

# Rank-one decomposition of probability tables

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- An index set  $N = \{1, 2, \dots, n\}$
- Variables  $X_i, i \in N$
- Each variable  $X_i$  takes values from a finite set  $\mathcal{X}_i$
- For  $A \subseteq N$  we use  $X_A$  to denote the multidimensional variable  $(X_i)_{i \in A}$
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## Definition

Assume  $A \subseteq N$ . **Table** is a function  $\psi : \mathcal{X}_A \rightarrow \mathbb{A}$ .

- If  $\mathbb{A} = [0, 1]$  and  $\sum_{x \in \mathcal{X}} \psi(x) = 1$  then  $\psi$  is a **probability table**.
- If  $\mathbb{A} = [0, 1]$  and there exists a set  $B \subset A \subseteq N$  such that for every  $x_B$  it holds  $\sum_{x_C} \psi(x_B, x_C) = 1$ , where  $C = A \setminus B$ , then  $\psi(X_C | X_B)$  is a **conditional probability table (CPT)**.

Example:  $A = \{1, 2, 3\}$  and  $B = \{1, 2\}$ . The table  $\psi(X_3 | X_1, X_2)$

$$\begin{pmatrix} (0.1, 0.9) & (0.3, 0.7) \\ (0.4, 0.6) & (0.9, 0.1) \end{pmatrix}$$

is a conditional probability table.

- $\mathbb{A} = \mathbb{R}$ , the set of all real numbers,
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# Multiplication of tables

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Assume two tables  $\psi_1 : \mathcal{X}_Q \rightarrow \mathbb{A}$  and  $\psi_2 : \mathcal{X}_R \rightarrow \mathbb{A}$ , where  $Q, R \subseteq N$ . The **product**  $\psi_1 \otimes \psi_2$  is a table  $\psi_3 : \mathcal{X}_{Q \cup R} \rightarrow \mathbb{A}$  such that for all  $x_{Q \cup R}$ :

$$\psi_3(x_{Q \cup R}) = \psi_1(x_Q) \cdot \psi_2(x_R) .$$

Example:  $Q = \{1, 2\}$  and  $R = \{1, 3\}$

$$\begin{pmatrix} a & b \\ c & d \end{pmatrix} \otimes \begin{pmatrix} (e, f) & (g, h) \end{pmatrix} = \begin{pmatrix} (ae, af) & (bg, bh) \\ (ce, cf) & (dg, dh) \end{pmatrix}$$

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Assume two tables  $\psi_1, \psi_2 : \mathcal{X}_Q \rightarrow \mathbb{A}$ , where  $Q \subseteq N$ .

The **sum**  $\psi_1 \oplus \psi_2$  is a table  $\psi_3 : \mathcal{X}_Q \rightarrow \mathbb{A}$  such that for all  $x_Q$ :

$$\psi_3(x_Q) = \psi_1(x_Q) + \psi_2(x_Q) .$$

Example:  $Q = \{1, 2\}$ .

$$\begin{pmatrix} a & b \\ c & d \end{pmatrix} \oplus \begin{pmatrix} e & f \\ g & h \end{pmatrix} = \begin{pmatrix} a+e & b+f \\ c+g & d+h \end{pmatrix}$$



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# Multiplicative decomposition of a table

In the rest of the presentation we will assume (without loss of generality) that  $A = N = \{1, 2, \dots, n\}$ .

## Definition

A table  $\psi : \mathcal{X}_N \rightarrow \mathbb{A}$  **factorizes** with respect to a system  $\{C_1, \dots, C_k\}$ ,  $C_j \subseteq N, j = 1, \dots, k$  iff there exist tables  $\psi_j : \mathcal{X}_{C_j} \rightarrow \mathbb{A}, j = 1, \dots, k$  such that  $\psi = \psi_1 \otimes \dots \otimes \psi_k$ .

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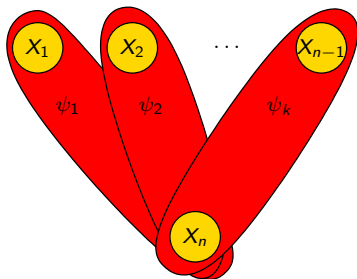
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If a table  $\psi : \mathcal{X}_N \rightarrow \mathbb{A}$  **factorizes** with respect to the system of all singletons (i.e.,  $C_j = \{j\}, j = 1, \dots, n$ ) then we say that table  $\psi$  has **rank one**.

Example:

$$\begin{pmatrix} (0,1) & (0,1) \\ (0,1) & (0,1) \end{pmatrix} = (1,1) \otimes (1,1) \otimes (0,1)$$

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# Rank-one decomposition of a table

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We say that table  $\psi : \mathcal{X}_N \rightarrow \mathbb{A}$  has **degree**  $r$  (in  $\mathbb{A}$ ) if there exist tables  $\psi_j : \mathcal{X}_N \rightarrow \mathbb{A}, j = 1, \dots, r$  of **rank one** such that  $\psi = \psi_1 \oplus \dots \oplus \psi_r$ .

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The minimal degree of a table  $\psi : \mathcal{X}_N \rightarrow \mathbb{A}$  is called rank of  $\psi$  (in  $\mathbb{A}$ ).

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$$\begin{aligned} \begin{pmatrix} (1,0) & (0,1) \\ (0,1) & (0,1) \end{pmatrix} &= \begin{pmatrix} (0,1) & (0,1) \\ (0,1) & (0,1) \end{pmatrix} + \begin{pmatrix} (1,-1) & (0,0) \\ (0,0) & (0,0) \end{pmatrix} \\ &= ((1,1) \otimes (1,1) \otimes (0,1)) \oplus ((1,0) \otimes (1,0) \otimes (1,-1)) \end{aligned}$$

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# Auxiliary variable $X'_n$

Rank-one decomposition of  $\psi : \mathcal{X}_N \rightarrow \mathbb{A}$  of degree  $r$  can be also written as

$$\psi(X_N) = \sum_{X'_n} \psi_i(X_1, X'_n) \otimes \dots \otimes \psi_i(X_n, X'_n) ,$$

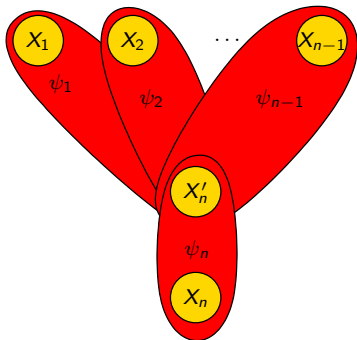
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# Motivation for table decompositions

- Decompositions allows more compact representation of tables. This **reduces space requirements**.
- Computations with decomposed tables are more efficient. This **reduces time requirements** during inference.
- The estimation of tables from data or from domain experts is easier and more reliable if they are decomposed.

**Multiplicative decomposition** is known and efficiently used for inference in probabilistic graphical models (Pearl, 1988) and (Lauritzen, Spiegelhalter, 1988).

**Rank-one decomposition** is relatively new (Díez and Galán, IJIS, 2002), (Vomlel, UAI'02), and (Savicky, Vomlel, IPMU'06). At this moment it allows efficient inference with some tables that cannot be multiplicatively decomposed.

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# Deterministic CPTs generated by functions

Now we are going to discuss tables of the form  $\psi(X_a | X_{N \setminus \{a\}})$  where  $a \in N$ .

Without loss of generality assume that  $a = n$ .

From now  $M$  will denote  $N \setminus \{n\}$ .

## Definition

Assume a function  $f : \mathcal{X}_M \rightarrow \mathcal{X}_n$ . We say that  $\psi_f(X_n | X_M)$  is **generated by function  $f$**  if

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Now we are going to discuss tables of the form  $\psi(X_a | X_{N \setminus \{a\}})$  where  $a \in N$ .

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# Rank of some deterministic CPTs

$\mathcal{X}_i = \{0, 1, \dots, a_i\}$ ,  $a_i \in \mathbb{N}$ , for  $i = 1, \dots, n - 1$ ,

Lemma (Rank lower bound)

*The rank of  $\psi_f$  is greater or equal to  $|\mathcal{X}_n|$ .*

Theorem (Rank of some deterministic tables)

If  $f : \mathcal{X}_M \rightarrow \mathbb{R}$  is

- $\min\{x_1, \dots, x_{n-1}\}$  or
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# Probabilistic tables of noisy functional dependence

## Definition

Assume a function  $f : \mathcal{X}_M \rightarrow \mathcal{X}_n$ . We say that  $\xi_f(\mathcal{X}_n | \mathcal{X}_M)$  represents **noisy functional dependence generated by function  $f$**  if there exists  $\psi_f(\mathcal{X}_n | \mathcal{X}_M)$  (deterministic core) generated by function  $f$  and tables  $\varphi_i : \mathcal{X}_i \times \mathcal{X}_i \rightarrow [0, 1]$ ,  $i = 1, \dots, n$  such that

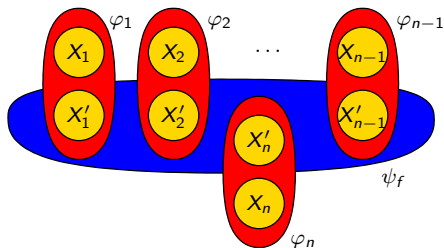
$$\xi_f(\mathcal{X}_n | \mathcal{X}_M) = \sum_{\mathcal{X}'_M} \psi_f(\mathcal{X}_n | \mathcal{X}'_M) \otimes_{i=1}^n \varphi_i(\mathcal{X}'_i, \mathcal{X}_i) .$$

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## Theorem

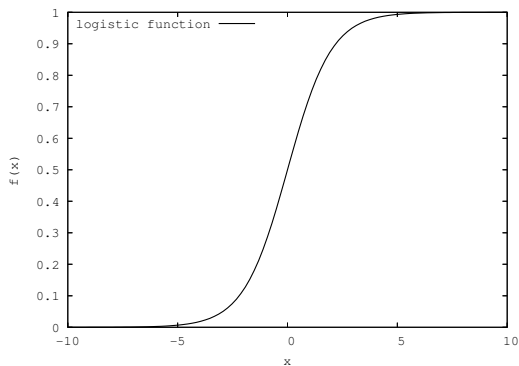
*Let tensor  $\xi$  represent the noisy functional dependence generated by function  $f$ . Then rank of  $\xi$  is less or equal to the rank of its deterministic core  $\psi_f$ .*

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Logistic function is well studied and broadly used, but it seems that tables generated by this function have a high rank.

## Definition

Assume  $\mathcal{X}_n = \{0, 1\}$ .  $\psi_\sigma(X_n | X_M)$  is table representing soft threshold if

$$\psi_\sigma(x_n | x_M) = \begin{cases} \sigma\left(\sum_{i=1}^{n-1} \alpha_i x_i + \beta\right) & \text{if } x_n = 1 \\ 1 - \sigma\left(\sum_{i=1}^{n-1} \alpha_i x_i + \beta\right) & \text{if } x_n = 0, \end{cases}$$

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# Cosine soft threshold function

Consider a family of functions parametrized by  $\ell = 1, 2, \dots$

$$\omega_\ell(t) = \sum_{j=1}^{\ell} c_j \cdot \cos(2j - 1) ,$$

where the coefficients  $c_j, j = 1, \dots, \ell$  are defined as the solution of the system of linear equations:

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By the properties of Vandermonde determinant the system has a unique solution.

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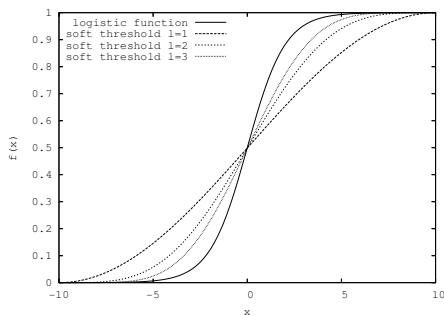
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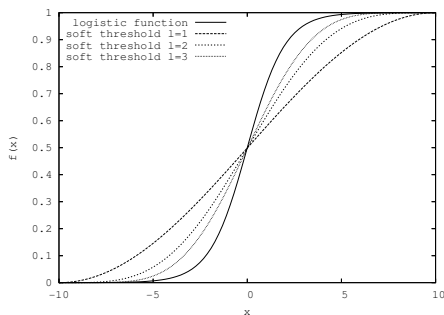
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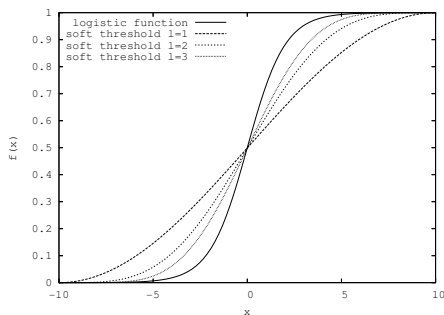
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