

# AN AUTOMATED RECOMMENDATION APPROACH TO SELECTION IN PERSONNEL RECRUITMENT

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## Abstract

*Many online recruitment platforms suffer from the inappropriateness of Boolean search methods for matching candidates with job requirements. While such platforms have so far been a successful means for decreasing personnel advertising cost, the huge amount of electronic candidate profiles has not yet been exploited to optimize search quality.*

*In this paper, using findings from an empirical survey on modern recruitment practices among Germany's top 1,000 enterprises and supported by findings from personnel selection theory, we identify a gap between the actual requirements of matching people with jobs and current e-recruitment procedures. Based on information systems research and drawing from selection and assessment theory, a framework for developing new matching methods is proposed. We describe the elements of a matching method using a probabilistic automated recommendation approach and then present first quite promising results from applying the algorithm to synthetic data.*

Keywords: automated recommendation, recruitment, selection and assessment, probabilistic modeling

## Introduction

Internet-based instruments for recruiting job candidates have significantly spread in recent years (König et al. 2003). Besides corporate homepages, job career portals (like monster.com) have driven this development. While companies post open job positions on these portals, job searchers use them to publish their profiles. Consequently, more and more job descriptions and candidate profiles are becoming accessible online. Although these vast amounts of digitally available candidate information represent a great opportunity for improving matching quality, this potential is largely unused since search functionality is currently mainly restricted to Boolean keyword search.

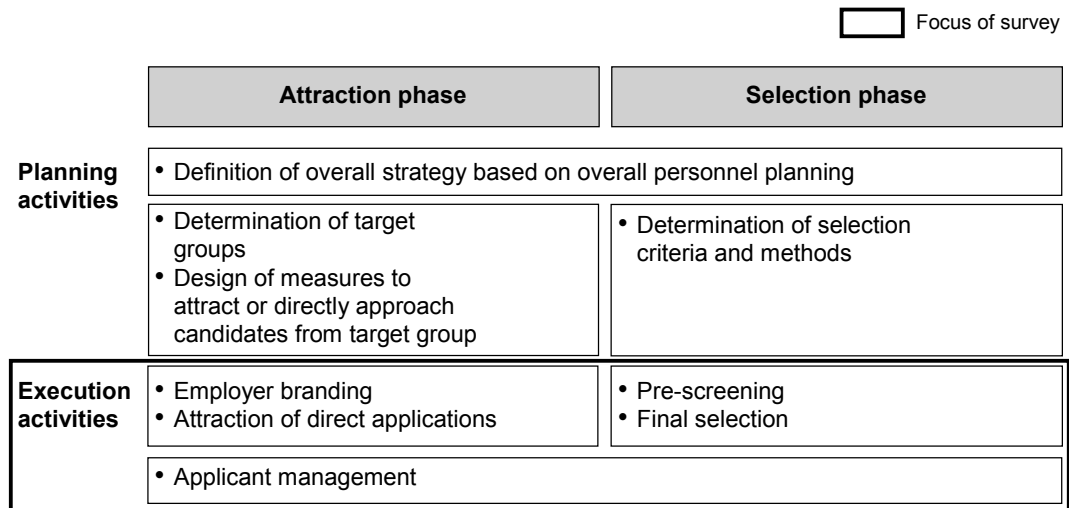
Current practices as well as theoretical considerations show that this type of search is inadequate for achieving a good fit between the requirements of the job to be filled and the aptitudes of the candidates found. Using personnel selection theory and recent findings from information systems research on automated recommendations, we develop a framework for personnel selection and demonstrate the operativeness of this model-based approach using experiments with synthetic data.

## Modern recruitment practices in Germany

As part of a research project on partner matching, we conducted a survey in 2002 with the largest 1,000 companies in Germany achieving a response rate of 19.6%. Before presenting results from this survey, the following section briefly introduces the recruitment function.

**The Recruitment function and its instruments**

The recruitment of employees is a core function in human resource management dealing with the sourcing of labor as one of the factors of production (see e.g. Wright and Storey 1997; Armstrong 1995). Two main recruitment phases can be distinguished (Figure 1): the *attraction phase* and the *selection phase* (Schneider 1995, pp. 24-25). Both consist of a planning and an execution part. The planning part determines the overall strategy and concrete measures to attract qualified employees as well as the specific selection methods. The execution part consists of two main groups of activities (König et al. 2003). *Employer branding* comprises all long-term marketing measures intended for establishing an attractive employer image and, thus, indirectly attracting qualified candidates. *Personnel attraction* aims at generating applications for concrete open job positions.



**Figure 1. Recruitment function**

The selection phase typically starts with the screening of resumes and other submitted application documents (e.g., references, certificates). This step is called *pre-screening* or *pre-selection*. The *final selection* of candidates is then conducted with the set of candidates that has not been filtered out during pre-screening (Kompa 1989, p. 114). Finally, *applicant management* serves as a supporting function. It includes the communication with applicants, the administration of applicant data and internal processes such as forwarding applications to the members of the organization involved in the selection decision.

Our survey concentrated on the execution activities (highlighted in Figure 1), particularly focusing on the use and effectiveness of different recruitment instruments. Typical attraction instruments are the following (Armstrong 1995, pp. 398-399; Albert 1998, pp. 56-62; König et al. 2003, p. 23; Schneider 1995, pp. 35-40):

- Job ads (print and online)
- Job postings/search requests at public and private labor agencies
- Direct search (recruitment and executive search consultants)
- Events (workshops, seminars, etc.)
- Job fairs
- Employee referrals
- Different multimedia instruments (e.g., online games)
- Active search in resume databases

After compiling a sufficient amount of applications, different selection instruments and methods can be used to identify the best candidate for the job. Later in this article we go into the aspects of selection in further detail by distinguishing sources of data from assessing attributes and predicting future behavior with the latter being the actual selection method.

**Results from a survey on modern recruitment practices in Germany**

The survey showed that internet-based recruitment instruments are already very common among large German companies with the corporate homepage being the most frequently used channel for attracting new employees (Figure 2a). An obvious reason are the relatively low costs for posting open job positions on the homepage compared to the costs for job ads on job

portals and even more in print media. While the use of online channels is already intense, the respondents are much more skeptic about their effectiveness (Figure 2b).

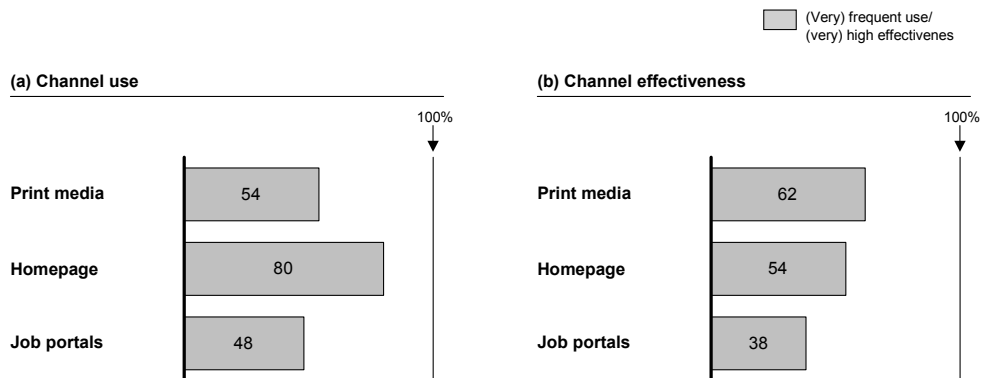


Figure 2. Use and effectiveness of personnel attraction channels

Taking a closer look on job portals, it can be observed that most companies use them in a similar way they use traditional channels, namely in order to post job ads (Figure 3). Hence, the actual potential of an electronic platform for matching jobs with candidates is currently not well exploited. Only 44% of those companies using job portals also employ them for actively searching for candidates. In additional interviews and case studies we found that many companies use this service only rarely because of a lack of data quality (structure and content) as well as of adequate search functionality (see König et al. 2003 for more details). A similar problem arises with direct applications received by companies. Only 12% of these applications are received through web-based, standardized forms as opposed to unstructured e-mail and paper-based applications. As a consequence, filtering and rating mechanisms are difficult to apply. Considering these findings, it is not surprising that the benefits generated by internet-based recruitment are mainly based on online job advertising (Figure 4).

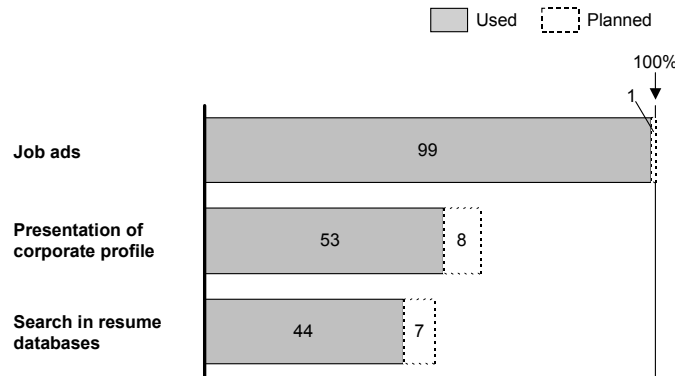


Figure 3. Used services of job portals<sup>1</sup>

<sup>1</sup> Only those companies using job portals as a channel for personnel attraction at least rarely are considered (N=172; 88% of all respondents)

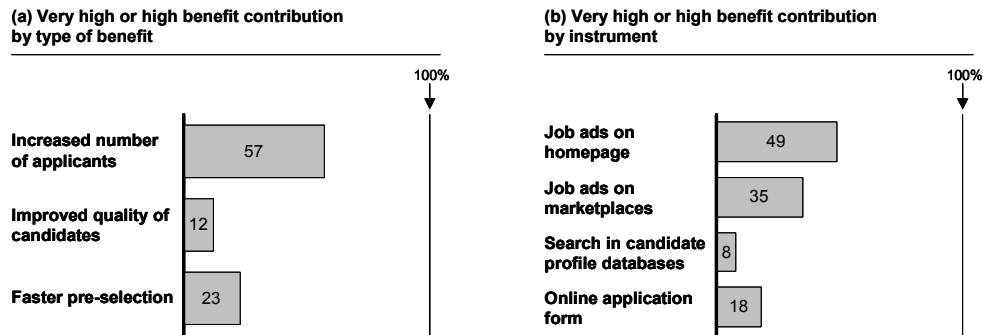


Figure 4. Benefits from e-recruitment

### Conclusions on the role of information systems in recruitment

In the past, information systems in recruitment have been mainly used for the storage of applicant contact data. According to the survey, only 21% of the respondents enter candidate profiles that go beyond pure contact information into an applicant tracking system. This in addition to the survey results presented in the previous section shows that the full potential that is created through the increased use of online platforms and the availability of digital information on job requirements and candidate profiles is not yet being exploited.

Recent information systems research dealing with the matching of information such as information filtering, automated recommendation and artificial neural networks presents approaches on how to better use these data (Foltz & Dumais 1992, Resnick and Varian 1997, Dallmüller 1998). Hence, the role of information systems in recruitment could potentially shift from pure administration to enabling new personnel selection methods.

### A framework for personnel selection

The bigger part of research on recruitment has been conducted on personnel selection rather than the attraction phase (Schneider 1995, p. 25; Kompa 1989, p. 6). The complexity of individual differences and the measurement of these differences constitute main challenges of this research (Cooper 1998, p. 5). The following section first introduces the theoretical foundations of selection and assessment. Then, a framework for developing an information systems supported assessment method based on personnel selection theory is suggested.

#### Theoretical foundations of selection and assessment

Candidates and jobs have to be matched on the basis of certain criteria which should be indicators of performance on the job (Schneider 1995, p. 50). Selection theory and more specifically the field of aptitude diagnosis mostly deal with the problem of predicting a candidate's aptitude according to these criteria. In selection theory, the information available at the time of the selection decision is called predictor data which consists of individual attributes. The method of prediction, i.e. the actual selection method, is called predictor (Schneider 1995, p. 56; Kompa 1989, p. 55).

The prediction itself refers to the assessment of the criteria based on the predictor data and a method-specific way of data combination (Kompa 1989, p. 76). Two general types of combining predictor data can be distinguished:

- *Mechanical combination*: this type of data combination is model- or rule-based, i.e. the predictor data is combined without human intervention. In order to achieve this, the data has to be quantifiable. The main advantage of mechanical combination is its objectivity and transparency. However, in many situations there are no empirically secured combination rules.
- *Clinical combination*: in this case a human assessor combines the gathered information using intuition and experience. While this seems to be subjective and unreliable, it sometimes shows better results than mechanical combination.

A very important concept in selection theory is the validity of the assessments. Among the different types of validity that are defined in literature (see Kompa 1989, pp. 67-76; Goldstein 1997, pp.529-534 for descriptions of these measures), criterion-oriented validity measures are the most prominent. They are based on the correlation between predictor and criterion. The difficulty lies in the fact that they try to measure the prognostic suitability of predictors despite any non-predictable interventions or changes in behavior which are external to the scope of the predictor.

Collecting the predictor data, i.e. the attributes, is another challenge in personnel selection. The major difficulty in dealing with human attributes is that not all of them are easily detectable or measurable (Jackson 1996, p. 57). Only physical attributes such as size or hair color, for example, can be easily observed. Others such as analytical abilities or personality traits are more complex theoretical constructs that might be perceived differently depending on how they are defined and tested. They cannot be defined and measured like physical objects. However, following the maxim "measure what is measurable, and make measurable what is not so" (Galilei), additional assumptions are made that relate such constructs to measurement methods. Especially personality test theory acts on this maxim.

There is some confusion whether a selection method refers to the assessment of a candidate's aptitude for a job according to the criteria (the actual prediction) or to the whole process from collecting the predictor data to the prediction. We use the term *assessment method* when referring to a certain way for measuring a human attribute. In the following section we also abolish the distinction between selection and assessment methods by treating a candidate's aptitude for a job as just another situation-dependent attribute.

Besides selection and assessment methods, different sources of data and instruments to gather data are distinguished (Kompa 1989, pp. 114-118; Armstrong 1995, pp. 405-411; Albert 1998, pp. 65-73):

- Application documents (including application letter, resume, certificates, references)
- Application forms
- Work samples
- Biographical questionnaires
- Tests
- Simulations (e.g., typing test)
- Interviews
- External expertise

Some of the above instruments to collect candidate information already include or imply a certain way to assess attributes. Tests, for example, usually already define which attributes are measured while, for example, resumes are just a source of information but do not define the assessment method itself. Interviews, on the other hand, are often applied in a way in which a candidate's aptitude is directly assessed without explicitly using attributes as intermediate predictor data.

Among the above instruments, applications for pre-selection and interviews and tests for final selection are very prominent. There is, however, a large gap between selection theory and corporate practice (Herriot and Anderson 1997, pp. 1-2; Kompa 1989, p. 38 and p. 67-76). In the following we propose a way to assess attributes based on digitally available assessments.

### ***An assessment framework***

Four types of attributes are distinguished depending on whether they are attached to an individual or a relationship between at least two individuals and on whether they are additionally related to a certain situation (e.g., a job) or not:

- *Individual vs. relational*: attributes can be either attached to an individual completely independent from other persons or they can depend on other persons. For example, the level of trust between two people is a typical relational attribute.
- *Independent vs. situational*: this differentiation is closely linked to the discussion in the previous section as we define job-specific aptitude as a situational attribute. Generally, situational attributes have different values depending on the situation they are related to.

One might argue that most human attributes are actually relational and even situational when, for example, doubting the assumption of invariance of psychological attributes over time (Armstrong 1995, p. 131) and in different situations. Different persons are perceiving someone else's personality (which in traditional trait theory would be defined as independent and individual) differently according to their own relationship to the other person and probably dependent on the situation (e.g., professional situation vs. leisure situation). In order to capture all aspects of a human attribute we consider it as a quadruple consisting of the following elements:

- Construct (e.g., analytical skills)
- Value (e.g., a grade)
- Method (e.g., diploma)
- Assessor (e.g., the university granting a diploma)

Having introduced the above categorization of attributes, we pick up the above made distinction of mechanical and clinical data combination for a general classification of assessment methods. The same differentiation can be made for the data collection part of an assessment (Kompa 1989, pp. 76-77). As any assessed attribute can again be used for another assessment, there is actually an infinite number of combining mechanical and clinical methods. For example, a clinical assessment of a candidate's aptitude for a job based on his resume uses among others the diploma grade for assessing his skills in a certain subject. The latter assessment which is input data for the final clinical assessment is a mechanical assessment because the diploma grade is determined based on certain rules. However, the input data for this assessment again

is partially based on clinical assessed data (e.g., oral examinations). An example for a purely mechanical procedure would be the assessment of someone's academic abilities by counting the number of his publications (neglecting the question whether this would really be a valid measure).

Based on this framework, the following chapter introduces a model-based automated recommendation approach that takes up the idea of situational and relational attributes and provides a tool for dealing with clinical assessments which in most cases take place at least once in the personnel selection process.

## Recommending candidates

Before specifying the model and applying it, we first present a brief introduction into the concepts of automated recommendation. The final section of this chapter then suggests how our approach could be used in practice to improve the personnel selection process.

### *Automated recommendation*

Automated recommendation systems have evolved with the interactive environment of the internet. While users of this vast communication network have access to large amounts of information items and product descriptions they have difficulties to find the right information or preferred products. In every day life, the process of finding and choosing the right things is usually supported by recommendations from other people that we trust or assume to have similar tastes, or we rely on reviews by trusted sources such as renowned newspapers. However, with the large amounts of information about preferences and interests being captured on the internet (e.g., in the form of site visits and transactions) this data can be used to automatically infer recommendations to individual users (Resnick and Varian 1997, p. 56; Sarwar et al. 2000, pp. 158-159).

Automated recommendation is usually distinguished into content-based filtering and collaborative filtering. While content-based methods recommend objects similar to those a user has preferred in the past, methods based on collaborative filtering identify other users with tastes similar to the current user and recommend objects those users have preferred (Balabanović and Shoham 1997, p. 66; Breese et al. 1998, p. 43). Hence, in the first case preference profiles of users have to be compared to object attributes and in the latter case the similarity of preference profiles has to be determined. When applying this approach to the general problem of assessing human attributes (or the more specific problem of predicting a candidate's aptitude), the preferences would correspond to the individual perception of someone else's attributes and to situational (e.g., job-specific) requirements. The object of preference would be the assessed person. It is obvious that this analogy makes only sense in the case of clinical assessments.

The model that we specify in the following section is built on a hybrid approach, i.e. both concepts, content-based filtering and collaborative filtering, are applied simultaneously. This helps to partially overcome the problem of rating data sparsity by leveraging synergies between the two approaches in a combined model (see for example Rashid et al. 2002: p. 127; Sarwar et al. 2000, p. 161; Melville et al. 2002, p. 187 for drawbacks of both approaches).

Another concept that we apply is the latent aspect model which mainly has been used for latent semantic analysis in information filtering (see for example Hofmann 1999). Hofmann and Puzicha (1999) as well as Popescul et al. (2001) and Schein et al. (2002) present latent aspect models for collaborative filtering and hybrid approaches. In a basic approach for collaborative filtering, we look at observations of user/object pairs  $(x,y)$  with

$$x \in X = \{x_1, \dots, x_n\} \text{ and}$$

$$y \in Y = \{y_1, \dots, y_m\}$$

where  $X$  is a set of users and  $Y$  is a set of objects. For the basic model, observations are just co-occurrences of users and objects representing events like "user  $x$  has accessed object  $y$ ", i.e. preference values are not explicitly considered. The aspect model can then be represented as a latent variable model using a latent aspect variable

$$z \in Z = \{z_1, \dots, z_k\}$$

which is associated with each observation  $(x,y)$ , assuming that  $x$  and  $y$  are independent conditioned on  $z$ . The model can then be depicted as shown in Figure 5a and the probability model can be written as:

$$P(x, y) = P(x) \sum_{z \in Z} P(z|x) \cdot P(y|z)$$

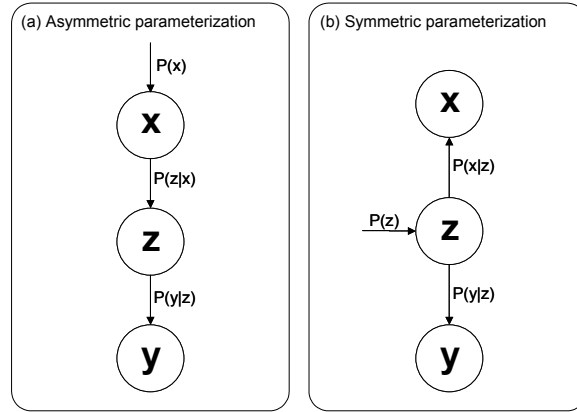


Figure 5. Basic latent aspect model

While this representation is intuitively very appealing, a symmetric formulation is used for estimating the parameters (Figure 5b). To re-parameterize the model, the identity

$$P(z) \cdot P(x|z) = P(x, z) = P(x) \cdot P(z|x)$$

is used leading to the following formulation:

$$P(x, y) = \sum_{z \in Z} P(z) \cdot P(x|z) \cdot P(y|z)$$

The model parameters are then estimated using the Expectation Maximization (EM) algorithm (Dempster et al. 1977). Very good introductions to the EM algorithm for latent aspect models can be found in Hofmann and Puzicha (1999, p. 689) and Popescul et al. (2001, p. 439). In the following section we use an extended latent aspect model that additionally considers content (or in our case human attributes) and is able to deal explicitly with preference values.

### Model specifications

So far the basic principles of the latent aspect model have been presented. Hofmann and Puzicha (1999, p. 689-690) introduced an additional variable  $v$  into the model representing a rating value. We depict such a model in Figure 6 together with a simple numeric example.

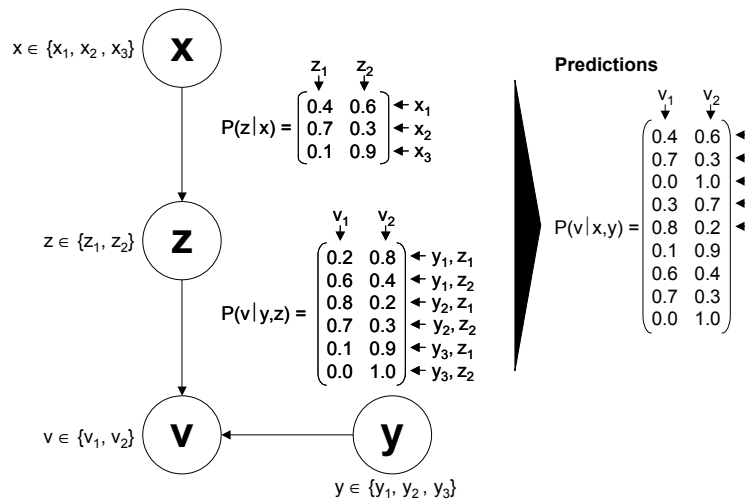


Figure 6. Numeric example of model parameters (asymmetric parameterization)

In our case, the variable  $x$  represents the assessor together with the construct (i.e., the attribute) to be assessed and the (clinical) assessment method that is used. The latter mainly defines which input data (e.g., a candidate's resume) is considered for assessing the attribute. The variable  $z$  stands for the latent aspects that influence the assessment, variable  $v$  is the assessed attribute value and variable  $y$  is the assessed person. By using this model structure, the assessed person is independent of  $x$ . This is a realistic assumption since the selection of the candidates to be assessed is not part of the assessment process itself.

The above model still represents a pure collaborative filtering approach. In order to leverage the knowledge of the input data for a specific assessment method (e.g., the resume data in the case of resume screening), we replace variable  $y$  with a variable  $a$  representing the attributes that are used as input data (Figure 7).

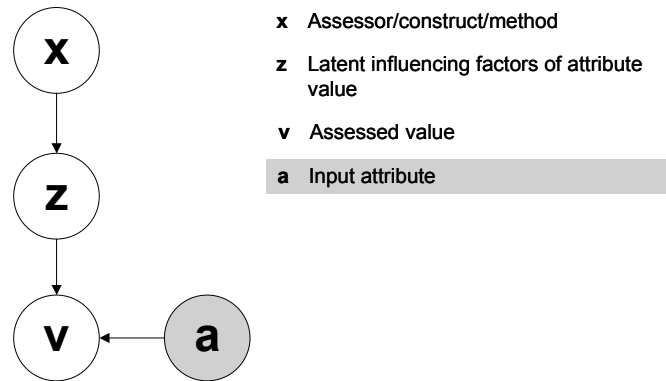


Figure 7. Hybrid assessment model

### Application of the model on synthetic candidate resumes

In order to show the feasibility of applying the latent aspect model to the assessment problem, we used synthetic resume data and resume screening as a form of clinical assessment to test the model. Therefore, we defined a target job description to be presented to the assessors. The target attribute to be assessed is the aptitude for this specific job with the domain consisting of the values 'qualified' and 'not qualified'. With a relatively small number of 70 candidates we had to limit the variety of possible input data and, hence, the variety of resumes.

In order to test both, the collaborative as well as the content-based effects of the model we used 4 assessors  $\{x_1, \dots, x_4\}$  in the model (with the construct to be assessed and assessment method remaining constant). The actual assessments, however, were conducted by only one person to eliminate the effects of too much variance in the assessments of the target attribute. The assessed values for profiles 1 to 15 were then assigned to  $x_1$ , for profiles 16 to 30 to  $x_2$ , and so forth (Figure 8) in a first test run. We also tested a complementary approach to deal with the sparsity problem which still exists even though we used a hybrid approach. In order to estimate the model parameters we used the 60 assigned assessment of the 70 candidate profiles to create an original rating matrix  $R$  that assigns assessed values to profiles:

$$R = (r_{x,y,v}) \text{ with } r_{x,y,v} = \begin{cases} 1 & \text{if assessor } x \text{ assesses the target attribute} \\ & \text{of person } y \text{ with value } v \\ 0 & \text{otherwise} \end{cases}$$

We then transformed the above matrix by treating the ratings of persons as ratings of all the attributes extracted from the resumes.<sup>2</sup> As many attributes are assigned to several profiles and, hence, might be observed several times with different values  $v$ , the entries of the transformed matrix are actually not either 0 or 1 but take values in the interval  $[0;1]$  according to the relative frequency of value  $v$  being assigned to attribute  $a$  by assessor  $x$ . As even in a realistic scenario the transformed value matrix is still rather sparse, we used simple linear interpolation to complement the matrix.

After estimating the model parameters, the assessments for candidate profiles 61 to 70 were then predicted by the model. The result is shown in Figure 8 with the signs "+" and "-" standing for the original assessments of these profiles which are used to test the prediction quality of the model. These assessments were conducted by the same person as the ones for profiles 1 to 60.

<sup>2</sup> The extraction of attributes from the resume was mainly done by mechanical, i.e. rule-based, assessments.

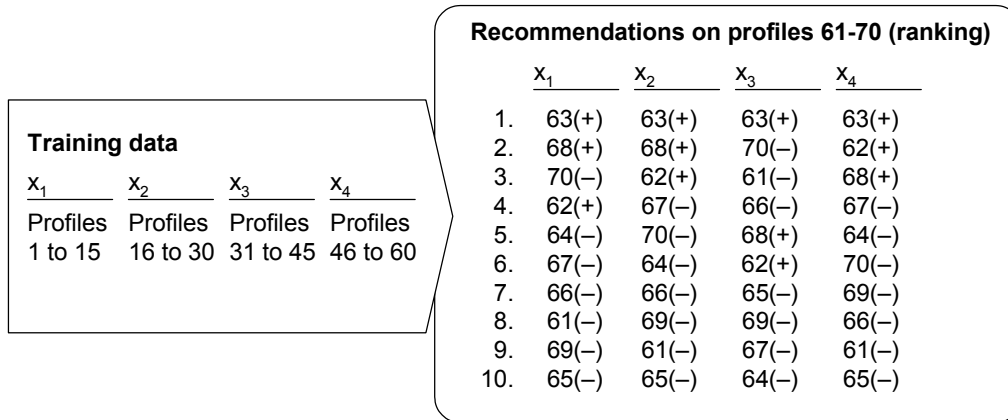


Figure 8. Test run results

In Figure 8 we ranked the profile numbers for each assessor variable according to their predicted probability to be 'qualified' for the job. The result shows a perfect match with the original assessments for the assessor variables  $x_2$  and  $x_4$  and a very good match for  $x_1$ .

However, due to the relatively low amount of training data (only 10 profiles per assessor) we assume that the full potential of the hybrid approach was not yet exploited. The 'content-based effects' might be much more significant for the result than the 'collaborative effects'. This was also shown by a second test run in which we used 40 profiles as training data and 30 profiles as test data. We estimated the model once in the hybrid mode as we did in the first run and then we estimated the model separately for each of the four assessor variables by only using the assessments assigned to the respective variable (pure content-based mode). The number of ranking errors was almost identical for both modes. For an additional error measure we used the actual predicted probabilities for the construct values and counted the number of false positives and false negatives (i.e., number of profiles that are actually 'not qualified' but predicted as 'qualified' and vice versa). For the hybrid mode we had 36 errors of 120 possible errors. The sum of the errors for pure content-based models was 48. While we can here see a better result for the hybrid mode, the number of errors seems to be rather high in both cases compared to the very good result when looking at the predicted candidate ranking. This is due to the fact that the predicted models seem to have bias in their overall level of probabilities. Hence, at least for small training data sets ranking is the preferred method for selecting the candidates.

### Implications on modern recruitment practices

The results of the first test runs have shown rather promising results. Basically the approach could be used for any combination of input data and target attribute to be assessed. Hence, during a selection process using several sources of candidate data and consisting of several levels of clinical as well as mechanical data combination the method might be useful at several points. However, it is probably not capable of automating larger parts of the process (although it might still be useful as an analytical tool). It is rather intended for instruments that are already based on electronic platforms, namely search in online resume databases and filtering processes in corporate applicant databases. Considering the results from the survey on modern recruitment practices that we presented this might have a significant positive impact on the benefits derived from e-recruitment.

### Conclusions and further research

Motivated by the results of the survey on modern recruitment practices we presented an approach to improve the quality of matching candidate profiles with job requirements based on recent research on automated recommendation. We used personnel selection theory to determine a well-founded framework for such an approach. The method we developed uses a probabilistic latent aspect model that is able of capturing a combination of different factors that might lead to a certain assessment. Using a small set of synthetic candidate profiles we were able to show the feasibility with first test runs. The estimated models successfully predicted the aptitude of candidates for a specific job profile.

Our future research will concentrate on further complementing the current estimation and prediction method since in a realistic scenario the variance of candidate as well as job profiles is much higher as in our current test data set and, therefore, the sparsity problem is much more severe. We will specifically look into relationships among assessors and into relational attributes such as trust to be used as an additional source of information for preference similarity.

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