An integrated e-recruitment system for automated personality mining and applicant ranking

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Received 19 October 2011
Revised 21 October 2011
3 February 2012
Accepted 25 March 2012

Abstract

Purpose – The purpose of this paper is to present a novel approach for recruiting and ranking job applicants in online recruitment systems, with the objective to automate applicant pre-screening. An integrated, company-oriented, e-recruitment system was implemented based on the proposed scheme and its functionality was showcased and evaluated in a real-world recruitment scenario.

Design/methodology/approach – The proposed system implements automated candidate ranking, based on objective criteria that can be extracted from the applicant's LinkedIn profile. What is more, candidate personality traits are automatically extracted from his/her social presence using linguistic analysis. The applicant's rank is derived from individual selection criteria using analytical hierarchy process (AHP), while their relative significance (weight) is controlled by the recruiter.

Findings – The proposed e-recruitment system was deployed in a real-world recruitment scenario, and its output was validated by expert recruiters. It was found that with the exception of senior positions that required domain experience and specific qualifications, automated pre-screening performed consistently compared to human recruiters.

Research limitations/implications – It was found that companies can increase the efficiency of the recruitment process if they integrate an e-recruitment system in their human resources management infrastructure that automates the candidate pre-screening process. Interviewing and background investigation of applicants can then be limited to the top candidates identified from the system.

Originality/value – To the best of the authors' knowledge, this is the first e-recruitment system that supports automated extraction of candidate personality traits using linguistic analysis and ranks candidates with the AHP.

Keywords Recruitment, Human resource management, Selection, Social networking sites, Data mining, Personality, E-recruitment, Personality mining, Recommendation systems, Analytic hierarchy process

Paper type Research paper

1. Introduction

The rapid development of modern information and communication technologies in the past few years and their introduction into peoples daily lives has greatly increased the amount of information available at all levels of their social environment (Neuman, 2010). People have been steadily turning to the web to improve their knowledge and skills (Ho *et al.*, 2010) as well as for career development (Jansen *et al.*, 2005). What is more, job seekers are increasingly using Web 2.0 services like LinkedIn and job search sites (Bizer and Rainer, 2005). On the other hand, a lot of companies use online knowledge management systems to hire employees, exploiting the advantages of the World Wide Web. These are termed e-recruitment systems and automate the process of

Internet Research
Vol. 22 No. 5, 2012
pp. 551-568

1066-2243
DOI 10.1108/10662241211271545

publishing positions and receiving CVs. The online recruitment problem is two sided: it can be seeker oriented or company oriented. In the first case the e-recruitment system recommends to the candidate a list of job positions that better fit his profile. In the second case recruiters publish the specifications of available job positions and the candidates can apply.

In online recruitment systems, candidates typically upload their CVs in the form of a document with a loose structure, which must be considered by an expert recruiter. However, this incorporates a great asymmetry of resources required from candidates and recruiters and potentially increases the number of unqualified applicants. This situation might be overwhelming to human resource (HR) agencies that need to allocate HRs for manually assessing the candidate resumes and evaluating the applicants' suitability for the positions at hand. Several e-recruitment systems have been proposed with an objective to automate and speed-up the recruitment process, leading to a better overall user experience and increasing efficiency. For example, SAT telecom reported 44 percent cost savings and a drop in the average time needed to fill a vacancy from 70 to 37 days (Pande, 2011) after deploying an e-recruitment system.

In this work we propose a novel approach for automated applicant ranking and personality mining, which is implemented in the form of a company-oriented e-recruitment system. Our objective is to limit interviewing and background investigation of applicants solely to the top candidates identified by the system. This can have a positive impact on the efficiency of the recruitment process and lead to significant cost savings. To showcase the effectiveness of the proposed schemes, we implemented and tested an integrated company-oriented e-recruitment system that automates the candidate evaluation and pre-screening process. The system was designed with the aim of being integrated with the companies' HR management infrastructure, assisting and not replacing the recruiters in their decision-making process. Our approach differs from existing systems in that applicants' evaluation is based on a pre-defined set of objective criteria that are assessed on a numerical scale, which are directly extracted from the applicant's LinkedIn profile. The candidate's personality characteristics are automatically extracted from his social presence, as shown in Faliagka *et al.* (2011a) and are also considered for the candidate's evaluation. The analytical hierarchy process (AHP) is employed for candidate ranking which allows the selection criteria to be compared to one another in a rational and consistent way, while their relative significance (weight) is controlled by the recruiters. The proposed system was deployed in a real-world recruitment scenario and a set of experimental results was derived and validated by expert recruiters. Our goal was to answer the following research questions:

- How effective the proposed system is in discriminating the top candidates and providing a rank that is consistent with the one provided by the expert recruiters?
- How accurate is the proposed automated personality mining method, using the human recruiter's input as a reference.

The rest of this work is organized as follows. In Section 2 we present the related work to this study, while in Section 3 we provide an overview of the proposed e-recruitment system architecture. In Section 4 a personality mining scheme is proposed, to extract applicant's personality traits from textual data available for the candidate in the web. In Section 5 the ranking algorithm based on AHP is detailed. The proposed system was implemented in the form of a web application whose design and implementation is presented in Section 6, while in Section 7 we present a set of experimental results that showcase the effectiveness of the system in a real-world recruitment scenario. Finally, Section 8 discusses the key findings and the main limitations of the present study and Section 9 concludes the paper.

2. Background

E-recruitment systems have seen an explosive expansion in the past few years (De Meo *et al.*, 2007), allowing HR agencies to target a very wide audience at a small cost. Applicant tracking systems (ATS) are now the standard for managing the recruiting process, by handling candidates' job applications and companies' job openings electronically. These systems are usually provided in the form of web applications, via Software as a Service model. Job openings from companies' ATS are often aggregated by internet "job board" services like Indeed and CareerJet that track millions of job openings and allow job seekers to perform simple keyword searches for positions in their preferred industry and location. Applicants typically apply for positions by uploading their resume, which is manually evaluated by expert recruiters. It must be noted though that a small fraction of overall applicants receives an offer or a call for a job interview. In (Ramar and Sivaram, 2010) a study was performed at an unnamed industry, which concluded that on average only one out of 120 applicants got selected in a job opening, while the ratio of recruited candidates that made it to the interview phase was approximately one out of 20. Thus, it follows that a degree of automation in the recruitment process to determine the candidates that clearly do not fit the position's specifications can lead to an increased efficiency and high cost savings.

Lead players in the area of e-recruitment systems such as JobVite and Monster have added a degree of automation in the screening process of the applicants' profiles, which is integrated with the traditional ATS functions. This automation ranges from easy to implement – and error prone – keyword queries (i.e. fetch candidates with ".Net" in their resume) to more sophisticated semantic matching techniques, an approach first proposed in Mochol *et al.* (2007). The latter associate semantically equivalent concepts from the user's CV with the job descriptions, using a dictionary of synonyms. Several schemes have been proposed in the literature for the automation of applicant profile screening, that combine techniques from classical IR and recommender systems. E-Gen system (Kessler *et al.*, 2007) performs analysis and categorization of unstructured job offers (i.e. in the form of unstructured text documents) as well as analysis and relevance ranking of candidates. The authors present a strategy that uses automated filtering and lemmatization of CVs which are represented as vectors, while applicant classification is based on support vector machines. CommOn framework (Radevski and Trichet, 2006) applies semantic web technologies in the field of HR management. In this framework the candidate's personality traits, determined through an online questionnaire filled-in by the candidate, are considered for recruitment. However, the process of applying to a job position is time-consuming, thus compromising the user friendliness of the system.

The aforementioned techniques, although useful, suffer from the discrepancies associated with inconsistent CV formats, structure and contextual information. What is more they are unable to evaluate some secondary characteristics associated with CVs, such as style and coherence, which are very important in CV evaluation. The authors envision e-recruitment systems integrated with the HR department's processes with an objective to support human recruiters in their decision-making process. E-recruitment systems' role should be to increase the efficiency of the recruitment process (e.g. by filtering clearly unqualified applicants) and not replace HR professionals in the applicant selection process. The proposed system extracts objective criteria from applicants' LinkedIn profiles, which are evaluated against the job positions' hiring criteria to estimate the relevance of each candidate. What is more, candidates' social presence is mined for features reflecting their personality. The authors envision traditional job-specific resumes being displaced by "live" profiles with the full candidate employment history in future e-recruitment systems. This will allow systems to easily evaluate the candidate's profile for a broad range of job positions and remove the complexity of generating (and subsequently parsing) free-text resumes.

3. System overview

The proposed e-recruitment system implements automated candidate ranking based on a set of credible criteria, which will be easy for companies to integrate with their existing HR management infrastructure. The system architecture is shown in Figure 1. We focus the present study on the exploitation of four complementary criteria, namely: education (in years of formal academic training), work experience (in months), loyalty (average number of months spent per job) and personality. When a position opens, the recruiter inputs the weight of each selection criterion at the job position module and

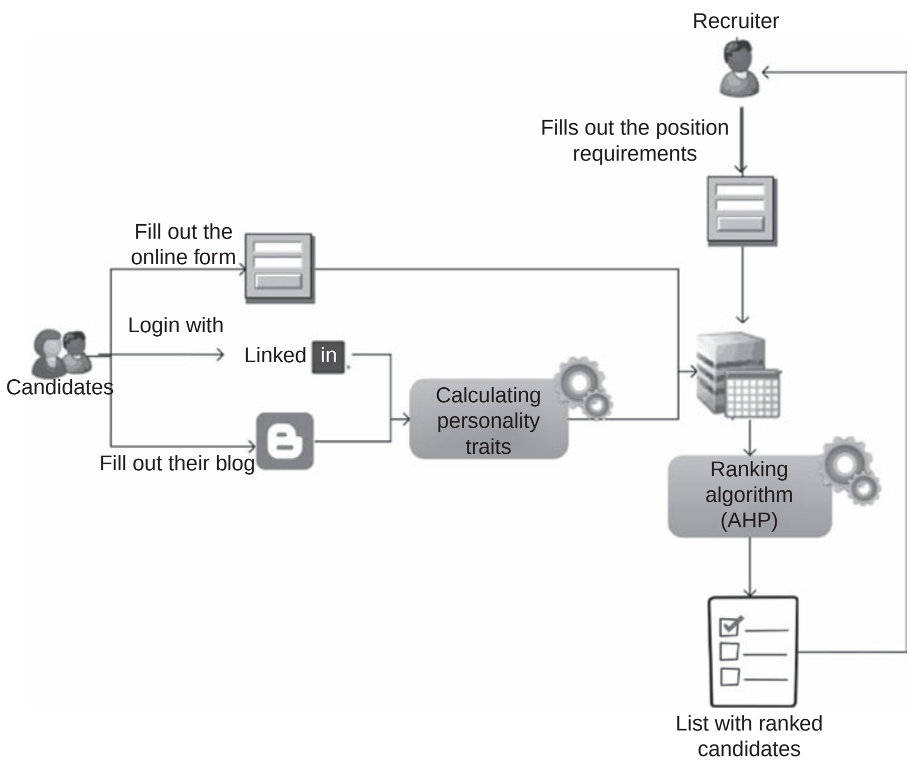

Figure 1.
Proposed system architecture

posts the position requirements. The recruitment process starts with the candidates applying for a job position at the job application module. The candidate is given the option to log into our system using his LinkedIn account credentials, which allows the system to automatically extract all relevant criteria required for candidate pre-screening, directly from the user's LinkedIn profile. On the other hand, for assessing the candidate's personality, we exploit textual data available for the candidate on Web 2.0 sites. The applicant is asked to enter his blog URL and if one is provided, the personality mining module applies linguistic analysis to the blog posts to derive features reflecting the author's personality traits.

The applicant's qualifications as well as his scores at the selection criteria are stored in the system's database. It must be noted here that during the job application process, the applicant is not required to manually enter information or participate in time-consuming personality tests as in (Radevski and Trichet, 2006). Thus, the user friendliness and the practicality of the system are not compromised. At the final step of the recruitment process, the applicant Ranking module outputs an overall rank of applicants. Each candidate's rank acts as a score of how well his profile fits the recruiter's specifications. Ranking is based on the AHP, which compares the applicants' scores at the relevant selection criteria. The recruiter is then able to review and re-rank the candidates changing the weights of the selection criteria. The recruitment process ends with the top candidates being called to participate in the interview process.

4. Personality mining

Applicant personality traits are crucial for applicant selection in many job positions, but are overlooked in existing e-recruitment systems. Typically, candidates' personality is assessed during the interview stage, which is reserved to the candidates that passed the pre-screening phase. However, gathering some preliminary data for the candidate's personality would be valuable in the pre-screening phase, especially in positions where the personality is regarded critical. Currently this task is undertaken by the recruiters, which are widely acclaimed to perform background checks on prospective employees, taking advantage of their web presence. However, it would be more effective to automate this task using web mining techniques (Faliagka *et al.*, 2011b) and text analysis programs (Faliagka *et al.*, 2011a).

In the Web 2.0 era there are large amounts of textual data for millions web users, that have been shown to be reliable predictors of user's personality. As mentioned, in our system the candidate is asked to provide a link to his blog, since it has been shown that blogs contain a range of linguistic characteristics that reflect aspects of a blogger's personality (Oberlander and Nowson, 2006). Previous works have shown that by applying linguistic analysis to blogs they can derive the author's personality traits (Oberlander and Nowson, 2006; Gill *et al.*, 2009), as well as his mood and emotions (Mishne, 2005). These studies are based on text analysis programs such as Linguistic Inquiry and Word Count (LIWC) to extract linguistic features which act as markers of the author's personality. LIWC tool (Pennebaker *et al.*, 2001) was developed by analyzing writing samples of several hundreds of university students, to correlate word use to personality traits. It uses a dictionary of word stems classified in certain psycholinguistic semantic and syntactic word categories. In Table I we can see an example of such word categories. LIWC analyzes written text samples by counting the relative frequencies of words that fall in each word category. Pennebaker and King have found significant correlations between these frequency counts and the author's personality traits (Pennebaker and King, 1999) as measured by the Big-Five personality dimensions.

Among the Big-Five personality dimensions, extraversion has received the most research attention, as it has been shown that it is adequately reflected through language use in written speech and it is possible to be discriminated through text analysis (Mairesse *et al.*, 2007). Extraversion is a crucial personality characteristic for candidate selection, especially in positions that interact with customers, while social skills are important for managing teams. What's more, it has been shown that charismatic speakers and people who dominate meetings are usually extroverts (Rienks and Heylen, 2006). Thus, in this work from the Big-Five personality dimensions we focus on extraversion due to its importance in candidate selection. Linguistic markers for extraversion are the use of many positive emotion words and social process words, but fewer negative emotion words (Pennebaker *et al.*, 2001). In this work, the extraversion score is estimated directly from LIWC scores (or frequencies), by summing the emotional positivity score and the social orientation score, also obtained from LIWC frequencies:

- Emotional positivity score was calculated as the difference between LIWC scores for positive emotion words and negative emotion words. Higher scores indicate higher emotional positivity.
- Social orientation score was obtained from LIWC as the frequency of social words (such as friend, buddy, coworker) and personal pronouns (the first person pronoun is excluded). High scores indicate a high degree of references to other people, and thus a high degree of sociability.

It must be noted here that extraversion score does not have a physical basis (i.e. we cannot say that a person is twice as extrovert because he has twice as high extraversion score) but rather quantifies the relative differences between individuals' degree of extraversion. For example, in (Argamon *et al.*, 2005) the authors label bloggers in the top third of the extraversion distribution as extroverts and the bottom third as introverts, while the rest of the sample is considered inconclusive. In this work we model extraversion via scalar values, rather than treating it as a classification problem (where each individual is marked as either introvert or extrovert). For reference, in Figure 2 we plot the distribution of extraversion scores for 100 job applicants with personal blogs, which were part of a large-scale recruitment scenario detailed in Section 7. Although one would expect that focussing our method in applicants with blogs could insert bias (e.g. bloggers could be regarded as more extravert than the average), the distribution shown in Figure 2 is apparently normal. This result is in accordance with previous research (Gill *et al.*, 2009).

Table I.
Example of LIWC word categories

Feature	Example
Anger words	Hate, kill, pissed
Metaphysical issues	God, heaven, coffin
Physical state/function	Ache, breast, sleep
Inclusive words	With, and, include
Social processes	Talk, us, friend
Family members	Mom, brother, cousin
Past tense verbs	Walked, were, had
References to friends	Pal, buddy, coworker

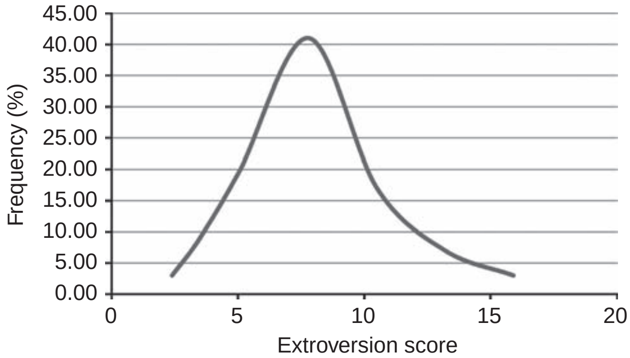

Figure 2. Distribution of the extraversion scores

5. Applicant ranking

Candidate ranking is the process of assigning scores to applicants, which reflects how well their profiles fit the recruiter's specifications. Ranks are derived from applicants' scores in individual criteria, i.e. education, work experience, loyalty and extraversion. The overall applicant rank is obtained from individual scores using the AHP (Saaty, 1990), which allows selection criteria to be compared to one another in a rational and consistent way. AHP is a decision-making technique for managing problems that involve the consideration of multiple criteria simultaneously. Each criterion has a different weight in the candidate rank, according to the requirements of the job position. AHP uses a multi-level hierarchical structure of objectives, criteria and alternatives, and provides a quantitative computational method for generating overall ranks based on a pairwise judgment of the criteria.

Assuming an hierarchical structure (Figure 3), nodes represent criteria and alternatives to be prioritized, while arcs reflect relationships between nodes in different levels. Each relationship (arc) represents a relative weight (or importance) of a node at Level L relating to a node at Level $L-1$, where $L=2, 3, \ldots, n$. In three-level AHP considered in this work, Levels 1-3 correspond to an overall goal, a group of criteria and a group of alternatives (i.e. the candidates to be evaluated), respectively. A decision maker can choose among the alternatives based on the relative importance of each one of them. The first step in the AHP process is to make pairwise comparisons of

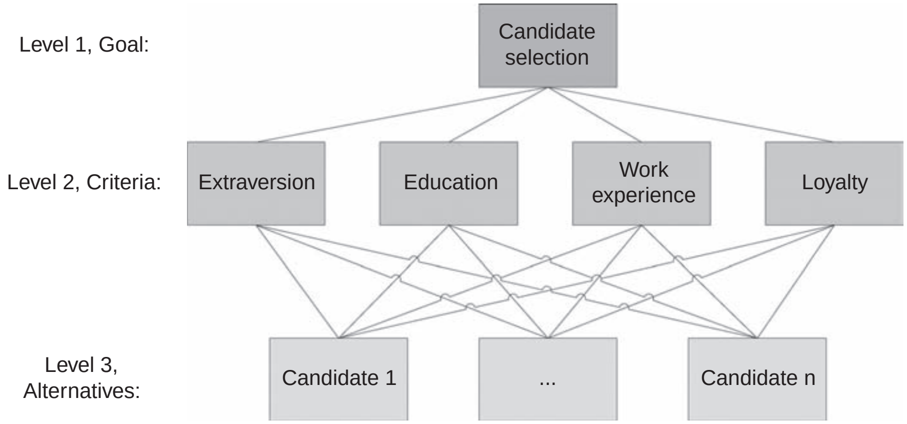

Figure 3. The model of AHP for our candidate selection problem

the selection criteria. Specifically, the recruiter has to compare the importance of the abovementioned criteria, entering weights. These weights rank the relative significance of each pair of criteria. For example, the recruiter has to decide how much more important is work experience from education. In terms of the rating scale used for quantifying pairwise comparisons, several approaches are available, although Saaty's (1990) linear scale (Table II) was the first proposed and has been used extensively. The result of the pairwise comparison process is reflected in matrix A, with w_i the weight of the ith criterion entered by the recruiter:

$$A = \begin{pmatrix} w_1/w_1 & w_1/w_2 & \dots & w_1/w_n \\ w_2/w_1 & w_2/w_2 & \dots & w_2/w_1 \\ \dots & \dots & \dots & \dots \\ w_n/w_1 & w_n/w_2 & \dots & w_n/w_n \end{pmatrix} \tag{1}$$

In the sequence, the normalized eigenvector of the matrix A is computed, which serves as the weight vector ω that quantifies the relative significance of selection criteria. The second step is the elicitation of candidates' pairwise comparison judgments with respect to each criterion in Level 2. Given n candidates to be pairwise compared, four $n \times n$ comparative matrices are formed, one per selection criterion at Level 2. Comparative matrix B_k ($k = 1, 2, \dots 4$) corresponds to the kth criterion:

$$B_k = (b_{ij}^k)_{n\times n} > 0, \quad b_{ij}^k = \frac{C_i^{(k)}}{C_j^{(k)}} \tag{2}$$

Parameter $C_i^{(k)}$ corresponds to the value of the kth criterion for the ith candidate. For each comparative matrix B_k, the normalized eigenvector X_k is computed, which is termed as the criterion's priority vector. Finally, the global priority vector R, with the candidates' final scores is computed with the linear combination of the weight vector ω with the priority vectors X_k:

$$R = \sum_{k=1}^{4} X_k \times \omega \tag{3}$$

Table II. The AHP fundamental scale

Intensity of importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Weak importance of one over another	Experience and judgment slightly favor one activity over another
5	Essential or strong importance	Experience and judgment strongly favor one activity over another
7	Demonstrated importance	An activity is strongly favored. Its dominance demonstrated in practice.
9	Absolute importance	The evidence favoring one activity is of the highest possible order
2,4,6,8	Intermediate values	When compromise is needed
Reciprocals of above nonzero	If activity i has one of the above nonzero numbers assigned to it when compared with activity j, then j has the reciprocal value when compared with i	

Since the pairwise comparison judgments are subjective, there is a concern regarding consistency. Thus, the consistency index (CI) was suggested to quantify the degree of inconsistency the AHP model can tolerate such that the judgment is still useful. Saaty (1990) suggests the following CI, random index (RI) and consistency ratio (CR) definitions:

$$CI = \frac{(\lambda_{\max})^{-n}}{n-1}, \quad CR = \frac{CI}{RI} \tag{4}$$

In (4) n is the number of candidates, $\lambda_{\max}$ the eigenvector of matrix A and the value of RI is obtained from Table III, based on the number of selection criteria. If the CR value is <0.1, the judgments are regarded reasonably consistent and therefore acceptable. If the CR is >0.10, then the judgments should be revised.

6. Implementation

The proposed e-recruitment system was fully implemented as a web application, in the Microsoft .Net development environment. In this section we will present the main application screens and discuss our design decisions and system implementation. The system is divided in the recruiter's side and the user's side.

6.1 Job application process (user's side)

Job applicants are given the option to authenticate using their LinkedIn account credentials (see Figure 4). This allows the system to automatically extract the selection criteria required for pre-screening from candidates' LinkedIn profile, so the user experience is streamlined. Users are authorized with LinkedIn API, which uses OAuth as its authentication protocol. After successful user authentication, an OAuth token is returned to our system which allows retrieving information from the candidate's private LinkedIn profile. It must be noted here that the system does not have direct access to the candidate's account credentials, which could be regarded as a security

Table III. Random index values according to selection criteria number

Selection criteria	1	2	3	4	5	6	7	8
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41

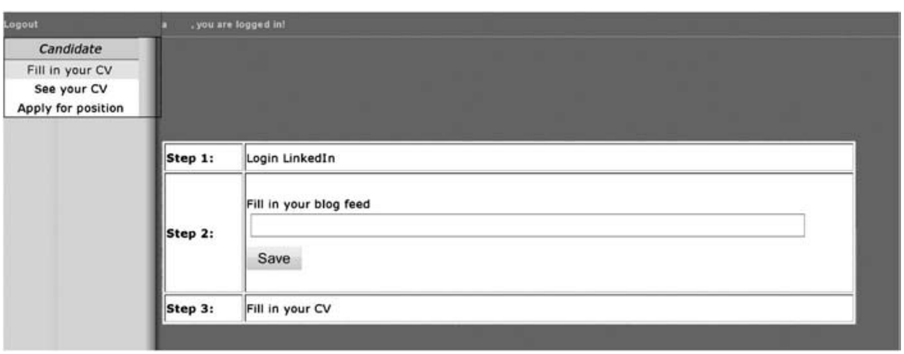

Figure 4. The candidate uses his LinkedIn account and fills in his blog feed

risk. Users without a LinkedIn profile are given the option to enter the required information manually.

As part of the job application process, the candidate is asked to fill-in the feed URI of his personal blog. This allows our system to syndicate the blog content and calculate the extraversion score with the personality mining technique presented in Section 4. Blog posts are input to the TreeTagger tool (Schmid, 1995) for lexical analysis and lemmatization. Then, using the LIWC dictionary which is distributed as part of the LIWC tool, our system classifies the canonical form of words output from TreeTagger in one of the word categories of interest (i.e. positive emotion, negative emotion and social words). Finally, after processing the 50 most recent blog posts, the system estimates the relative frequencies of the aforementioned word categories and calculates the applicant's extraversion score. The candidate can then apply for one or more of the available job positions. The system stores the job application(s) along with the candidate's scores in the selection criteria in the database and the candidate is notified via e-mail to participate in an interview if he passes the pre-screening phase.

6.2 Recruitment process (recruiter's side)

After authenticating with their account credentials, recruiters have access to the recruitment module, which gives them rights to post new job positions and evaluate job applicants. In Figure 5 the new position panel can be seen, where the recruiter must fill-in the position title, the position description and the weights to be used for applicant ranking. Specifically, the recruiter has to compare the importance of the abovementioned criteria, entering weights that rank the relative significance of each pair of criteria as discussed in Section 5. Finally, in the "rank candidates" menu, shown in Figure 5, the recruiter is presented with a list of all available job positions and the candidates that have applied for each one of them. Upon the recruiter's request the system estimates each applicant's rank and sorts them accordingly. The recruiter can change the weights of the selection criteria and re-rank the candidates, until he is satisfied with the results.

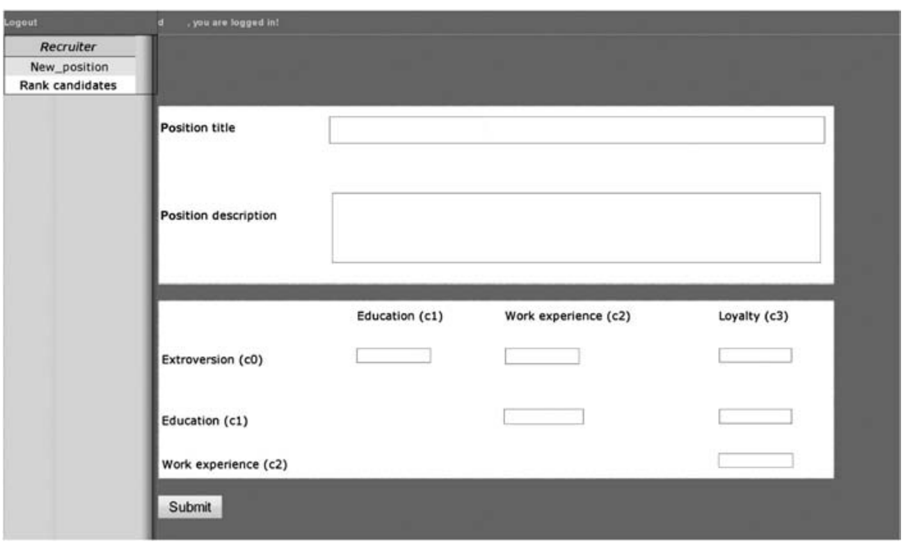

Figure 5.
New job position panel

7. Experimental evaluation

The proposed system was deployed in a real-world recruitment scenario to investigate its effectiveness in ranking job applicants. The purpose of our investigation was twofold: first, to test how effective the proposed system is in providing an accurate rank of top candidates for a certain position and second, to estimate the accuracy of the proposed personality mining method.

7.1 Data collection

In our recruitment scenario we compiled a corpus of 100 applicants with a LinkedIn account and a personal blog, since these are key requirements of the proposed system. The applicants were selected randomly via Google blog search API with the sole requirement of having a technical background, as indicated by the blog metadata, as well as a LinkedIn profile. Specifically, we used the Google profile search API to search for bloggers in the "technology" industry. The search results were manually inspected and only bloggers with a LinkedIn profile associated with their blogs were taken into account. What is more, blogs with no autobiographical content (e.g. technical blogs) were excluded from our study, as they carried no information regarding the author's personality. Our corpus of job applicants was formed by choosing the first 100 blogs returned from the profile search API that fulfilled our preconditions. The corpus selection process is not expected to introduce bias to our experimental results, as it is independent of the candidate selection criteria (i.e. all bloggers in the technology industry have the same chance of being selected as part of the corpus regardless of work experience, personality or loyalty).

We also collected three representative technical positions announced by an unnamed IT company with different requirements, as shown in Table IV. The use of different requirements per position is expected to test the ability of our system to match candidate's profiles with the appropriate job position. It can be seen that the sales engineering position favors a high degree of extraversion, while experience is the most important feature for senior programmers. Junior programmers are mainly judged by loyalty (a company would not invest in training an individual prone to changing positions frequently) as well as education. It must be noted here that though the focus of our pilot scenario was on technical positions, the procedures used were not specific to these positions, thus our analysis is also applicable to other industries.

7.2 Experimental results

In our experimental setup we assume that each applicant in the corpus has applied for all available job positions. For each job position, applicants were ranked according to their suitability for the job position both by the system (automated ranking) and by an expert recruiter, based on a set of pre-defined selection criteria. Due to the subjectivity of the extraversion criterion, a set of experiments was performed to assess the accuracy of the personality mining process (Section 7.2.1). The extraversion score of each candidate was compared against the score assigned by an expert recruiter, who had

	Extraversion	Education	Experience	Loyalty
Sales engineer	0.31	0.24	0.31	0.14
Junior programmer	0.12	0.32	0.18	0.38
Senior programmer	0.11	0.22	0.43	0.24

Table IV. Offered positions and corresponding weights per selection criterion access to the same blog posts as the system. The difference between these scores (grading error) was quantified with the cumulative distribution function (CDF) as well as the correlation coefficient (Spearman's ρ) of these scores.

For each job position the system calculated the pairwise comparison matrix A based on (1). Our system ranks the candidates with the AHP as detailed in Section 5, calculating the priority vectors (one per criterion) and the candidate's final scores. An example of these calculations for the sales engineer position is shown in Table V, for five out of 100 applicants due to space limitations. The applicants were also evaluated by a human recruiter in collaboration with the university's HR office and a ranking of the top candidates was provided for each offered position. In order to achieve consistent results, the weights of the selection criteria were selected by the same expert recruiters that provided the candidate rankings. The recruiter's rankings for each position were compared to the rankings output by the system, to assess whether the system can provide a rank consistent with the one provided by the recruiter (see Section 7.2.2).

7.2.1 Personality mining evaluation results. In this section we evaluate the effectiveness of the personality mining approach, as presented in Section 4, for accurately grading the applicants' personality. As mentioned in Section 4, our system exploits textual data extracted from the candidate's blog to extract his extraversion score. The extraversion score of each of the 100 candidates is compared against the corresponding score assigned by an expert recruiter, who had access to the same blog posts as the system. To evaluate the accuracy of the automated personality grading, using the human recruiter's scores as a reference, we calculated the CDF of the absolute grading error, shown in Figure 6. It can be seen that for 80 percent of the applicants the error is <1.5 grade in a grading scale of 0-5, while the correlation

Table V.
Local and global priorities

	Extraversion	Education	Work experience	Loyalty	Final score
Candidate 1	0.0097	0.0073	0.00058	0.0016	0.0052
Candidate 2	0.01	0.0098	0.0016	0.0015	0.0064
Candidate 3	0.0092	0.0073	0.0002	0.0005	0.0047
Candidate 4	0.018	0.0098	0.016	0.0051	0.0136
Candidate 5	0.012	0.01	0.035	0.049	0.0240
…	…	…	…	…	…

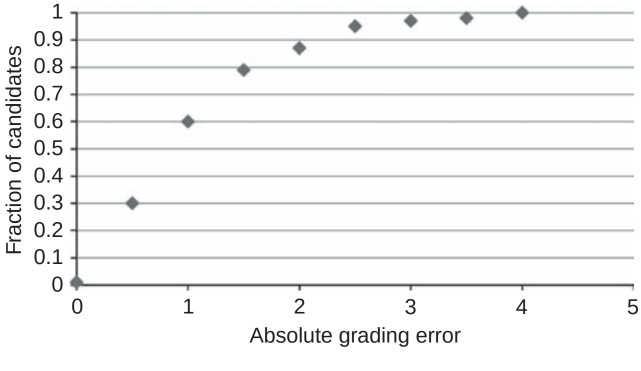

Figure 6.
CDF of the absolute grading error, with recruiter's score as reference

coefficient (Spearman's ρ) between the recruiter's and the system's scores was measured 0.63. Thus, it follows that the personality mining process implemented in our system can be trusted for a pre-assessment of the applicant's personality.

It must be noted here that the system's and the recruiter's extraversion scores were initially expressed in a different rating scale. Thus a rescaling of both scores was performed in the grading scale 0-5 before measuring the grading errors.

7.2.2 Ranking evaluation results. As mentioned earlier, we envision our system being used in collaboration with the companies' HR department for compiling the list of top-ranked employees, which will be considered for employment. Our goal in this e-recruitment scenario is to compare the rankings output from the system with the ones provided by human recruiters for three different offered positions. The system's performance is evaluated based on how effective it is in discriminating the top candidates and providing a rank that is consistent with the one provided by the human recruiters. Three metrics were used for comparing rankings; the simplest one is the overlap size of the top-k list selected by the system and the human recruiter for each job position, where $k = 25$ corresponds to 25 percent of overall applicants. In practice, k will correspond to the number of applicants that pass to the next stage of the recruitment process. The second metric is the correlation coefficient (Spearman's ρ) of the top-k candidates per job position. It is calculated on the common list of top-k applicants of both rankings. The third metric is the mean absolute difference (ranking error) of top-k candidate's ranks. The performance metrics for all three positions can be seen in Table VI. To provide a more intuitive representation of ranking correlations, we plotted the pairs of ranks (system rank, recruiter rank) for the common top-25 applicants per job position on a 2D plane (see Figure 7). Pairs that lie on (or are close to) the diagonal indicate that the system and the recruiter agree on a rank, while points above and below the diagonal indicate candidates where the recruiter and the system assigned a different rank.

	Top-k	Correlation	Ranking error
Sales engineer	19 (76%)	0.72	4.15
Junior programmer	21 (84%)	0.75	3.9
Senior programmer	9 (36%)	0.49	7

Table VI. Performance evaluation metrics per job position

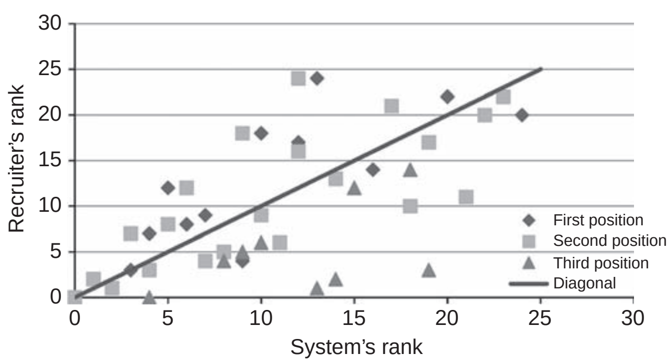

Figure 7. System and recruiter rank for the common top-k applicants per position

It can be seen that the consistency of the ranking provided by the system is highly dependent on the nature of the offered position. For the sales position, the applicant score is dominated by the highly subjective extraversion score, thus increasing the uncertainty of the overall rank. Nevertheless, the system was able to output a top-25 list that overlapped by 76 percent with the one provided by the recruiter and had a rank correlation index of 0.72. On the other hand the selection of junior programmer candidates is based on more objective criteria such as loyalty and education, thus resulting in a very high overlapping degree of 84 percent and a rank correlation index of 0.75. Finally regarding the senior programmer's position, the system exhibits a poor performance with a 36 percent overlapping degree and 0.49 correlation index. This can be attributed to the complexity of evaluating an applicant's CV for a senior position which typically requires domain experience and specific qualifications, that cannot be easily captured by pre-defined selection criteria employed in our system. In this scenario the recruiter favored the applicants with experience in web technologies that was the position's domain while the recruitment system considered overall experience, which explains the disparity in the rankings. Nevertheless the system was able to filter out clearly unqualified applicants that should not have applied for the position, thus it still would be useful as a "first line of defense."

8. Discussion

In this paper we have presented a novel approach for ranking job applicants in online recruitment systems. The proposed system relies on objective criteria extracted from the applicant's LinkedIn profile and subjective criteria extracted from their social presence, to rank candidates and infer their personality traits. A prototype system was developed based on the proposed scheme, which was deployed in a large-scale pilot scenario to investigate its effectiveness in the real world. The purpose of our investigation was twofold: first, to test how effective the proposed system is in providing an accurate rank of top candidates for a certain position, and second to estimate the accuracy of the proposed personality mining method.

Regarding the social mining method proposed in this work, our system was able to successfully assess candidates' extraversion, with a grading error of <1.5 grades in a grading scale of 0-5 for 80 percent if candidates and a correlation coefficient (Spearman's ρ) between the recruiter's and the system's scores of 0.63. This degree of correlation is significant, as trying to replicate the actual scores assigned by the recruiter to the users' extraversion is a hard problem. Regarding the applicant ranking problem, it was found that the system was able to successfully discriminate the top candidates for a given job position, and provide a candidate ranking with an average error of ± 4 positions. However, the ranking accuracy was found to be highly dependent on the nature of the offered positions, so these numbers are expected to vary depending on the characteristics of individual job positions. Specifically, the system's accuracy was found to deteriorate for positions with complex requirements (e.g. domain-specific work experience) that cannot be captured by pre-defined selection criteria. In any case the proposed system was able to filter out clearly unqualified applicants.

8.1 Limitations and ethical issues

As mentioned earlier, the system's accuracy deteriorates for senior positions with complex requirements. This is partly due to the fact that the prototype system cannot currently distinguish domain-specific experience, but rather counts overall months of work experience. Another limitation comes from the inherent complexity of automatically evaluating the applicants' personality. It was shown that the personality mining system performed consistently when given high quality input (i.e. mostly autobiographical blogs) but these may not always be available. In the future we plan to incorporate more sources of textual data that reflect the author's personality, such as the applicant's Facebook account.

The proposed system never resorts to web crawling and mining techniques to associate users with their social web presence, as – aside of the apparent ethical implications – this would increase the possibility of decisions based on false, or incomplete information. The candidate is asked to voluntarily provide a link to his personal blog and is advised against submitting a technical blog, which typically contains very few linguistic features that can act as personality markers. However, we acknowledge that there is still a possibility of judging candidates based on incomplete or outdated information (e.g. candidates without fully updated LinkedIn profiles). Blind confidence in automated e-recruitment systems could have a high societal cost, jeopardizing the right of individuals to equal opportunities in the job market. We believe that the recruiting decision should always be in the hands of HR professionals; however, the promise of automated e-recruitment systems to drastically cut costs is compelling so they cannot be entirely ruled-out, especially in the massive scale of agencies' web sites that host thousands or even millions of CVs and job positions.

8.2 Theoretical implications

In this work, we have proposed a new approach for predicting human recruiters' judgment regarding the relevance of job applicants to a specific position, based on the AHP. What is more, we have contributed a better understanding of the automated applicant screening process in e-recruitment systems, focussing on applicants' LinkedIn profiles rather than job-specific resumes. We argued that to successfully derive candidate rankings, e-recruitment systems need access to the candidate's full profile (i.e. full employment history and education) as well as the recruiters' selection criteria. We have shown that after careful parameterization, which includes assigning weights to a set of candidate selection criteria, the proposed scheme can output consistent candidate rankings compared to the ones assigned by expert recruiters. Finally, we have shown that it is possible to derive features reflecting a candidates' personality by performing linguistic analysis to his personal blog. These can serve as selection criteria in job positions where personality traits are important for applicant selection.

8.3 Practical implications

It has been shown that companies can increase the efficiency of the recruitment process and significantly cut costs, by integrating e-recruitment systems in their HR management infrastructure. The efficiency can be further increased with the advent of automated e-recruitment systems that support candidate pre-screening and ranking, as interviewing and background investigation can then be limited to the top candidates identified by the system. In the proposed system, applicants are allowed to apply for a job position with their LinkedIn profile, instead of uploading a job-specific resume. This allows employers to access the applicant's full employment history and group of contacts, and gives them the chance to automatically evaluate the candidate's profile for a broad range of job positions without the complexity of parsing a full-text resume.

Job seekers must also be prepared for the new era of social recruitment, investing in a fully updated LinkedIn profile and an extensive list of contacts. Keeping a personal blog or participating in online discussions and communities may also give them significant visibility and increase their job offers. According to a survey published by the prominent ATS provider JobVite[1], more than 80 percent of the 600 employers surveyed reported employing LinkedIn for recruiting and most check the applicants' LinkedIn profiles if provided. Automated screening tools can drastically speed-up this process, generating reports of candidates' social profiles.

Third parties (i.e. recruiting agencies) that provide social mining and automatic screening services must respect local laws that protect the users' privacy. For example, in the USA these agencies are within the bounds of the FCRA law (i.e. they are considered "consumer reporting agencies") which requires the users to complete a certification that allows the agency to collect and process their social profile. Finally, it must be noted that special attention must be paid in the choice of selection criteria, so that employers don't face liabilities. For example, companies must avoid gender- or age-related selection criteria as they are prohibited by the legislation in many countries (e.g. by the "Americans with Disabilities Act" and the "Age Discrimination in Employment Act" in the USA). Care should be taken to also avoid illegal biases, i.e. accidentally using selection criteria that indirectly exclude applicants that have a protected characteristic (such as being a certain gender, age or religion).

9. Conclusions

In this work, a novel approach for recruiting job applicants was proposed and implemented in the form of a company-oriented e-recruitment system. The proposed system employs AHP for candidate ranking based on criteria that can be extracted from the applicant's LinkedIn profile and performs linguistic analysis on candidates' blogs to infer their personality characteristics. The proposed e-recruitment system was tested in a large-scale pilot scenario, which included three different offered positions and 100 job applicants. The application of our approach revealed that it is effective in identifying the job applicants' extraversion and rank them accordingly. The candidate rankings and the extraversion scores output by the system were cross-compared to the scores provided from expert recruiters. It was found that with the exception of senior positions that required domain experience and specific qualifications, our system performed consistently with an average ranking error of ± 4 positions.

9.1 Future work

The authors plan a number of enhancements for the proposed system as a future work. To begin with we plan to incorporate semantic matching techniques, to count applicants' work experience in fields that are relevant to the job position. This is expected to improve our system's accuracy in senior positions. What's more, we plan to incorporate more sources of textual information and incorporate a filtering mechanism for low quality input (e.g. exclude technical blogs from the personality mining process). This will ensure that personality mining is not based on incomplete data and increase its accuracy. Finally, we plan to include more personality dimensions (e.g. Conscientiousness, Agreeableness) to broaden the scope of the proposed system.

Note

1. http://recruiting.jobvite.com/resources/social-recruiting-survey.php

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Further reading

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