Identifying great teachers through their online presence

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Abstract. Teachers' evaluation is a very tricky task as there are a lot of criteria, objective and not that are important to identify the suitability of a teacher to a specific class. A teacher's background as his education and experience, his personality even the students of the class are some of the important criteria that take part in his evaluation. In this work we propose a novel approach for teacher online evaluation. We implemented a prototype system which extracts a set of objective criteria from the teachers' LinkedIn profile, and infers their personality characteristics using linguistic analysis on their Facebook and twitter posts. Machine learning algorithms were used to solve the ranking problem.

Keywords: e-recruitment systems, personality mining, personality traits, social web mining, recommendation systems, teacher evaluation

1 Introduction

Successful teachers are not just those who are well-educated and possess the required knowledge to communicate to students. Teachers are also judged on the basis of their personality, as personality is considered the most important factor for learning and academic achievement in the field of learning and education and it is a common belief that teachers with certain personality traits are able to teach more efficiently ([1], [2]). Numerous studies have examined which personality characteristics could have a positive or a negative effect in the performance of a teacher categorizing them as liked (excellent, effective, good, qualified) or disliked (hated, amateur and inefficient) ([3], [4], [5], [6], [7]). According to studies, teachers are distinguished as liked or disliked based on three criteria: academic qualifications, relationship with students, and personality traits ([4], [6], [8], [9], [10]). As to the third domain, the personalities of teachers, teachers should be humble ([4]; [11]), polite and friendly [12], serious, eager to teach, fond of their job ([8], [12]), warm, cheerful, and well-balanced [13]. In addition, teachers should have creative and flexible viewpoints and high levels of cognitive proficiency and creativity ([4]; [7], [14], [15]). Furthermore, some studies

adfa, p. 1, 2011.

on the characteristics put emphasis on conscientiousness ([8], [12]), agreeableness ([4], [13]), openness to experience, and extroverted personality traits in order to yield positive educational results ([4]; [7], [14]). In the relevant literature, the approach which includes all the aforementioned features is the Big-Five Personality Model [16]. This personality model is adapted in the present approach and is presented in section 3.

There are tests available (in the form of questionnaires) that evaluate the personality characteristics of an individual in the relative literature appropriately designed on the basis of the respective theoretical personality model. People responsible for recruiting personnel in big firms or for hiring people in job positions that pose by nature specific personality prerequisites use either special purpose questionnaires/tests or interviews to evaluate the adequacy of a candidate for a certain position. Nowadays though, the amount of information available at all levels of people's social environment has drastically increased [17] and they have been steadily turning to the web for social interaction and recreation, but also in order to improve their knowledge and skills [18], career development [19], as well as for searching for a job. Job seekers are increasingly using web 2.0 services like LinkedIn and job search sites [20], while 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 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 on-line 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 HR agencies that need to allocate human resources 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% cost savings and a drop in the average time needed to fill a vacancy from 70 to 37 days [21] after deploying an e-recruitment system.

When recruiting concerns teacher positions the process could be performed online provided that we can have some unbiased feedback on the personality of the candidate teacher. Social web data (coming from Facebook, Twitter, Linkedin, etc.) can be the source of such feedback especially in the case of active users, if we can interpret social web activities in personality traits demonstrated.

In this work, we have implemented an integrated system that automates the teachers' evaluation process. Its objective is to calculate the teachers' relevance scores, which reflect how well their profile fits the positions' specifications. The system is a variation of the e-recruitment system presented in [22], [23], [24] customized for assessing the desired personality traits of teachers. The next sections provide details regarding the architecture of the proposed system comprising three main modules, followed by the description of the personality module. The discussion moves to the pilot recruitment scenario that was used to evaluate the effectiveness of the proposed approach and the paper ends with the main conclusions reached.

2 Architecture

The proposed system implements automated candidate ranking based on a set of credible criteria. In this study we focus on 4 complementary selection criteria, namely: Education (in years of formal academic training), Work Experience, Skills and Personality. The system architecture, which is shown in Fig. 1, consists of the following components:

- *Job Application module:* It implements the input forms that allow the teachers to apply for a class. The teacher is given the option to log into our system using his LinkedIn account credentials, which allows the system to automatically extract all objective selection criteria directly from the user's LinkedIn profile.
- *Personality mining module*: If the candidate's twitter URL is provided, it applies linguistic analysis to his tweets to derive features reflecting the author's personality. The linguistic analysis is done using the LIWC tool that uses a dictionary of word stems classified in certain psycholinguistic semantic and syntactic word categories [25]. The teacher can also sign in using his Facebook account and our system uses his posts in the linguistic analysis in addition to the tweets.
- *Applicant Grading module*: It combines the candidate's selection criteria to derive the candidate's relevance score for the applied position. The grading function is derived through supervised learning algorithms.

Each teacher's qualifications, as well as his relevance score are stored in the system's database. At the end of the recruitment process, the top teachers are called to participate in the interview process. 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. Thus, the user friendliness and the practicality of the system are maintained.

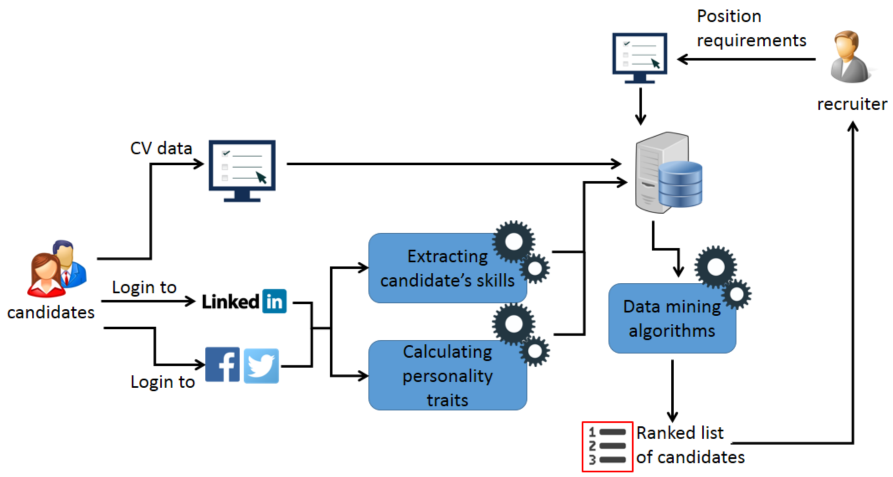


Fig. 1. System's architecture

3 Job Application module

The proposed 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.

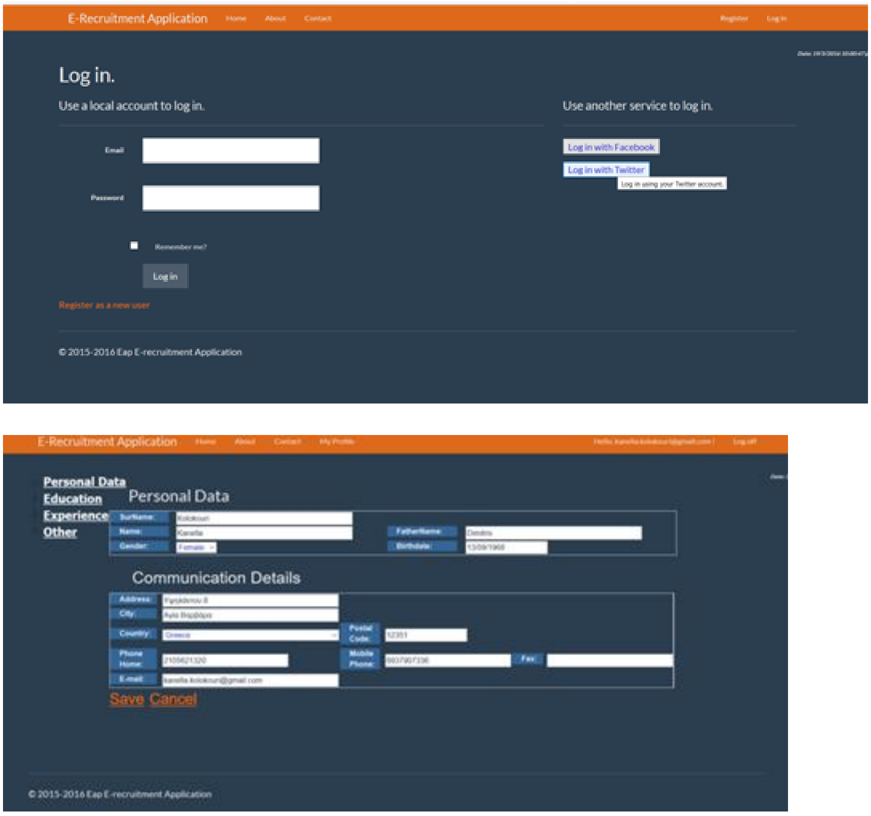
3.1 Recruitment process (recruiter's side)

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. For each new job position a recruiter can define the prerequisites for the position and the skills that are desirable for the specific class. In the "rank teachers" menu, 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 applicants' relevance scores and ranks them accordingly. This is achieved by calling the corresponding Weka classifier, via calls to the API provided by Weka. The recruiter can modify the candidate ranking, by assigning his own relevance scores to the candidates, as shown in Fig. 5. This will improve the future performance of the system, as the recruiter's suggestions are incorporated in the system's training set and the ranking model is updated. It must be noted here that the ranking model is initialized as a simple linear combination of the selection criteria, until sufficient input is provided from the recruiters to build a training set.

3.2 Job application process (teacher's side)

Teachers are given the option to authenticate using their LinkedIn account credentials (see Fig. 1) to apply for one or more of the available job positions. This allows the system to automatically extract the selection criteria required from the applicants' 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 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 login with his twitter credentials. This allows our system to syndicate the twitter content and calculate the personality score with the personality mining technique presented below.



4 Extracting teacher's personality

The Big-Five Personality Model is the most commonly used in academic psychology, and is also known as NEO PI-R. It measures the personality traits on five domains namely: neuroticism, extraversion, openness to experience, agreeableness and conscientiousness. Studies have examined the relation between its domains and students' evaluation of teaching. One such study [26] that was based on teacher evaluation done by their students and aimed at investigating liked, disliked and neutral teachers, concluded that the most important personality traits of "liked" teachers are extroversion, conscientiousness, agreeableness, emotional stability, and openness. "Disliked" teachers have such personality traits as introversion, suspiciousness and antagonism towards others, emotional instability, an easy-going nature/carelessness, and consistency/cautiousness.

In this work we focus on the extroversion personality trait, due to its importance in identifying "liked" teachers. Moreover, it has been shown that extroversion is sufficiently reflected in written speech and can be identified through text analysis. Specifically, the emotional positivity and social orientation of candidates, both directly extracted from LIWC frequencies, can act as predictors of extroversion trait. We estimate the extraversion score directly from LIWC scores (or frequencies), by summing the emotional positivity score and the social orientation score, also obtained from LIWC frequencies, as we proposed in [23]. The main difference is that we no longer use blog posts but Facebook posts and tweets as they currently are concerned the most popular social applications. Finally, we used the regression model which was trained in a previous work [23] that predicts the candidates' extraversion from their LIWC scores in the {posemo, negemo, social} categories. The regression model selected as a predictor of the extraversion score was proposed in [27], due to its good accuracy and low complexity. Equation (1) corresponds to the linear model that minimizes the Mean Square Error between actual values assigned by the recruiter and predicted scores output by the model:

$$E = S + 1.335 * P - 2.250 * N \tag{1}$$

where E is the extraversion score, *S* the frequency of social words (such as friend, buddy, coworker) returned from LIWC, *P* the frequency of positive emotion works and *N* the frequency of negative emotion words.

5 Final ranking

In this work we employ machine learning techniques to solve the problem of ranking candidate teachers. In the ranking problem, a scoring function h(x) outputs the relevance score, which reflects how well a teacher's profile fits the requirements of a given position. The problem of ranking candidates can be modeled as a regression problem, where the scoring function is learned with supervised learning techniques. Then the ranked list of candidates is derived by applying the learned function to the original list of candidates. The scoring function h(x) derives the teacher's relevance degree y_i from the values of his feature vector x_i. The feature vector x_i consists of a set of m attributes $\{a_1, \ldots, a_m\}$ that correspond to the candidate's selection criteria. These can be either continuous variables (representing a feature assessed on numerical scale) or Boolean variables (i.e., whether a candidate has a desired skill or not). The actual scoring function is typically unknown and an approximation is derived from the training set D. In the proposed system the training set consists of a set of N previous candidate selection examples, given as an input to the system:

$$D = \{(x_i, y_i) \mid x_i \in R^m, y_i \in R\}_{i=1}^{N}$$

6 Pilot scenario

Our system was tested with in a real-world pilot scenario. Specifically, the teachers of a private elementary school agreed to participate in a scenario that we set up specifically to test the reliability of our system. The teachers logged in the system with their LinkedIn credentials and applied for a job position that was also announced through the system. The objective criteria were calculated using the LinkedIn data and then the teachers were connected to their Facebook and Twitter account (if available) so as to extract and calculate their extroversion scores.

The same teachers were also evaluated manually by the school administrator, who evaluated the academic qualifications and assessed their extroversion using face-to-face interviews in a grading scale of 0-5. The automated scores were compared to the manual scores using Weka [28] and the learning-to-rank models were evaluated. Specifically, we used Weka to test the correlation of the scores output from the system (i.e. model predictions) with the actual scores assigned by the recruiters, using the Pearson's correlation coefficient metric.

The performance of the proposed system is evaluated based on how effective it is in discriminating the top candidates 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=8 corresponds to 20% of overall applicants. The second metric is the correlation coefficient (Spearman's rho) of the top-k candidates per category. The third metric is the mean absolute difference (ranking error) of top-k candidate's ranks. It can be seen in TABLE I that the system's scores are accurate enough since it was able to achieve a correlation coefficient of up to 0.72, it outputs a top-8 list that overlapped 75% and the ranking error reached 2.6.

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Table 1. Performance evaluation metrics

K=8	Top-k	Correlation	Ranking error
Candidates	6 (75%)	0.72	2,6

7 Conclusions

In this paper we have presented a novel approach for ranking teachers in online recruitment systems. The proposed scheme relies on objective criteria extracted from the applicants' LinkedIn profile and subjective criteria extracted from their social presence, to estimate applicants' relevance scores and infer their personality traits. Candidate ranking is based on machine learning algorithms that learn the scoring function based on training data provided by the school administrator. An integrated system was implemented based on the proposed scheme. We validated the system with real-world data in order to investigate potentially better fine-tuning in the algorithm that assesses the personality scores, and set up recruitment scenarios in various domains.

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