# Bayesian networks in outplacement

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**Abstract**
There are large collections and sets of data about the employees that are going to lose their jobs, economic crisis, markets and business developments, candidates, career opportunities, abilities, knowledge ... in the field of outplacement today. Causal or inference networks are used in a number of areas to represent patterns of influence among variables. They consist of connected causal relations. Generally, causality can be seen as any natural ordering in which knowledge of an event influences opinion concerning another event. This influence can be logical, physical, temporal, or simply conceptual. In this paper we present a study of using Bayesian networks (BN) in the domain of outplacement where BN are especially appropriate because of their symbolic representation, handling of uncertainty, where different scenarios are possible by given evidences. We show a use of BN in the case of study where we use the BN as tool for the prediction the proper of domain of activity to be followed by a person who is going to lose his job.

**Keywords:** Bayesian networks, decision making, outplacement.

**JEL Classification:** 34B45, 62C12

# Reţele Bayesiane utilizate în outplacement

**Rezumat**
Exista o multitudine de informatii legate de persoane care sunt pe cale sa-si piarda locul de munca, de criza economica, de dezvoltarea viitoare a unor piete si afaceri, de numarul de candidati existenti pe piata la un anumit moment si de calitatea acestora, de viitoarele oportunitati profesionale pe care le ofera piata, abilitatile, cunostintele candidatilor ... toate influentand intr-un fel sau altul procesul de outplacement (relocare a angajatilor care sunt pe cale sa fie disponibilizati).
Retelele cauzale sunt folosite in unele situatii pentru a prezenta influenta dintre variabile. Ele constau in relatii cauzale conectate. In general, cauzalitatea poate fi privita ca orice ordine naturala in care se cunoaste influenta unui eveniment asupra altui eveniment. Aceasta influenta poate fi de natura logica, fizica, temporara sau un simplu concept.In aceasta lucrare prezentam un studiu in care folosim retelele Bayesiene (BN) in domeniul outplacement-ului, acestea fiind in mod special utilizate datorita posibilitatii de a fi reprezentate simbolic, de a releva conditiile de incertitudine existente, in care sunt posibile diferite scenarii avand in vedere conditiile sau unele caracteristici date. Vom prezenta folosirea retelelor Bayesiene intr-un studiu de caz in care vom folosi aceste retele ca un instrument pentru a identifica / prezice domeniul cel mai propice de activitate pe care poate sa il urmeze o persoana ce urmeaza sa fie disponibilizata in momentul concedierii.

**Cuvinte cheie:** Bayesian networks, decision making, outplacement.

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## 1. INTRODUCTION

The connection between causation and conditional independence was studied by Spohn (1980) [5 ], and later investigated with special focus on Bayesian networks in [3 ] (Pearl, 2000). Bayesian networks have a long history in statistics, and can be traced back at least to the work in

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[ 2] (Minsky, 1963). In the first half of the 1980s they were introduced to the field of expert systems trough work by Pearl (1982) and Spiegelhalter and Knill-Jones (1984).

Causal or inference networks are used in a number of areas to represent patterns of influence among variables. They consist of connected causal relations. Generally, causality can be seen as any natural ordering in which knowledge of an event influences opinion concerning another event. This influence can be logical, physical, temporal, or simply conceptual.

## 2. OUTPLACEMENT

What is *outplacement*? Outplacement consists on practical support from professional consultants designated to help people who have to leave a company, move to the next stage of their careers and find a new job elsewhere. Outplacement will help these people to recover from the shock of losing their job and find a route to what they want to do in the future.

Here are some definitions of *outplacement*. According to MACMILLAN Dictionary, "*outplacement* is the process of finding new jobs for people in your company who have been forced to leave because their job no longer exists". According to The American Heritage Dictionary of the English Language, Fourth Edition, "*outplacement* is the process of facilitating a terminated employee's search for a new job by provision of professional services, such as counseling, paid for by the former employer". According to BNET Business Dictionary, "*outplacement* is a program of resources, information, and advice provided by an employing organization for employees who are about to be laid off. Outplacement agencies typically help by drafting résumés, offering career guidance, providing practice interviews, and placing laid off employees in new jobs. Outplacement programs are often put into place well before the laid off employees leave the employer and, in the case of large-scale layoff programs, may remain in place for several years."

In practice *outplacement* helps people to focus on the options available to them at a certain moment or in the near future, and to make the right choices for their future career. That means that *outplacement* helps people to choose their next direction in their career, to prepare themselves for the job market, and guides them through this complex process.

It is important to know that *outplacement* can not guarantee jobs for all candidates; but it puts individuals in a much better position to find a new job quickly.

*Outplacement* includes all the main elements of career transition: helping candidates to recover their footing, analyzing skill-sets and mapping out a route to a suitable role. As we mentioned before, it doesn't mean that these people will most find a job for sure. However after a given period the candidates were not able to find a job, they have all the necessary information to find one in the near future and they have to do it on their own.

Due to the financial crisis that affects on developing economies, restructuring and lay-offs are much more of a fact of life, which means people are much less likely to be traumatized about this kind of experience and they have to be prepared to face it.

During the outplacement process, a consultant will objectively assess the candidate's career strengths – often creating a personal analysis – and compare them to what employers are looking for. Benchmarking is difficult and depends on many factors. To do it effectively, the consultant must be clear about how the candidate's strengths *add value*, considering the needs of the employment market.

The necessary steps to be followed during the process are:

1. Evaluation of the candidate's strengths and weakness
2. Establish what the current employment market requires
3. *Link* the candidate's strengths with the needs noticed in the market
4. Define how the candidate's strengths add value, given the needs of the market.

## 3. BAYESIAN NETWORKS

Bayesian networks are DAGs (directed acyclic graphs) in which the node represent variables, the arcs signify the existence of direct causal influences between the linked variables and the strengths of these influences are expressed by forward conditional probabilities.

**Definition.** A DAG *D* is said to be an *I*-map of a dependency model *M* if every d-separation condition displayed in *D* corresponds to a valid conditional independence relationship in *M*, i.e., if for every three disjoint sets of vertices *X*, *Y*, and *Z* we have

$$< X \mid Z \mid Y >_D \Rightarrow I(X,Z,Y)_M \ .$$

A DAG is a *minimal I*-map of *M* if none of its arrows can be deleted without destroying its *I*-mapness.

**Definition.** Given a probability distribution *P* on a set of variables *U*, a DAG $D=(U,\vec{E})$ is called a *Bayesian network* of *P* iff *D* is a minimal *I*-map of *P*.

We now address the task of constructing a Bayesian network for any given distribution *P*.

**Definition.** Let $M$ be a dependency model defined on a set $U=\{X_1,X_2,...,X_n\}$ of elements, and let *d* be an ordering $(X_1,X_2,...,X_i,...)$ of the elements of *U*. The *boundary strata* of *M* relative to *d* is an ordered set of subsets of *U*, $(B_1,B_2,...,B_i,...)$ , such that each $B_i$ is a Markov boundary of $X_i$ with respect to the set $U_{(i)}=\{X_1,X_2,...,X_{i-1}\}$, i.e., $B_i$ is a minimal set satisfying $B_i \subseteq U_{(i)}$ and $I(X_i,B_i,U_{(i)}-B_i)$. The DAG created by designating each $B_i$ as parents of vertex $X_i$ is called a *boundary DAG* of *M* relative to *d*.

**Theorem.** Let *X*, *Y*, and *Z* be three disjoint subsets of variables from *U*. If *I(X,Z,Y)* stands for the relation "*X* is independent of *Y*, given *Z*" in some probabilisyic model *P*, then *I* must satisfy the following four independent conditions:

- Symmetry: $I(X,Z,Y) \Leftrightarrow I(Y,Z,X)$ (a)
- Decomposition: $I(X,Z,Y \cup W) \Rightarrow I(X,Z,Y) \,\&\, I(X,Z,W)$ (b)
- Weak Union: $I(X,Z,Y \cup W) \Rightarrow I(X,Z \cup W,Y)$ (c)
- Contraction: $I(X,Z,Y) \,\&\, I(X,Z \cup Y,W) \Rightarrow I(X,Z,Y \cup W)$ . (d)

If *P* is strictly positive, Then a fifth condition holds:

- Intersection: $I(X,Z \cup W,Y) \,\&\, I(X,Z \cup Y,W) \Rightarrow I(X,Z,Y \cup W)$ (e)

**Theorem.**[Verma 1986] Let M be any semi-graphoid (i.e., any dependency model satisfying the axioms of eqs.(a) through (d) ). If *D* is a boundary *DAG* of *M* relative to any ordering *d*, then *D* is a minimal *I*-map of *M*.

**Corollary.** Given a probability distribution $P(x_1,x_2,...,x_n)$ and any ordering *d* of the variables, the *DAG* created by designating as parents of $X_i$ any minimal set $\Pi_{X_i}$ of predecessors satisfying

$$P(x_i \mid \Pi_{X_i}) = P(x_i \mid x_1,...,x_{i-1}), \qquad \Pi_{X_i} \subseteq \{X_1,X_2,...,X_{i-1}\}$$

is a Bayesian network of *P*. If *P* is strictly positive, Then all of the parent sets are unique and the Bayesian network is unique (given *d*).

**Corollary.** Given a *DAG D* and a probability distribution $P$, a necessary and sufficient condition for *D* to be a Bayesian network of *P* is that each variable *X* be conditionally independent of all its non-descendants, given its parents $\Pi_X$, and that no proper subset of $\Pi_X$ satisfy this condition.

The "necessary" part holds because every parent set $\Pi_X$ *d*-separates *X* from all its non-descendants. The "sufficient" part holds because *X*'s independence of all its non-descendents means *X* is also independent of its predecessors in a particular ordering *d*.

**Corollary.** If a Bayesian network *D* is constructed by the boundary-strata method in some ordering *d*, then any ordering *d'* consistent with the direction of arrows in *D* will give rise to the same network topology.

STRUCTURING THE NETWORK

Let any joint distribution $P(x_1, x_2,..., x_n)$ and an ordering *d* on the variables in *U*. We start by choosing $X_1$ as a root and assign to it the marginal probability $P(x_1)$ dictated by $P(x_1, x_2,..., x_n)$. Next, we form a node to represent $X_2$; if $X_2$ is dependent on $X_1$, a link from $X_1$ to $X_2$ is established and quantified by $P(x_2 | x_1)$. Otherwise, we leave $X_1$ and $X_2$ unconnected and assign the prior probability $P(x_2)$ to node $X_2$. At the *i*-th stage, we form the node $X_i$, draw a group of directed links to $X_i$ from a parent set $\Pi_{X_i}$, and quantify this group of links by the conditional probability $P(x_i | \Pi_{X_i})$. The result is a directed acyclic graph that represents many of the independencies embedded in $P(x_1, x_2,..., x_n)$, i.e., all the independencies that follow logically from the definitions of the parent sets.

Conversely, the conditional probabilities $P(x_i | \Pi_{X_i})$ on the links of the *DAG* should contain all the information necessary for reconstructing the original distribution function. We get the product

$$P(x_1, x_2,..., x_n) = P(x_n | x_{n-1},..., x_1)P(x_{n-1} | x_{n-2},..., x_1)\cdots P(x_3 | x_2, x_1)P(x_2 | x_1)P(x_1)$$
$$= \prod_{\mathrm{i}} P(x_i | \Pi_{X_i})$$

The parents of $X_i$ are those variables judged to be *direct causes* of $X_i$ or to have *direct influence* on $X_i$. An important feature of the network representation is that it permits people to express directly the fundamental, qualitative relationships of direct influence; the network augments these with derived relationships of *indirect influence* and preserves them, even if the numerical assigments are just sloppy estimates. The addition to the network of any new node *Y* requires that the knowledge provider identify a set $\Pi_Y$ of variables that bear directly on *Y*, assess the strength of this relationship, and make no commitment regarding the effect of *Y* on variables outside $\Pi_Y$.

QUANTIFYING THE LINKS

Suppose we are given a *DAG D* in which the arrows pointing to each node $X_i$ emanate from a set $\Pi_{X_i}$ of parent nodes judged to have direct influence on $X_i$. To specify consistently the strengths of these influences, one need only assess the conditional probabilities $P(x_i | \Pi_{X_i})$ by some functions $F_i(x_i, \Pi_{X_i})$ and make sure these assessments satisfy

$$\sum_{x_i} F_i(x_i, \Pi_{X_i}) = 1$$

where $0 \le F_i(x_i, \Pi_{X_i}) \le 1$ and the summation ranges over the domain of $X_i$. This specification is complete and consistent because the product form

$$P_a(x_1, x_2,..., x_n) = \prod_i F_i(x_i, \Pi_{X_i})$$

constitutes a joint probability distribution that supports the assessed quantities. In other words, if we compute the conditional probabilities $P_a(x_i \mid \Pi_{X_i})$ dictated by $P_a(x_1,...,x_n)$, the original assessment $F_i(x_i,\Pi_{X_i})$ will be recovered:

$$P_a(x_i \mid \Pi_{X_i}) = \frac{P_a(x_i,\Pi_{X_i})}{P_a(\Pi_{X_i})} = \frac{\sum\limits_{x_j \notin (x_i \cup \Pi_{X_i})} P_a(x_1,...,x_n)}{\sum\limits_{x_j \notin \Pi_{X_i}} P_a(x_1,...,x_n)} = F_i(x_i,\Pi_{X_i}).$$

Moreover, all the independencies dictated by the choices of $\Pi_{X_i}$ are embodied in $P_a$.

*DAG*s constructed by this method will be called *Bayesian belief networks* or *causal networks* interchangeably, the former emphasizing the judgmental origin and probabilistic nature of the quantifiers and the latter reflecting the directionality of the links.

## 4. PRACTICAL EXAMPLE

For a certain employee who is about to be laid off ( I ), the outplacement agency considers certain minimum requests/set of skills (c1,...,c7) and maps out a route to a number of suitable roles for that candidate (d1, d2, d3, d4).

In this case study we considered that the employee who is about to be laid-off, named the Candidate (I), graduated the Academy of Economic Studies, Banking and Finance Specialty, has two years experience as a human resources specialist and 1.5 years experience as payroll specialist in the HR Department. The Candidate has also very strong English knowledge and good IT skills (Office Package). During the University, the Candidate liked all the accounting courses and he considers having certain skills for the economic activity, even if he has a solid experience in HR field.

We have also considered that the outplacement agency tested the candidate (I) using a set of tests (t1 and t2).

We chose the suitable roles for the candidate (d1, d2, d3, d4) considering his professional and educational background and the needs of the employment market. These roles are defined as follows:

d1 – Human resources inspector

d2 – Recruitment specialist

d3 – Accountant

d4 – Financial/economic specialist (economist)

The criteria we chose to establish minimum requests for these roles are:

c1 – field of study

c2 – human resources inspector certificate

c3 – the professional experience necessary for a candidate in order to be eligible for completing a certain type of activity

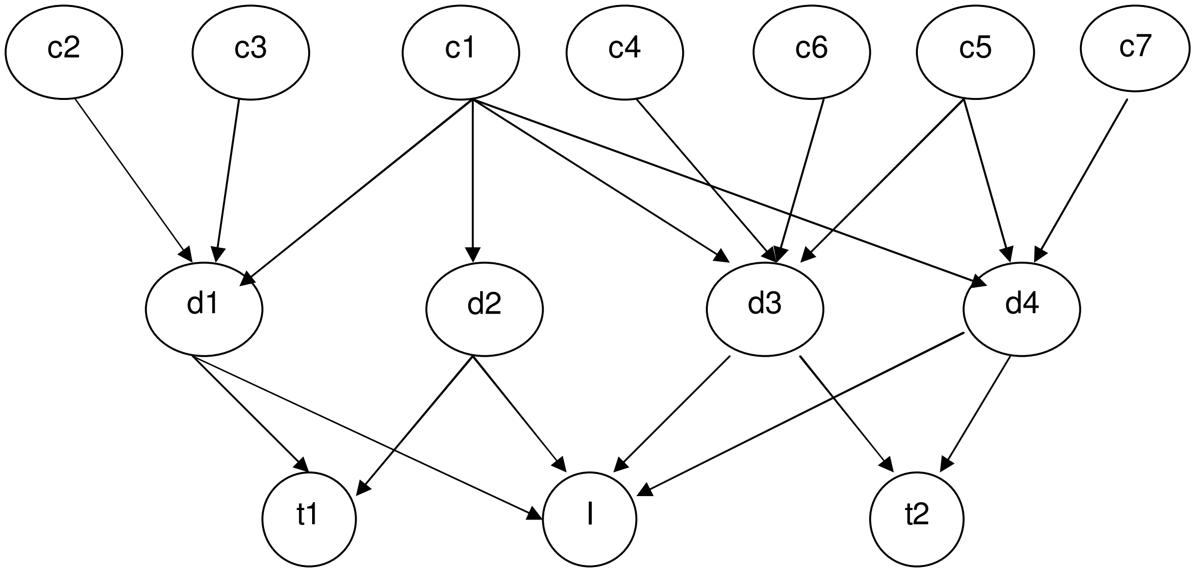
c4 – month-end and year-end closing operations

c5 – good command of economic, accounting, banking and finance legislation

c6 – technical abilities, very good knowledge of Office Package (Excel, Word, Power Point) and certain accounting and payroll systems

c7 – minimum 1 year in the economic field

In the figure bellow, this example looks like a causal network.




Causal relations are described by uncertain implications and direction of causality is from top to bottom. Note that some effects have more one cause and that some causes produce more than one effect.

In order to solve the problem described above we used ABEL (a probabilistic argumentation system).

The fictitious knowledge of the Candidate are modeled as show below.

(1) $c2 \wedge a2 \rightarrow d1, c3 \wedge a3 \rightarrow d1, c1 \wedge a1 \rightarrow d1, a8 \rightarrow d1,$
$d1 \rightarrow (c2 \wedge a2) \vee (c3 \wedge a3) \vee (c1 \wedge a1) \vee a8$

(2) $c1 \wedge a9 \rightarrow d2, a10 \rightarrow d2, d2 \rightarrow (c1 \wedge a9) \vee a10$

(3) $c1 \wedge a11 \rightarrow d3, c4 \wedge a12 \rightarrow d3, c5 \wedge a13 \rightarrow d3, c6 \wedge a14 \rightarrow d3, a15 \rightarrow d3,$
$d3 \rightarrow (c1 \wedge a11) \vee (c4 \wedge a12) \vee (c5 \wedge a13) \vee (c6 \wedge a14) \vee a15$

(4) $c1 \wedge a16 \rightarrow d4, c5 \wedge a17 \rightarrow d4, c7 \wedge a18 \rightarrow d4, a19 \rightarrow d4,$
$d4 \rightarrow (c1 \wedge a16) \vee (c5 \wedge a17) \vee (c7 \wedge a18) \vee a19$

(5) $d1 \wedge a20 \rightarrow t1, d2 \wedge a21 \rightarrow t1, a22 \rightarrow t1,$
$t1 \rightarrow (d1 \wedge a20) \vee (d2 \wedge a21) \vee a22$

(6) $d1 \wedge a23 \rightarrow I, d2 \wedge a24 \rightarrow I, d3 \wedge a25 \rightarrow I, d4 \wedge a26 \rightarrow I, a27 \rightarrow I,$
$I \rightarrow (d1 \wedge a23) \vee (d2 \wedge a24) \vee (d3 \wedge a25) \vee (d4 \wedge a26) \vee a27$

(7) $d3 \wedge a28 \rightarrow t2, d4 \wedge a29 \rightarrow t2, a30 \rightarrow t2,$
$t2 \rightarrow (d3 \wedge a28) \vee (d4 \wedge a29) \vee a30$

Supposed that the following probabilities are known:

| | | | | | | |
|---|---|---|---|---|---|---|
| p(a1)=0.6 | p(a2)=0.1 | p(a3)=0.1 | p(a4)=0.3 | p(a5)=0.7 | p(a6)=0.6 | p(a7)=0.1 |
| p(a8)=0.7 | p(a9)=0.8 | p(a10)=0.3 | p(a11)=0.1 | p(a12)=0.7 | p(a13)=0.8 | p(a14)=0.3 |

p(a15)=0.6 p(a16)=0.9 p(a17)=0.6 p(a18)=0.2 p(a19)=0.4 p(a20)=0.8 p(a21)=0.4

p(a22)=0.5 p(a23)=0.2 p(a24)=0.4 p(a25)=0.5 p(a26)=0.5 p(a27)=0.2 p(a28)=0.8

p(a29)=0.7 p(a30)=0.9

As a result of the two tests the candidate passed, the outplacement consultant obtains the following results:

QUERY:<DSP d1>
0.930
QUERY:<DPL d1>
0.930
QUERY:<DSP d2>
0.876
QUERY:<DPL d2>
0.876
QUERY:<DSP d3>
0.987
QUERY:<DPL d3>
0.987
QUERY:<DSP d4>
0.983
QUERY:<DPL d4>
0.983.

In conclusion, considering the candidate's professional and educational background and the needs of the employment market, the consultant considers that the most suitable role for the candidate is d3.

## 5. CONCLUSIONS

The main advantages of the BN formalism in outplacement are its flexibility and strong links with how the employers, employees and HR professionals can make decisions and predict the proper domain of activity to be followed by laid off employees.

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