactorExponential.↩ h

9.32 EFG::strct::FactorsAdder Class Reference

Inheritance diagram for EFG::strct::FactorsAdder:



Public Member Functions

- void addConstFactor (const distribution::DistributionCnstPtr &factor)

  add a shallow copy of the passed const factor to this model
- void copyConstFactor (const distribution::Distribution &factor)

  add a deep copy of the passed const factor to this model
- template< typename DistributionIt >
  void absorbConstFactors (const DistributionIt &begin, const DistributionIt &end, const bool copy)

  adds a collection of const factors ot this model. Passing copy = true, deep copies are created and inserted in this model. Passing copy = false, shallow copies are created and inserted in this model.

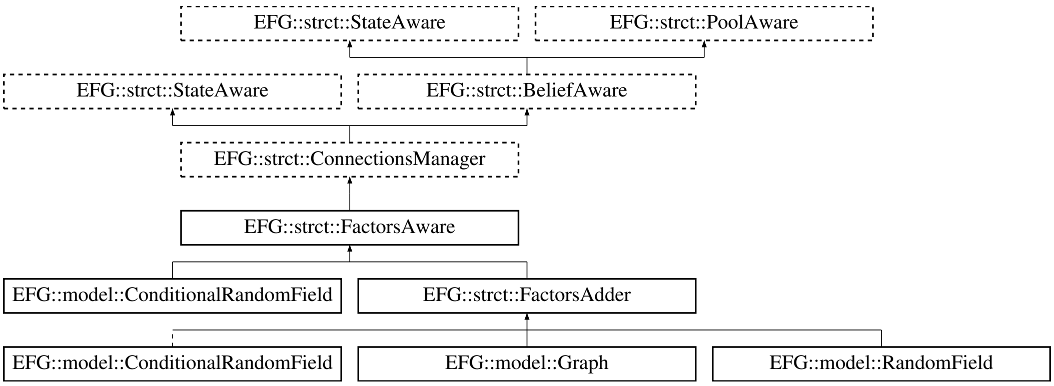
Additional Inherited Members

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/FactorsManager.↩
  h

9.33 EFG::strct::FactorsAware Class Reference

Inheritance diagram for EFG::strct::FactorsAware:



Public Member Functions

- const std::unordered_set< distribution::DistributionCnstPtr > & getConstFactors () const

Protected Attributes

- std::unordered_set< distribution::DistributionCnstPtr > **const_factors**

Additional Inherited Members

9.33.1 Member Function Documentation

9.33.1.1 getConstFactors()

```
const std::unordered_set<distribution::DistributionCnstPtr>& EFG::strct::FactorsAware::get↩
ConstFactors ( ) const [inline]
```

Returns

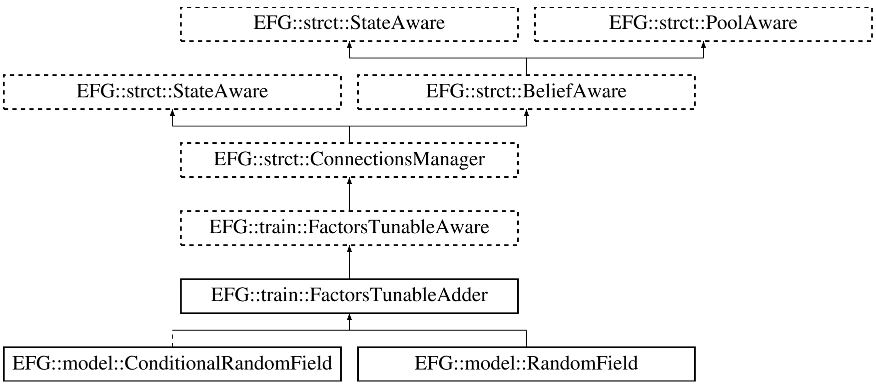
the collection of const factors that are part of the model. Tunable factors are not accounted in this collection.

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/FactorsManager.↩
h

9.34 EFG::train::FactorsTunableAdder Class Reference

Inheritance diagram for EFG::train::FactorsTunableAdder:



Public Member Functions

- void addTunableFactor (const FactorExponentialPtr &factor, const std::optional< categoric::VariablesSet > &group_sharing_weight=std::nullopt)

  add a shallow copy of the passed tunable expoenential factor to this model.
- void copyTunableFactor (const distribution::FactorExponential &factor, const std::optional< categoric::↩
VariablesSet > &group_sharing_weight=std::nullopt)

  add a deep copy of the passed tunable expoenential factor to this model.
- template<typename FactorExponentialIt >
void absorbTunableFactors (const FactorExponentialIt &begin, const FactorExponentialIt &end, const bool copy)

  adds a collection of tunable expoenential factors ot this model. Passing copy = true, deep copies are created and inserted in this model. Passing copy = false, shallow copies are created and inserted in this model.
- void absorbTunableClusters (const FactorsTunableAware &source, const bool copy)

  adds a collection of tunable expoenential factors ot this model, preserving the fact that elements in the same cluster should share the weight. Passing copy = true, deep copies are created and inserted in this model. Passing copy = false, shallow copies are created and inserted in this model.

Protected Member Functions

- TunerPtr & **findTuner** (const categoric::VariablesSet &tuned_vars_group)

Additional Inherited Members

9.34.1 Member Function Documentation

9.34.1.1 addTunableFactor()

```
void EFG::train::FactorsTunableAdder::addTunableFactor (
            const FactorExponentialPtr & factor,
            const std::optional< categoric::VariablesSet > & group_sharing_weight = std:↩
:nullopt )
```

add a shallow copy of the passed tunable expoenential factor to this model.

Parameters

the	factor to insert
an	optional group of variables specifying the tunable factor that should share the weight with the one to insert. When passing a nullopt the factor will be inserted without sharing its weight.

9.34.1.2 copyTunableFactor()

```
void EFG::train::FactorsTunableAdder::copyTunableFactor (
            const distribution::FactorExponential & factor,
            const std::optional< categoric::VariablesSet > & group_sharing_weight = std:↩
:nullopt )
```

add a deep copy of the passed tunable expoenential factor to this model.

Parameters

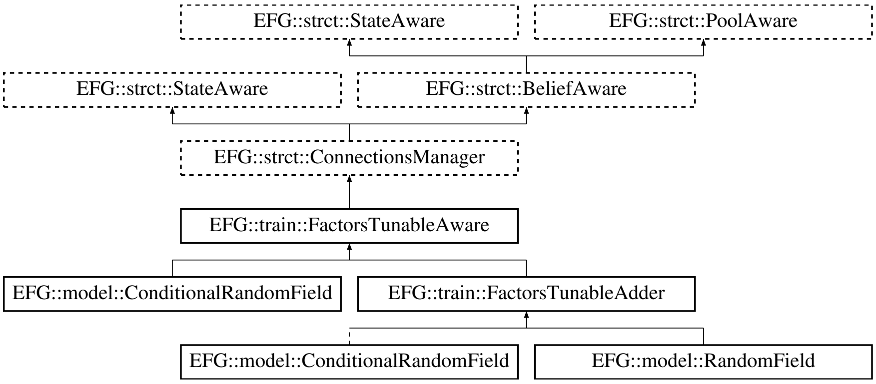
the	factor to insert
an	optional group of variables specifying the tunable factor that should share the weight with the one to insert. When passing a nullopt the factor will be inserted without sharing its weight.

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/trainable/FactorsTunable↩
Manager.h

9.35 EFG::train::FactorsTunableAware Class Reference

Inheritance diagram for EFG::train::FactorsTunableAware:



Public Member Functions

- const std::unordered_set< FactorExponentialPtr > & getTunableFactors () const

  Get the collections of tunable exponential factors.
- std::vector< std::vector< FactorExponentialPtr > > getTunableClusters () const

  Get the clusters of tunable exponential factors. Elements in the same cluster, shares the weight.
- std::vector< float > getWeights () const
- void setWeights (const std::vector< float > &weights)
- std::vector< float > getWeightsGradient (const TrainSet::Iterator &train_set_combinations, const std::size_t threads=1)

Protected Member Functions

- virtual std::vector< float > **getWeightsGradient_** (const TrainSet::Iterator &train_set_combinations)=0

Protected Attributes

- std::unordered_set< FactorExponentialPtr > **tunable_factors**
- Tuners **tuners**

9.35.1 Member Function Documentation

9.35.1.1 getWeights()

```
std::vector<float> EFG::train::FactorsTunableAware::getWeights ( ) const
```

Returns

the weights of all the tunable factors that are part of the model. The same order assumed by getTunableClusters() is assumed.

9.35.1.2 getWeightsGradient()

```
std::vector<float> EFG::train::FactorsTunableAware::getWeightsGradient (
            const TrainSet::Iterator & train_set_combinations,
            const std::size_t threads = 1 )
```

Returns

the gradients of the weights of all the tunable factors that are part of the model, w.r.t a certain training set. The same order assumed by getTunableClusters() is assumed.

Parameters

the	training set to use
the	number of threads to use for the gradient computation

9.35.1.3 setWeights()

```
void EFG::train::FactorsTunableAware::setWeights (
            const std::vector< float > & weights )
```

Returns

sets the weights to use for of all the tunable factors that are part of the model. The same order assumed by getTunableClusters() should be assumed.

Exceptions

in	case the number of specified weights is inconsistent

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/trainable/FactorsTunable←Manager.h

9.36 EFG::io::File Class Reference

Public Member Functions

- **File** (const std::string &path)
- const std::string & **parent_str** () const
- std::string **str** () const

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/io/File.h

9.37 EFG::distribution::GenericCopyTag Struct Reference

The documentation for this struct was generated from the following file:

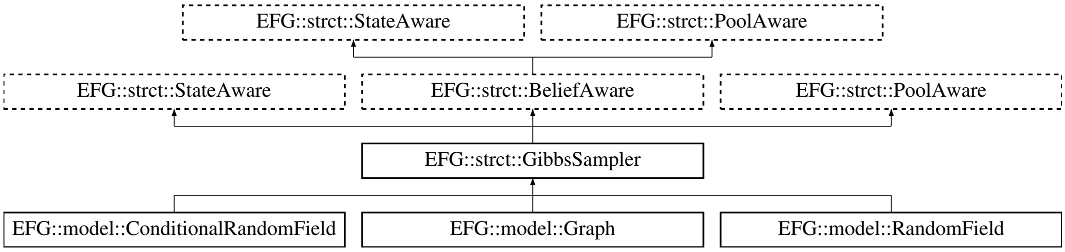
- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/distribution/Factor.h

9.38 EFG::strct::GibbsSampler Class Reference

Refer also to `https://en.wikipedia.org/wiki/Gibbs_sampling`.

`#include <GibbsSampler.h>`

Inheritance diagram for EFG::strct::GibbsSampler:



Classes

- struct SamplesGenerationContext

Public Member Functions

- std::vector< categoric::Combination > makeSamples (const SamplesGenerationContext &context, const std::size_t threads=1)

    Use Gibbs sampling approach to draw empirical samples. Values inside the returned combiantion are ordered with the same order used for the variables returned by getAllVariables().

Additional Inherited Members

9.38.1 Detailed Description

Refer also to `https://en.wikipedia.org/wiki/Gibbs_sampling`.

9.38.2 Member Function Documentation

9.38.2.1 makeSamples()

```
std::vector<categoric::Combination> EFG::strct::GibbsSampler::makeSamples (
            const SamplesGenerationContext & context,
            const std::size_t threads = 1 )
```

Use Gibbs sampling approach to draw empirical samples. Values inside the returned combiantion are ordered with the same order used for the variables returned by getAllVariables().

In case some evidences are set, their values will appear as is in the sampled combinations.

Parameters

number	parameters for the samples generation
number	of threads to use for the samples generation

The documentation for this class was generated from the following file:

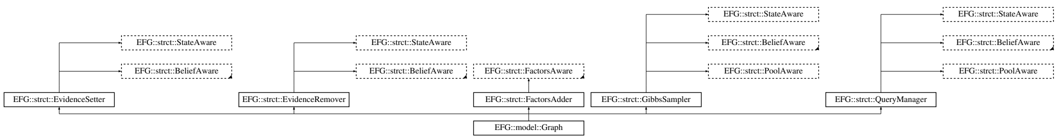
- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/GibbsSampler.h

9.39 EFG::model::Graph Class Reference

A simple graph object, that stores only const factors. Evidences may be changed over the time.

`#include <Graph.h>`

Inheritance diagram for EFG::model::Graph:



Public Member Functions

- **Graph** (const Graph &o)
- Graph & **operator=** (const Graph &)=delete
- void absorb (const strct::ConnectionsManager &to_absorb, const bool copy)

    Gather all the factors (tunable and constant) of another model and insert/copy them into this object.

Additional Inherited Members

9.39.1 Detailed Description

A simple graph object, that stores only const factors. Evidences may be changed over the time.

9.39.2 Member Function Documentation

9.39.2.1 absorb()

```
void EFG::model::Graph::absorb (
            const strct::ConnectionsManager & to_absorb,
            const bool copy )
```

Gather all the factors (tunable and constant) of another model and insert/copy them into this object.

Parameters

the	model whose factors should be inserted/copied
when	passing true the factors are deep copied, while in the contrary case shallow copies of the smart pointers are inserted into this model.

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/model/Graph.h

9.40 EFG::strct::GraphState Struct Reference

Public Attributes

- categoric::VariablesSoup **variables**
- Nodes **nodes**
- HiddenClusters **clusters**
- Evidences **evidences**

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/components/State↩
Aware.h

9.41 EFG::categoric::Group Class Reference

An ensemble of categoric variables. Each variable in the ensemble should have its own unique name.

`#include <Group.h>`

Public Member Functions

- Group (const VariablesSoup &group)
- Group (const VariablePtr &var)
- template<typename... Vars>
  Group (const VariablePtr &varA, const VariablePtr &varB, const Vars &...vars)
- void replaceVariables (const VariablesSoup &new_variables)
  replaces the group of variables.
- bool **operator==** (const Group &o) const
- void add (const VariablePtr &var)
- template<typename... Vars>
  void **add** (const VariablePtr &var, const Vars &...vars)
- std::size_t size () const
- const VariablesSoup & getVariables () const
- const VariablesSet & getVariablesSet () const

Protected Attributes

- VariablesSoup **group**
- VariablesSet **group_sorted**

9.41.1 Detailed Description

An ensemble of categoric variables. Each variable in the ensemble should have its own unique name.

9.41.2 Constructor & Destructor Documentation

9.41.2.1 Group() [1/3]

```
EFG::categoric::Group::Group (
            const VariablesSoup & group )  [explicit]
```

Parameters

the	initial variables of the group

Exceptions

when	passing an empty collection
when	passing a collection containing multiple times a certain variable

9.41.2.2 Group() [2/3]

```
EFG::categoric::Group::Group (
            const VariablePtr & var )  [explicit]
```

Parameters

the	initial variable to put in the group

9.41.2.3 Group() [3/3]

```
template<typename...  Vars>
EFG::categoric::Group::Group (
```

```
            const VariablePtr & varA,
            const VariablePtr & varB,
            const Vars &...  vars )  [inline]
```

Parameters

the	first initial variable to put in the group
the	second initial variable to put in the group
all	the other initial variables

Exceptions

when	passing a collection containing multiple times a certain

9.41.3 Member Function Documentation

9.41.3.1 add()

```
void EFG::categoric::Group::add (
            const VariablePtr & var )
```

Parameters

the	variable to add in the group

Exceptions

in	case a variable with the same name is already part of the group

9.41.3.2 getVariables()

```
const VariablesSoup& EFG::categoric::Group::getVariables ( ) const  [inline]
```

Returns

the ensamble of variables as an unsorted collection

9.41.3.3 getVariablesSet()

```
const VariablesSet& EFG::categoric::Group::getVariablesSet ( ) const  [inline]
```

Returns

the ensamble of variables as a sorted collection

9.41.3.4 replaceVariables()

```
void EFG::categoric::Group::replaceVariables (
            const VariablesSoup & new_variables )
```

replaces the group of variables.

Exceptions

In	case of size mismatch with the previous variables set: the sizes of the 2 groups should be the same and the elements in the same positions must have the same domain size

9.41.3.5 size()

```
std::size_t EFG::categoric::Group::size ( ) const
```

Returns

the size of the joint domain of the group. For example the group <A,B,C> with sizes <2,4,3> will have a joint domain of size 2x4x3 = 24

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/categoric/Group.h

9.42 EFG::categoric::GroupRange Class Reference

This object allows to iterate all the elements in the joint domain of a group of variables, without precomputing all the elements in such domain. For example when having a domain made by variables = { A (size = 2), B (size = 3), C (size = 2) }, the elements in the joint domain that will be iterated are: <0,0,0> <0,0,1> <0,1,0> <0,1,1> <0,2,0> <0,2,1> <1,0,0> <1,0,1> <1,1,0> <1,1,1> <1,2,0> <1,2,1> After construction, the Range object starts to point to the first element in the joint domain <0,0,...>. Then, when incrementing the object, the following element is pointed. When calling get() the current pointed element can be accessed.

```
#include <GroupRange.h>
```

Public Types

- using **iterator_category** = std::input_iterator_tag
- using **value_type** = Combination
- using **pointer** = Combination ∗
- using **reference** = Combination &

Public Member Functions

- GroupRange (const Group &variables)
- **GroupRange** (const GroupRange &o)
- pointer **operator->** () const
- reference **operator∗** () const
- GroupRange & operator++ ()

  Make the object to point to the next element in the joint domain.
- bool **isEqual** (const GroupRange &o) const

Static Public Member Functions

- static GroupRange **end** ()

9.42.1 Detailed Description

This object allows to iterate all the elements in the joint domain of a group of variables, without precomputing all the elements in such domain. For example when having a domain made by variables = { A (size = 2), B (size = 3), C (size = 2) }, the elements in the joint domain that will be iterated are: <0,0,0> <0,0,1> <0,1,0> <0,1,1> <0,2,0> <0,2,1> <1,0,0> <1,0,1> <1,1,0> <1,1,1> <1,2,0> <1,2,1> After construction, the Range object starts to point to the first element in the joint domain <0,0,...>. Then, when incrementing the object, the following element is pointed. When calling get() the current pointed element can be accessed.

This object should be recognized by the compiler as an stl iterator.

9.42.2 Constructor & Destructor Documentation

9.42.2.1 GroupRange()

```
EFG::categoric::GroupRange::GroupRange (
            const Group & variables )  [explicit]
```

Parameters

the	group of variables whose joint domain must be iterated

9.42.3 Member Function Documentation

9.42.3.1 operator++()

`GroupRange& EFG::categoric::GroupRange::operator++ ( )`

Make the object to point to the next element in the joint domain.

Exceptions

if	the current pointed element is the last one.

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/categoric/GroupRange.h

9.43 std::hash$<$ EFG::categoric::Variable $>$ Struct Reference

Public Member Functions

- std::size_t **operator()** (const EFG::categoric::Variable &subject) const

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/categoric/Variable.h

9.44 EFG::Hasher$<$ T $>$ Struct Template Reference

Public Member Functions

- std::size_t **operator()** (const std::shared_ptr$<$ T $>$ &subject) const

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/misc/SmartPointerUtils.h

9.45 EFG::strct::HiddenCluster Struct Reference

Clusters of hidden node. Each cluster is a group of connected hidden nodes. Nodes in different clusters are not currently connected, due to the model structure or the kind of evidences currently applied.

```
#include <StateAware.h>
```

Public Attributes

- std::set< Node * > **nodes**
- Cache< std::vector< ConnectionAndDependencies > > **connectivity**

9.45.1 Detailed Description

Clusters of hidden node. Each cluster is a group of connected hidden nodes. Nodes in different clusters are not currently connected, due to the model structure or the kind of evidences currently applied.

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/components/State↩ Aware.h

9.46 EFG::strct::HiddenNodeLocation Struct Reference

Public Attributes

- HiddenClusters::iterator **cluster**
- Node * **node**

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/components/State↩ Aware.h

9.47 EFG::io::xml::Importer Class Reference

Static Public Member Functions

- template<typename Model >
  static void importFromFile (Model &model, const File &file_path)
  parse the model (variables and factors) described by the specified file and tries to add its factors to the passed model.

9.47.1 Member Function Documentation

9.47.1.1 importFromFile()

```
template<typename Model >
static void EFG::io::xml::Importer::importFromFile (
            Model & model,
            const File & file_path )  [inline], [static]
```

parse the model (variables and factors) described by the specified file and tries to add its factors to the passed model.

Parameters

recipient	of the model parsed from file
location	of the model to parse and add to the passed one

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/io/xml/Importer.h

9.48 EFG::io::json::Importer Class Reference

Static Public Member Functions

- template<typename Model >
  static void importFromFile (Model &model, const File &file_path)

  imports the structure (variables and factors) described in an xml file and add it to the passed model
- template<typename Model >
  static void importFromJson (Model &model, const nlohmann::json &source)

  parse the model (variables and factors) described by the passed json and tries to add its factors to the passed model.

9.48.1 Member Function Documentation

9.48.1.1 importFromFile()

```
template<typename Model >
static void EFG::io::json::Importer::importFromFile (
            Model & model,
            const File & file_path )  [inline], [static]
```

imports the structure (variables and factors) described in an xml file and add it to the passed model

Parameters

the	model receiving the parsed data
the	path storing the xml to import

9.48.1.2 importFromJson()

```
template<typename Model >
static void EFG::io::json::Importer::importFromJson (
```

```
Model & model,
const nlohmann::json & source )  [inline], [static]
```

parse the model (variables and factors) described by the passed json and tries to add its factors to the passed model.

Parameters

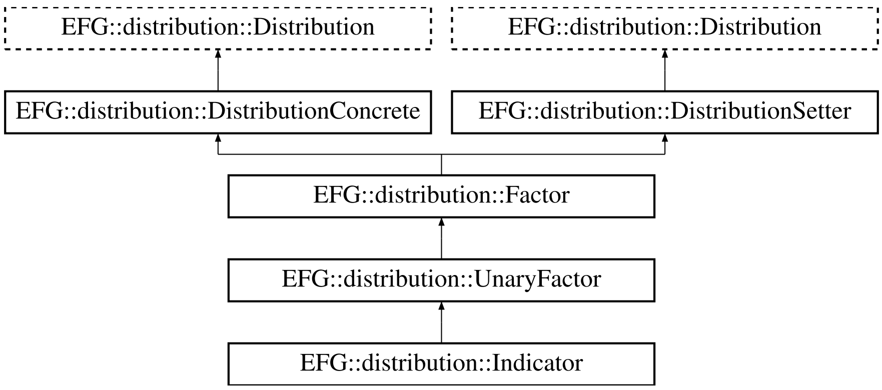
recipient	of the model parsed from file
json	describing the model to parse and add to the passed one

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/io/json/Importer.h

9.49 EFG::distribution::Indicator Class Reference

Inheritance diagram for EFG::distribution::Indicator:



Public Member Functions

- **Indicator** (const categoric::VariablePtr &var, const std::size_t value)

Additional Inherited Members

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/SpecialFactors.h

9.50 EFG::train::TrainSet::Iterator Class Reference

an object able to iterate all the combinations that are part of a training set or a sub portion of it.

```
#include <TrainSet.h>
```

Public Member Functions

- Iterator (const TrainSet &subject, const float percentage)
  involved train set
- template<typename Predicate >
  void **forEachSample** (const Predicate &pred) const
- std::size_t size () const

9.50.1 Detailed Description

an object able to iterate all the combinations that are part of a training set or a sub portion of it.

9.50.2 Constructor & Destructor Documentation

9.50.2.1 Iterator()

```
EFG::train::TrainSet::Iterator::Iterator (
            const TrainSet & subject,
            const float percentage )
```

involved train set

Parameters

the	percentage of combinations to extract from the passed subject. Passing a value equal to 1, means to use all the combinations of the passed subject.

9.50.3 Member Function Documentation

9.50.3.1 size()

```
std::size_t EFG::train::TrainSet::Iterator::size ( ) const
```

Returns

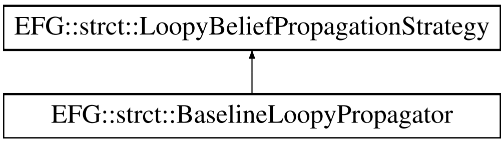
number of combinations considered by this train set iterator.

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/trainable/TrainSet.h

9.51 EFG::strct::LoopyBeliefPropagationStrategy Class Reference

Inheritance diagram for EFG::strct::LoopyBeliefPropagationStrategy:



Public Member Functions

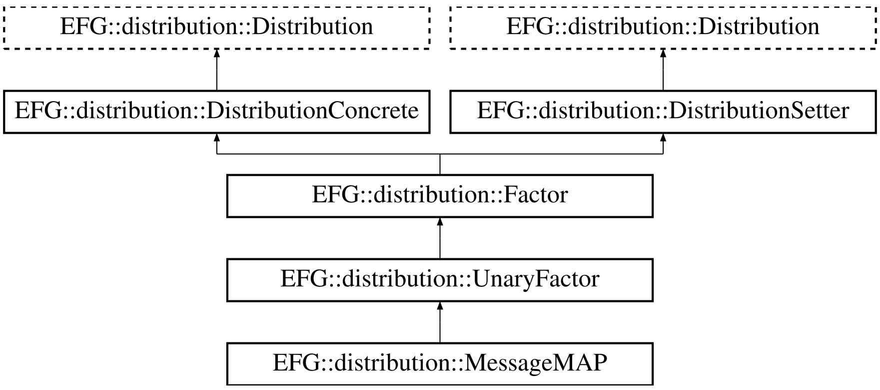
- virtual bool **propagateBelief** (HiddenCluster &subject, const PropagationKind &kind, const PropagationContext &context, Pool &pool)=0

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/components/Belief↩ Aware.h

9.52 EFG::distribution::MessageMAP Class Reference

Inheritance diagram for EFG::distribution::MessageMAP:



Public Member Functions

- **MessageMAP** (const UnaryFactor &merged_unaries, const distribution::Distribution &binary_factor)

Additional Inherited Members

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/SpecialFactors.h

9.53 EFG::MessagesMerger Class Reference

Static Public Member Functions

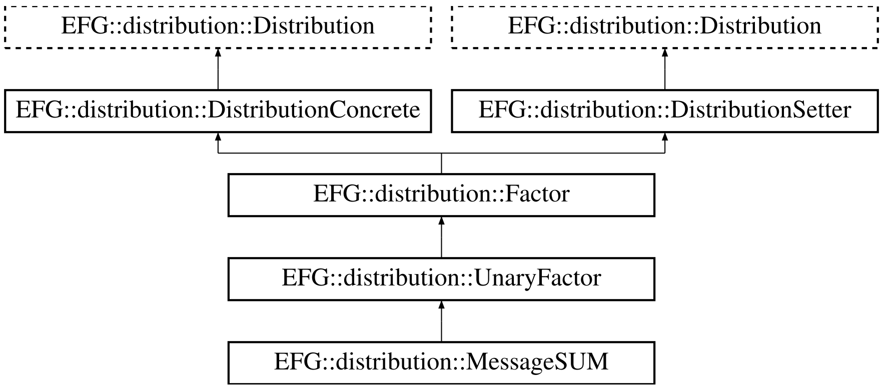
- template<typename T1 , typename T2 , typename... Slices>
  static std::string **merge** (const T1 &first, const T2 &second, const Slices &...args)

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/Error.h

9.54 EFG::distribution::MessageSUM Class Reference

Inheritance diagram for EFG::distribution::MessageSUM:



Public Member Functions

- **MessageSUM** (const UnaryFactor &merged_unaries, const distribution::Distribution &binary_factor)

Additional Inherited Members

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/SpecialFactors.h

9.55 EFG::strct::Node Struct Reference

Public Attributes

- categoric::VariablePtr **variable**
- std::map< Node ∗, std::unique_ptr< Connection > > **active_connections**
- std::map< Node ∗, std::unique_ptr< Connection > > **disabled_connections**
- std::vector< distribution::DistributionCnstPtr > **unary_factors**
- Cache< const distribution::UnaryFactor > **merged_unaries**

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/components/State↩
  Aware.h

9.56 EFG::strct::Pool Class Reference

Public Member Functions

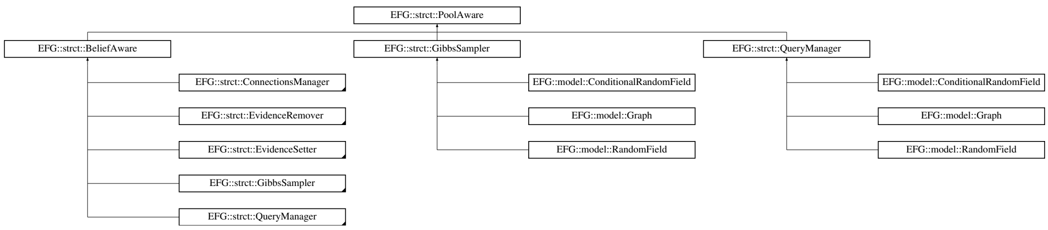
- **Pool** (const std::size_t size)
- void **parallelFor** (const std::vector< Task > &tasks)
- std::size_t **size** () const

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/components/Pool↩ Aware.h

9.57 EFG::strct::PoolAware Class Reference

Inheritance diagram for EFG::strct::PoolAware:



Classes

- class ScopedPoolActivator

Protected Member Functions

- void **resetPool** ()
- Pool & **getPool** ()
- void **setPoolSize** (const std::size_t new_size)

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/components/Pool↩ Aware.h

9.58 EFG::strct::PropagationContext Struct Reference

Public Attributes

- std::size_t max_iterations_loopy_propagation

  maximum number of iterations to use when trying to calibrate a loopy graph

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/components/Belief↩ Aware.h

9.59 EFG::strct::PropagationResult Struct Reference

a structure that can be exposed after having propagated the belief, providing info on the encountered structure.

`#include <BeliefAware.h>`

Public Attributes

- PropagationKind **propagation_kind_done**
- bool **was_completed**
- std::vector< ClusterInfo > **structure_found**

9.59.1 Detailed Description

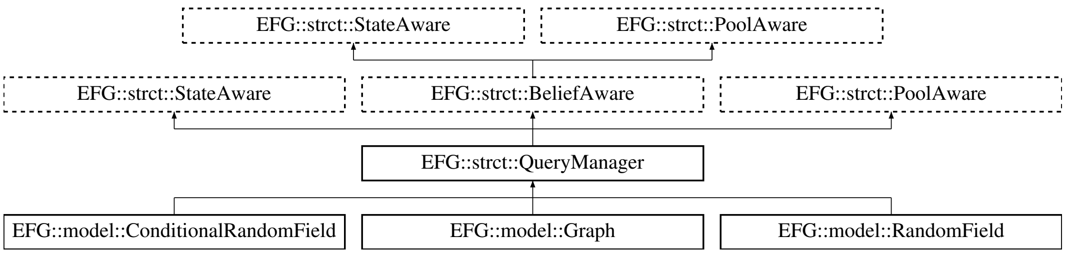
a structure that can be exposed after having propagated the belief, providing info on the encountered structure.

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/components/Belief↩ Aware.h

9.60 EFG::strct::QueryManager Class Reference

Inheritance diagram for EFG::strct::QueryManager:



Public Member Functions

- std::vector< float > getMarginalDistribution (const categoric::VariablePtr &var, const std::size_t threads=1)
- std::vector< float > getMarginalDistribution (const std::string &var, const std::size_t threads=1)

    same as getMarginalDistribution(const categoric::VariablePtr &, const std::size_t), but passing the name of the variable, which is internally searched.
- distribution::Factor getJointMarginalDistribution (const categoric::Group &subgroup, const std::size_↩ t threads=1)
- distribution::Factor getJointMarginalDistribution (const std::vector< std::string > &subgroup, const std::size↩ _t threads=1)

    same as getJointMarginalDistribution(const categoric::VariablesSet &, const std::size_t), but passing the names of the variables, which are internally searched.
- std::size_t getMAP (const categoric::VariablePtr &var, const std::size_t threads=1)
- std::size_t getMAP (const std::string &var, const std::size_t threads=1)

    same as getMAP(const categoric::VariablePtr &, const std::size_t), but passing the name of the variable, which is internally searched.
- std::vector< size_t > getHiddenSetMAP (const std::size_t threads=1)

Additional Inherited Members

9.60.1 Member Function Documentation

9.60.1.1 getHiddenSetMAP()

```
std::vector<size_t> EFG::strct::QueryManager::getHiddenSetMAP (
            const std::size_t threads = 1 )
```

Returns

the Maximum a Posteriori estimation of the hidden variables, conditioned to the last set of evidences. Values are ordered with the same order used by the set of variables returned in getHiddenVariables()

Parameters

the	number of threads to use for propagating the belief before returning the result.

9.60.1.2 getJointMarginalDistribution() [1/2]

```
distribution::Factor EFG::strct::QueryManager::getJointMarginalDistribution (
            const categoric::Group & subgroup,
            const std::size_t threads = 1 )
```

Returns

a factor representing the joint distribution of the subgraph described by the passed set of variables.

Parameters

the	involved variables
the	number of threads to use for propagating the belief before returning the result.

Exceptions

when	some of the passed variable names are not found

9.60.1.3 getJointMarginalDistribution() [2/2]

```
distribution::Factor EFG::strct::QueryManager::getJointMarginalDistribution (
```

```
            const std::vector< std::string > & subgroup,
            const std::size_t threads = 1 )
```

same as getJointMarginalDistribution(const categoric::VariablesSet &, const std::size_t), but passing the names of the variables, which are internally searched.

Exceptions

in	case the passed set of variables is not representative of a valid group

9.60.1.4 getMAP()

```
std::size_t EFG::strct::QueryManager::getMAP (
            const categoric::VariablePtr & var,
            const std::size_t threads = 1 )
```

Returns

the Maximum a Posteriori estimation of a specific variable in the model, conditioned to the last set of evidences.

Parameters

the	involved variable
the	number of threads to use for propagating the belief before returning the result.

Exceptions

when	the passed variable name is not found

9.60.1.5 getMarginalDistribution()

```
std::vector<float> EFG::strct::QueryManager::getMarginalDistribution (
            const categoric::VariablePtr & var,
            const std::size_t threads = 1 )
```

Returns

the marginal probabilty of the passed variable, i.e. P(var|observations), conditioned to the last set of evidences.

Parameters

the	involved variable
the	number of threads to use for propagating the belief before returning the result.

Exceptions

when	the passed variable name is not found

The documentation for this class was generated from the following file:

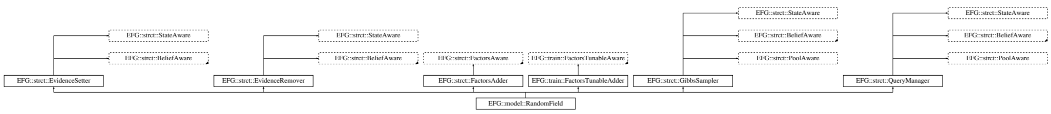
- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/QueryManager.h

9.61 EFG::model::RandomField Class Reference

A complete undurected factor graph storing both constant and tunable factors. Evidences may be changed over the time.

`#include <RandomField.h>`

Inheritance diagram for EFG::model::RandomField:



Public Member Functions

- **RandomField** (const RandomField &o)
- RandomField & **operator=** (const RandomField &)=delete
- void absorb (const strct::ConnectionsManager &to_absorb, const bool copy)

  Gather all the factors (tunable and constant) of another model and insert/copy them into this object. Tunable factors (Exponential non constant) are recognized and inserted/copied using the train::FactorsTunableAdder interface. All the others inserted/copied using the strct::FactorsAdder interface.

Protected Member Functions

- std::vector< float > **getWeightsGradient_** (const train::TrainSet::Iterator &train_set_combinations) final

Additional Inherited Members

9.61.1 Detailed Description

A complete undurected factor graph storing both constant and tunable factors. Evidences may be changed over the time.

9.61.2 Member Function Documentation

9.61.2.1 absorb()

```
void EFG::model::RandomField::absorb (
            const strct::ConnectionsManager & to_absorb,
            const bool copy )
```

Gather all the factors (tunable and constant) of another model and insert/copy them into this object. Tunable factors (Exponential non constant) are recognized and inserted/copied using the train::FactorsTunableAdder interface. All the others inserted/copied using the strct::FactorsAdder interface.

Parameters

the	model whose factors should be inserted/copied
when	passing true the factors are deep copied, while in the contrary case shallow copies of the smart pointers storing the factors are inserted into this model.

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/model/RandomField.h

9.62 EFG::distribution::CombinationFinder::Result Struct Reference

Searches for matches. For example assume having built this object with a bigger_group equal to $<$A,B,C,D$>$ while the variables describing the distribution this finder refers to is equal to $<$B,D$>$. When passing a comb equal to $<$0,1,2,0$>$, this object searches for the immage associated to the sub combination $<$B,D$>$ = $<$1,0$>$.

```
#include <CombinationFinder.h>
```

Public Attributes

- CombinationRawValuesMap::const_iterator **map_iterator**
- float **value**

9.62.1 Detailed Description

Searches for matches. For example assume having built this object with a bigger_group equal to $<$A,B,C,D$>$ while the variables describing the distribution this finder refers to is equal to $<$B,D$>$. When passing a comb equal to $<$0,1,2,0$>$, this object searches for the immage associated to the sub combination $<$B,D$>$ = $<$1,0$>$.

Parameters

the	combination of values referring to the bigger_group, which contains the sub combination to search.

Returns

an object storing the sub combination (in case it is explicitly instanciated, otherwise an end iterator is returned) as well as the image associated to it.

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/distribution/Combination←
Finder.h

9.63 EFG::strct::GibbsSampler::SamplesGenerationContext Struct Reference

Public Attributes

- std::size_t **samples_number**
- std::optional< std::size_t > delta_iterations

  number of iterations used to evolve the model between the drawing of one sample and another
- std::optional< std::size_t > seed

  sets the seed of the random engine. Passing a nullopt will make the sampler to generate a random seed by using the current time.
- std::optional< std::size_t > transient

  number of samples to discard before actually starting the sampling procedure.

9.63.1 Member Data Documentation

9.63.1.1 transient

`std::optional<std::size_t> EFG::strct::GibbsSampler::SamplesGenerationContext::transient`

number of samples to discard before actually starting the sampling procedure.

When nothing is specified, 10 times delta_iterations is assumed.

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/GibbsSampler.h

9.64 EFG::strct::PoolAware::ScopedPoolActivator Class Reference

Public Member Functions

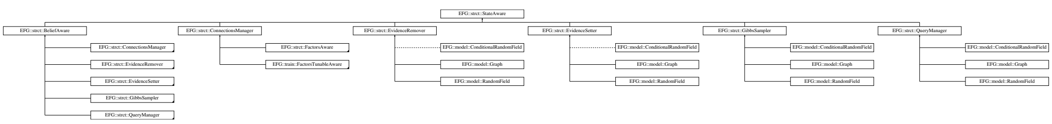
- **ScopedPoolActivator** (PoolAware &subject, const std::size_t new_size)

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/components/Pool↩
Aware.h

9.65 EFG::strct::StateAware Class Reference

Inheritance diagram for EFG::strct::StateAware:



Public Member Functions

- const categoric::VariablesSoup & getAllVariables () const
- categoric::VariablesSet getHiddenVariables () const
- categoric::VariablesSet getObservedVariables () const
- const Evidences & getEvidences () const
- categoric::VariablePtr findVariable (const std::string &name) const
- **StateAware** (const StateAware &)=delete
- StateAware & **operator=** (const StateAware &)=delete
- **StateAware** (StateAware &&)=delete
- StateAware & **operator=** (StateAware &&)=delete

Protected Member Functions

- const GraphState & **getState** () const
- GraphState & **getState_** ()
- std::optional< NodeLocation > **locate** (const categoric::VariablePtr &var) const
- std::optional< NodeLocation > **locate** (const std::string &var_name) const

9.65.1 Member Function Documentation

9.65.1.1 findVariable()

```
categoric::VariablePtr EFG::strct::StateAware::findVariable (
            const std::string & name ) const
```

Returns

the variable in the model with the passed name

Exceptions

in	case no variable with the specified name exists in this model

9.65.1.2 getAllVariables()

```
const categoric::VariablesSoup& EFG::strct::StateAware::getAllVariables ( ) const  [inline]
```

Returns

all the variables that are part of the model.

9.65.1.3 getEvidences()

```
const Evidences& EFG::strct::StateAware::getEvidences ( ) const  [inline]
```

Returns

all the variables defining the evidence set, together with the associated values

9.65.1.4 getHiddenVariables()

```
categoric::VariablesSet EFG::strct::StateAware::getHiddenVariables ( ) const
```

Returns

all the variables defining the hidden set of variables

9.65.1.5 getObservedVariables()

```
categoric::VariablesSet EFG::strct::StateAware::getObservedVariables ( ) const
```

Returns

all the variables defining the evidence set

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/components/State↩ Aware.h

9.66 EFG::train::TrainInfo Struct Reference

Public Attributes

- std::size_t threads = 1

  Number of threads to use for the training procedure.
- float stochastic_percentage = 1.f

  1 means actually to use all the train set, adopting a classical gradient based approach. A lower value implies to a stochastic gradient based approach.

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/trainable/ModelTrainer.h

9.67 EFG::train::TrainSet Class Reference

Classes

- class Iterator

    an object able to iterate all the combinations that are part of a training set or a sub portion of it.

Public Member Functions

- TrainSet (const std::vector< categoric::Combination > &combinations)
- const std::vector< categoric::Combination > & **getCombinations** () const
- Iterator **makeIterator** () const
- Iterator **makeSubSetIterator** (const float &percentage) const

9.67.1 Constructor & Destructor Documentation

9.67.1.1 TrainSet()

```
EFG::train::TrainSet::TrainSet (
            const std::vector< categoric::Combination > & combinations )  [explicit]
```

Parameters

the	set of combinations that will be part of the train set.

Exceptions

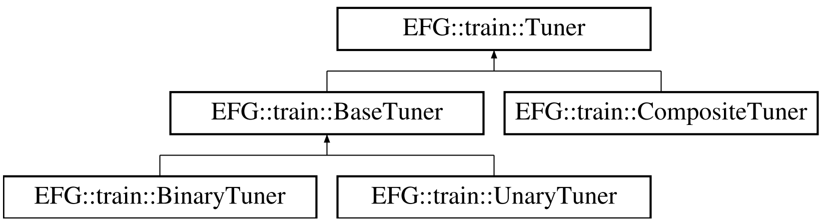
if	the combinations don't have all the same size
if	the combinations container is empty

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/trainable/TrainSet.h

9.68 EFG::train::Tuner Class Reference

Inheritance diagram for EFG::train::Tuner:



Public Member Functions

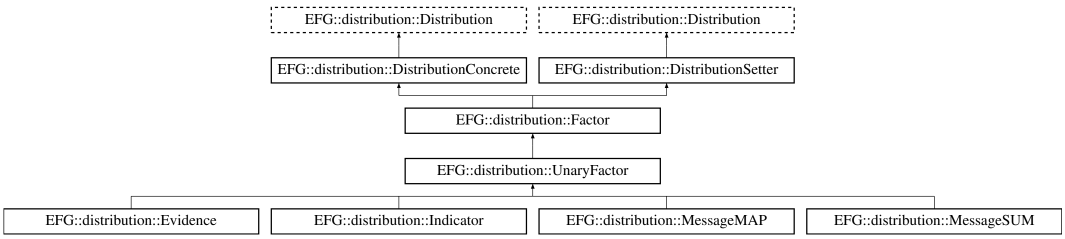
- virtual float **getGradientAlpha** (const TrainSet::Iterator &iter)=0
- virtual float **getGradientBeta** ()=0
- virtual void **setWeight** (const float &w)=0
- virtual float **getWeight** () const =0

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/trainable/tuners/Tuner.h

9.69 EFG::distribution::UnaryFactor Class Reference

Inheritance diagram for EFG::distribution::UnaryFactor:



Classes

- struct DontFillDomainTag

Public Member Functions

- **UnaryFactor** (const categoric::VariablePtr &var)
- **UnaryFactor** (const std::vector$<$ const distribution::Distribution $*$ $>$ &factors)
- const categoric::VariablePtr & **getVariable** () const
- void **merge** (const Distribution &to_merge)
- void **normalize** ()

Protected Member Functions

- **UnaryFactor** (const categoric::VariablePtr &var, const DontFillDomainTag &)

Static Protected Attributes

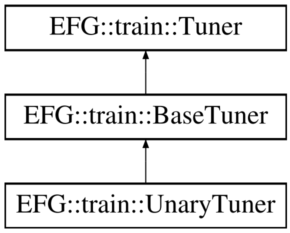
- static const DontFillDomainTag **DONT_FILL_DOMAIN_TAG**

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/SpecialFactors.h

9.70 EFG::train::UnaryTuner Class Reference

Inheritance diagram for EFG::train::UnaryTuner:



Public Member Functions

- **UnaryTuner** (strct::Node &node, const std::shared_ptr< distribution::FactorExponential > &factor, const categoric::VariablesSoup &variables_in_model)
- float **getGradientBeta** () final

Protected Attributes

- strct::Node & **node**

Additional Inherited Members

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/trainable/tuners/Unary←
Tuner.h

9.71 EFG::strct::UniformSampler Class Reference

Public Member Functions

- std::size_t **sampleFromDiscrete** (const std::vector< float > &distribution) const
- void **resetSeed** (const std::size_t &newSeed)

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/structure/GibbsSampler.h

9.72 EFG::distribution::UseSimpleAntiCorrelation Struct Reference

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/distribution/Factor.h

9.73 EFG::distribution::UseSimpleCorrelation Struct Reference

The documentation for this struct was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/distribution/Factor.h

9.74 EFG::categoric::Variable Class Reference

An object representing an immutable categoric variable.

`#include <Variable.h>`

Public Member Functions

- Variable (const std::size_t &size, const std::string &name)
- std::size_t **size** () const
- const std::string & **name** () const
- bool **operator==** (const Variable &o) const

Protected Attributes

- const size_t **Size**
- const std::string **Name**

9.74.1 Detailed Description

An object representing an immutable categoric variable.

9.74.2 Constructor & Destructor Documentation

9.74.2.1 Variable()

```
EFG::categoric::Variable::Variable (
            const std::size_t & size,
            const std::string & name )
```

Parameters

domain	size of this variable
name	used to label this varaible.

Exceptions

passing	0 as size
passing	an empty string as name

The documentation for this class was generated from the following file:

- /home/andrea/Desktop/GitProj/Easy-Factor-Graph/src/header/EasyFactorGraph/categoric/Variable.h

Index