A Neuro-Fuzzy Approach to Assess the Soft Skills Profile of a PhD

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Abstract. In this paper a framework aimed at representing the soft skills profile of a job seeker by means of a 2-tuple fuzzy linguistic approach and a Neuro fuzzy controller is presented.

The framework can be used in many contexts, in this work it is employed for designing a recommender system of candidates for recruiting agencies. The recommender system's Neuro fuzzy controller simulates the decision of a Human Resource (HR) manager in evaluating the soft skills profile of a candidate and proposes only the best profiles w.r.t. a set of preferences. The framework has been developed in the context of the Find Your Doctor (FYD) start up and applied to the PhD recruiting task, but it is easily applicable to any recruiting activity.

Keywords: 2-tuple fuzzy linguistic approach · Neuro-fuzzy controller · User profile

1 Introduction

In the last few years, several European countries have provided many support programs to help the transition of PhD graduates outside the academic research, but other states, especially in the Mediterranean area, are still far less accustomed to exploit this professional background. In Italy, in particular, the majority of job-placement agencies hardly even handle PhD profiles and Doctors are alone in the task of gaining visibility towards Human Resources (HR) offices and employers, who have little idea on how PhDs' experiences and curriculum vitae may be employed and enhanced in companies.

In fact, the majority of job-matching portals available online used by large companies HR offices and recruitment agencies are systems where PhDs are mostly in disadvantage compared to people with previous experience in business. In this context, most job-matching portals are usually based on searching keywords in a candidates CV, but the taxonomy used in job advertisings (also called *job vacancies*) is set on the vocabulary of the employers and usually does not match the words that a PhD would use to describe his/her experience. Many candidates and HR managers report that PhDs often score well in job-interviews,

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but are mostly cut out from the selection at an earlier stage, due to low-level keywords filtering.

As a consequence, the need to define a system able to support a HR team in the recruitment activity of PhDs candidates is compelling. The idea has been born in the context of the Find Your Doctor (FYD) startup, which aims at becoming an important instrument dedicated to PhDs who are undergoing the transition outside Academia, with the mission of outlining the value of the research background as an asset for the development of companies and society as a whole. Within FYD a novel job-matching semi-automatic tool called SOON "Skills Out Of Narrative" is developed; it is based on a *narrative* approach for the soft skills: starting with a questionnaire of open questions, a semi-structured interview leads the candidate to reason on a given number of macro-skills usually considered important by employers, such as communication, relation, rigor, ability to face uncertainty and more. The focus is on the so-called soft skills [1], since the words used to express comparable content may vary more across contexts than for technical expertise. The questionnaire is designed to promote the candidate to first describe the meaning that he/she attributes to a given skill and only then to self-evaluate with respect to it, possibly grounding this evaluation in an actual experience. By the analysis of the text is then possible to infer a-posteriori a taxonomy that covers the possible meanings attributed to a certain skill by the respondent as described in [3].

Aim of this paper is to present an approach aimed at building a decision-support, pre-filtering tool able to guide the choices of a HR manager of a company in the PhD's profiles evaluations. In particular the representation of the soft skills of a PhD' profile is carried out by applying the fuzzy linguistic model presented by Porcel and Herrera-Viedma in [18]. Then, the obtained profile representation is used to design a novel recommendation system for PhD employment in the context of the FYD activity. The designed recommender system is able to periodically select and highlight in a pool of new profiles, those that better fulfill a set of preferences the HR Manager stated beforehand. The approach proposed in this paper has been studied in the PhD recruiting use case, but it can be easily extended for any kind of recruitment activity just by changing the reference skills taxonomy.

The novelty of this work is based on the way in which the profiles used by the recommender system are obtained, through the implementation of a Neuro fuzzy controller. Such a controller is indeed capable of learning the soft skills and of calculating a set of inference rules that are shown to be very similar to those that an HR human expert should otherwise calculate each time for each selected profile and for each individual skill. The claim of this work is emphasized by the definition of a trained model, whose behavior will be fully personalized since computed on a training dataset of pairs (profile, set of soft skills) that represents the decision behavior of a certain HR Manager rather than another. The remaining of the paper is organized as follow. After a brief summary of the related works already presented in the literature in Sect. 2, and a brief overview of the fuzzy linguistic model in Sect. 3, the soft skills profiles are defined in

Sect. 4. The overall architecture of the implemented approach is then reported in Sect. 5, while Sect. 6 describes the Neuro Fuzzy controller. Some preliminary experiments are presented and discussed, together with the obtained results, in Sect. 7, while Sect. 8 concludes with some final remarks.

2 Related Work

Several literature's studies, commissioned by the European Union, show that a good percentage of PhDs, who graduate across Europe, are not going to find long-term occupation in the Academia, but will eventually migrate towards both private and public companies and organizations [5]. In this area the skills identification is becoming one of the most important aspects for the HR team that have to spend the most part of the time in the profile analyses. Some works implement, for this reason, approaches based on machine learning and fuzzy systems to handle, for example the employability [12], that, together with skills, takes into account personal attributes for the teaching strategies development. Other works are based on cloud profile matching systems [6], while others again examine human resource (HR) practitioners subjective evaluations of job applicants as a function of specific traits, together with the assessment methods used to measure those traits [22].

On a different perspective, the automatic extraction of meaningful information from unstructured texts has been mainly devoted to support the e-recruitment process [14], e.g., to help human resource departments to identify the most suitable candidate for an open position from a set of applicants or to help a job seeker in identifying the most suitable open positions. For example, the work described in [20] proposes a system which aims to analyze candidate profiles for jobs, by extracting information from unstructured resumes through the use of probabilistic information extraction techniques as Conditional Random Fields [13]. Differently, in [23] the authors define Structured Relevance Models (SRM) and describe their use to identify job descriptions and resumes vocabulary, while in [10] a job recommender system is developed to dynamically update the job applicant profiles by analyzing their historical information and behaviors. Finally, the work described in [17] illustrates the use of supervised and unsupervised classifiers to match candidates to job vacancies suggesting a ranked list of vacancies to job seekers.

In a previous paper [3], a methodology based on machine learning aimed at extracting the soft skills of a PhD from a textual, self-written, description of her competencies was described: in that work, the soft skills were classified with respect to a proprietary taxonomy that includes around 60 different soft skills gathered into 6 skills areas. In this paper, the fuzzy representation of the PhD' soft skills profile based on the 2-tuple FML presented in Sect. 3 has been adopted. This proposal allows the HR operators to deal with the vagueness and uncertainty that are common when they assess the soft skills of a candidate during an interview, allowing a very flexible representation. Moreover, this proposal facilitates the creation of an enhanced PhD's profile by suggesting skills recognized by the ML classifier to be included into the evaluation performed by the HR operator.

3 A Brief Overview on the 2-Tuple Fuzzy Linguistic Approach

The Fuzzy Linguistic Model (FML) is based on the concept of linguistic variable [24], which has been successfully applied in many contexts as, for instance, Information Retrieval (IR) [9] and decision making [7]. The 2-tuple Fuzzy Linguistic Model [8] is built on FML with the aim to create a continuous representation model of information. This work considers the 2-tuple FLM [8], in order to create a continuous representation model of information.

Let $S = \{s_0, ..., s_n\}$ be the set of linguistic terms with odd cardinality where $s_{n/2}$ represents an indifference value, the other terms are symmetrically distributed around it. Each label is assumed to be represented by means of a triangular membership function, and all terms are distributed on an ordered scale. In this context, if a linguistic aggregation operator [7] computes a value $\alpha \in [0, n]$, and $\alpha \notin \{0, ..., n\}$, then an approximate function is used to represent the result in S. In this framework α is represented by means of 2-tuples (s_i, β_i), $s_i \in S$ and $\beta_i \in [-0.5, 0.5)$, where s_i is the linguistic label of the information, and β_i is a numerical value expressing the translation of the original result α to the closest index label i, within the linguistic term set S. This 2-tuple representation model defines a set of transformation functions between numeric values and 2-tuples: $\Delta(\alpha) = (s_i, \beta_i)$ and $\Delta^{-1}(s_i, \beta_i) = \alpha \in [0, n]$. The model also includes a negation operator, and a comparison of 2-tuple and aggregation operators [8]. Another important parameter is the "granularity of uncertainty", i.e, the cardinality of the set S of linguistic terms. This granularity can be different concept by concept, therefore the full approach also proposes a linguistic hierarchy based model to deal with it.

4 Dealing with the PhD' Soft Skills Profiles by Using the 2-Tuple Fuzzy Linguistic Approach

At the core of its activity, this system provides companies with PhDs' profiles that include both structured information, as for instance names, date of graduation, and non-structured or partially structured information, as curriculum vitae, textual descriptions of their competencies, reports of talks with the HR team.

4.1 Creating the PhDs Profiles

There are several techniques that can be applied to create the PhD profile, at present the vector based representation developed by the Information Retrieval researchers is investigated for the documents representation. In the vector based model a document D is represented as an *m-dimensional* vector, where each dimension corresponds to a distinct term and m is the total number of terms used in the collection of documents.

From this basis, in this approach a profile RP is composed by two vectors, $RP = (H, S)$ where H is the vector representing the hard skills of the PhD, while S represents her soft skills. The hard skills vector H is written as $(w_1, ..., w_m)$, where w_i is the weight of skill h_i that indicates its importance, while m is the number of skills defined in the European Skills/Competences, Qualifications and Occupations (ESCO) taxonomy[1]. The soft skills vector S is written as $(x_1, ..., x_n)$, where x_j is the weight of skill s_j and n is the number of skills defined in the soft skills FYD taxonomy described in [2]. If the profile RP does not contain a skill s_j or h_i then the corresponding weight is zero. The vector H is extracted from the PhD cv text, while the vector S is created extracting the skills information from the pills questionnaire. After a preprocessing phase in which the raw text is divided into sentences, each sentence is analyzed to extract the skills. At the moment two different solutions are developed and tested for this task: the first proposal is based on machine learning techniques and it has been presented in [3]. The second solution is based on Language Models and is an on-going research. At the end of this phase the PhD's profile RP is stored in the *Profile DB* and sent to the Evaluation Module for the recommendation phase.

PhD Soft Skills Representation. As already described, a PhD Profile RP is represented as a couple of skills vectors (H, S). H represents the PhD's hard skills while S is a vector of soft skills. In this paper the focus is on the soft skills vector. Every item of the vector is a linguistic 2-tuple value representing the degree the PhD possesses that soft skill. Note that a positional notation is used: $S = (s_1, s_2, .., s_k)$, where $s_j \in S$, with $j = \{1, ..., 60\}$, describes the linguistic degree assigned to the $j-th$ skill of the PhD. In order to allow a high flexibility we adopt a representation with 11 labels (L^{11}) to assess each skill (s_j).

- $L^{11} = \{L_0 = Null = N, l_1 = VeryVeryLow = VVL, l_2 = VeryLow = VL, l_3 = Low = L, l_4 = AlmostMedium = AM, l_5 = Medium = M, l_6 = MoreThanMedium = MM, l_7 = AlmostHigh = AH, l_8 = High = H, l_9 = VeryHigh = VH, l_{10} = Full = F\}$.

PhD Profile Computation. The vector of soft skills S is computed by taking into account two contributions. The first contribution to S is a vector HR of 60 skills, which represents the assessment the HR operator performs during an interview with the candidate. To allow a flexible assessment, but avoiding at the same time an excessive overhead for the HR operator, this vector adopts a representation with 5 labels (L^5) plus the NC value (NC = not classified) to describe each skill. Note that during an interview the HR operators explicitly assess only a few skills (usually 6 or 7), all other skills are set to NC by default.

[1] http://ec.europa.eu/social/main.jsp?catId=1326&langId=en.

– $L^5 = \{l_0 = VeryLow = VL, l_1 = Low = L, l_2 = Medium = M, l_3 = High = H, l_4 = Full = F\}$.

The second contribution to S is the vector ML of 60 skills that represents the automatic assessment of the candidate performed by the machine learning based classifier, presented in [3]. The ML classifier analyses the textual self description each PhD is required to provide when she enrolls to the database.

Each skill s_j of the PhD profile RP is computed in this way: (1) if HR($s_j = NC$) and ML($s_j = value$) then RP($s_j = value$); (2) otherwise the output value is computed by a fuzzy controller employing a Sugeno approach [21] with a *center of area* defuzzification. The set of rules describing the controller behavior has been manually evaluated on a set of 580 profiles with the contribution of the HR team in order to simulate the decision process of the HR operator. One of the core activity was to compare the set of rules automatically computed on a training dataset given by a HR manager with the rules manually created for a Mamdani [15] controller by the same person. Aim of this comparison is to show that the training of a Sugeno controller produces a set of rules so similar to those manually created by the HR manager to be considered an "automatic substitute" of the HR manager herself.

4.2 Recommending the Best PhD Profile for a Given Company

In this phase the HR manager receives, twice a week, a notification containing the best PhDs profiles w.r.t. the vision of the company represented as a vector of soft skills preferences (the *Soft-Skills Manager Interests* $HRMI$). The *Evaluation module* in Fig. 1 computes the distance between $HRMI$ and the soft skills component of the profiles RPs (S). At present the distance between S and $HRMI$ is simply computed by using the cosine similarity as follows:

$$sim(HRMI, SSRP) = \frac{HRMI * S}{\|HRMI\| \|S\|} \tag{1}$$

The Profiles are ranked w.r.t. this soft skills similarity value, while at this stage the hard skills vector allows the HR manager to automatically filter out profiles not in line with her actual interests on technical competencies.

5 Profiles Recommendation to Support the HR Manager Activity

In this section, the architecture of a personalized decision support tool able to recommend the best PhDs' profiles to a given HR manager is presented. As shown in Fig. 1, the HR manager receives, twice a week, a report containing the best profiles analized by the tool w.r.t. the company vision in terms of employed soft skills, in figure the *Interesting R.Profiles.* As previously described, the PhD registering to the job agency portal is asked to provide two textual descriptions of her competencies: a *curriculum vitae (CV)* and the questionnaire called "pills".

The technical competencies (or *hard skills*) of the PhD are extracted from the CV and saved in a vector as presented in [4]. However, no further discussion is given to those skills: the focus of this paper is indeed on the reasoning that computes the soft skills vector and on the selection of the PhDs profiles that better fulfill a set of preferences given by a HR manager. This set of preferences is manually assessed by the HR manager by using the HR Manager interface. The output produced is a vector, the *Soft-Skills Manager Interests*, containing a preference value for all the 60 skills in the FYD taxonomy [2].

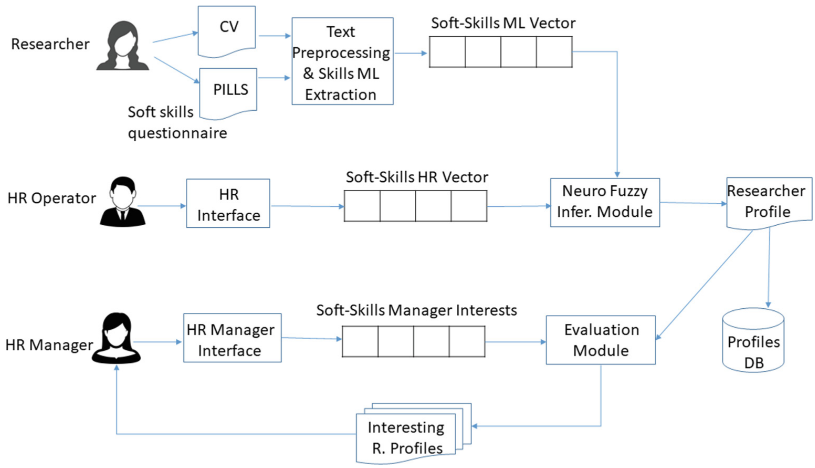


Fig. 1. The architecture of the recommender tool SOON.

Besides the hard skills, the *Text Preprocessing & Skills ML Extraction* module is in charge to extract a soft skills vector (in figure is the *Soft-Skills ML Vector*) from the textual content of the "pills". In most organization, recruiting agencies in particular, the HR manager does not meet personally all candidates but she is helped by a team of collaborators (in figure *HR Operators*), who are in charge to interview the PhDs. In this approach the HR Operator, during the interview, compiles a report regarding his evaluation of the soft skills of the candidate via a simple interface (in figure *HR Interface*) that guides the compilation of the *Soft-Skills HR Vector*. Please note that even if a complete evaluation of the candidate would require an assessment of each of the 60 soft skills available in the FYD taxonomy, this is not necessary here, and the operator is required to give an explicit assessment only to the few skills (usually 6/7) he really saw during the interview. The others skills in the *Soft-Skills HR Vector* are automatically set to NC (*not classified*). The two soft skills vectors are used by the *Neuro Fuzzy Inference Module* to compute the final soft skill vector that composes the PhD Profile RP. At this point, all profiles are saved in the *Profiles DB*, while the *Evaluation Module* compares the PhD Profiles w.r.t. the *Soft-Skills Manager*

Interests vector, and the most interesting profiles emerged in this comparison are then proposed to the HR Manager.

6 The Neuro-Fuzzy Approach

As previously reported, the approach implements a Neuro-fuzzy system aimed at supporting the evaluation of PhDs candidates by the HR manager. Given a certain dataset, the Neuro-fuzzy controller "learns" the rules that, from a certain input, produce a given output simulating the decision pattern the HR manager used when creating the dataset. In other words, the Neuro-fuzzy controller learns the reasoning used by the manager when evaluating profiles: in particular, the approach automates the definition of all the inference rules referring to a certain set of soft-skills inputs that otherwise have to be manually defined each time by the HR operator, and checked by the HR manager.

Generally speaking, Neuro-Fuzzy computing is a well defined methodology that integrates neural and fuzzy metrics. As also reported in the literature [25], one of the most important aspects regards the capability to incorporate the generic advantages of artificial neural networks, like massive parallelism, robustness, and learning in data-rich environments into a fuzzy system, where the modeling of imprecise and qualitative knowledge as well as the transmission of uncertainty is possible through the use of fuzzy logic.

The Adaptive Neuro Fuzzy Inference System (ANFIS) provides a systematic and directed approach for model building and gives the best possible design settings. Inspired by the idea of basing the fuzzy inference procedure on a feed-forward network structure, Jang proposed a fuzzy neural network model [11], employed to model nonlinear functions and identify nonlinear components on-line in a complex control system. In fact, such a system is able to bring the learning capabilities of neural networks for the fuzzy inference system definition.

In this work the defined Neural Network is responsible of the soft skills learning. The implemented Sugeno Fuzzy Inference System calculates a set of inference rules and selects the most performing skill. The final soft skill vector S that composes the overall PhD Profile RP is then produced as output.

6.1 The Neural Network Architecture

In order to incorporate the capability of learning from input/output data sets into a fuzzy inference system, a corresponding adaptive neural network is generated. An adaptive network is a multilayer neural network consisting of nodes and directional links through which nodes are connected.

As shown in Figure layer 1 is the input layer, layer 2 describes the membership functions of each fuzzy input. Layer 3 is the inference layer and normalization is performed in layer 4. Layer 5 gives the output and layer 6 is the defuzzification layer. The layers consist of fixed and adaptive nodes. Each adaptive node performs a particular function (the node function) on incoming signals, as explained in [25].

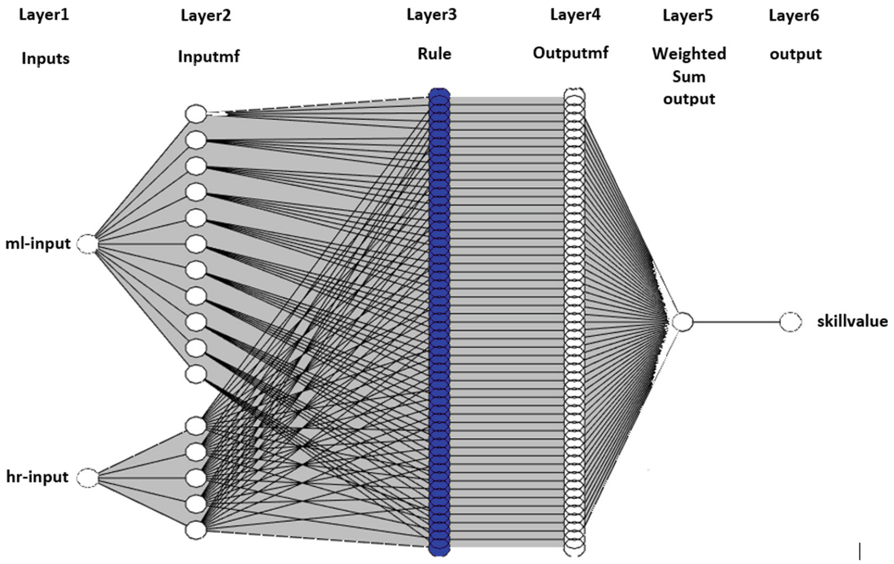


Fig. 2. Backpropagation neural network architecture

The learning module tunes the membership functions of a Sugeno-type fuzzy inference system by using the training input output data. In particular, it may consist of either BackPropagation (BP) [19], based on gradient descent optimization algorithm, or hybrid learning algorithm, based on the combination of Least Square Error (LSE) and gradient used into the BP [16] (Fig. 2).

The learning rule specifies how the parameters of adaptive nodes should be changed to minimize a prescribed error measure [11]. The change in values of the parameters results in change in shape of membership functions associated with fuzzy inference system. After a learning phase, the controller is able to generate the appropriate actions for the desired task.

The set of produced inference rules are shown to be very similar to those that an HR human expert should otherwise calculate each time for each selected profile and for each individual skill. We can claim the Neuro-fuzzy controller learns the reasoning used by the manager when evaluating profiles, therefore we can create a "personalized automatic manager" for any Company, just having the Company old candidates profiles dataset to train the controller.

7 A Preliminary Set of Experiments and Discussion

A first set of experiments has been carried out in order to test and validate the defined architecture. The details of the dataset and the parameter's setting are reported in the following.

The input variables of the designed Sugeno ANFIS correspond, respectively, to the skill evaluation vector ML produced by the machine learning based classifier previously implemented [3] (mlinput) and to the human resource expert evaluation vector HR (hrinput). As previously reported, the output corresponds to the skill value produced by the Neuro-Fuzzy evaluation that will contribute to define the resource profile soft skills vector.

The inputs are preprocessed and defined in a range from -0.5 to 0.5 (not included) values. The 75% of the dataset is used for the Neural Network training, while the remaining 25% is used for checking to validate the model. More precisely 435 PhDs define the training set and 145 define the test set.

Then, after a first initial tuning, as explained in Sect. 4 the inputs adopt "triangular" membership functions, with, respectively, 11 and 5 nodes for "machine learning based classifier vector" ML and "human resource expert evaluation vector" HR input variables.

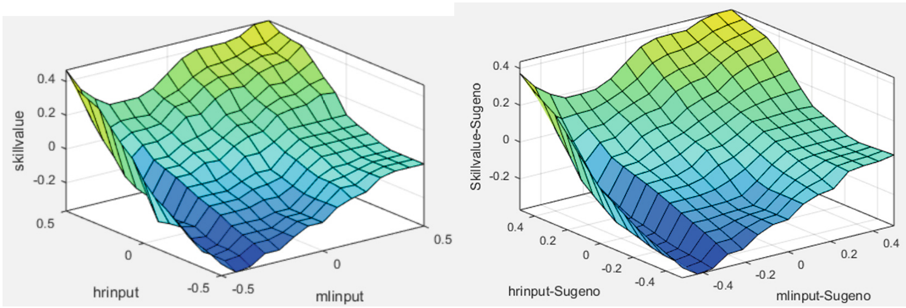
The membership functions are aggregated by using a "T-Norm Product" operator to construct the Fuzzy $IF-THEN$ rules with a fuzzy antecedent part and "linear" consequent. The total number of rules is equal to 55, corresponding to the vector product of the nodes defined at level 2 of the neural network. All the rules detailed into $Layer3$ are calculated by the Sugeno Fuzzy Inference System.

The Neuro Fuzzy controller has been trained for 150 epochs, by using the most simple and widely used for neural network training, BackPropagation algorithm, particularly suitable for the learning of supervised multi layer neural networks [19]. After the training phase, the overall Neuro Fuzzy performances have been evaluated by testing the ANFIS model.

This Neuro Fuzzy approach has been validated by comparing the results obtained by applying the Neuro Fuzzy "trained" rules with the results obtained by applying a Fuzzy Mamdani controller where the rules are defined by an HR expert team. The surfaces in Fig. 3a and b show the results obtained. In particular, Fig. 3a shows the results coming from the Fuzzy Mamdani controller according to the rules manually defined by the HR manager on the test dataset, while Fig. 3b shows the results coming from the Neuro Fuzzy controller simply trained on the same dataset, with the rules defined by the ANFIS evaluation.

The surface values are displayed on a color scale from -0.5 (blue color) to 0.5 (not included) (green color) showing that the Neuro Fuzzy approach associates more importance to the HR evaluation with respect to the machine learning based one. The machine learning based evaluation is aimed at integrating and supporting the HR evaluation but it never overcomes it. Note that, according to the figure, when *hrinput* is high, *skilloutput* is high even with low *mlinput* values, while with low *hrinput* values *skilloutput* is still low even if *mlinput* values are high.

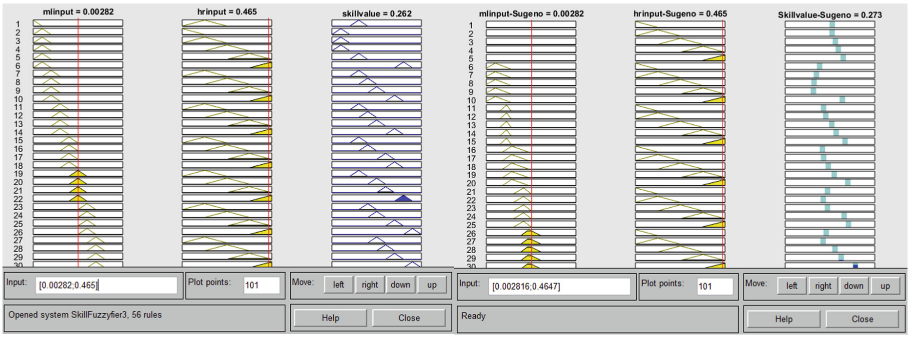
Even if the results are very similar (and this shows that the Neuro fuzzy controller "simulates" the HR expert reasoning), the graphic representation of the surfaces highlights how the Neuro Fuzzy approach presents a more harmonious surface, in which maximum and minimum values are reached with more precision (represented by the greater intensity of colors displayed by the surface). The results obtained from the two surfaces allow to say that the Neuro Fuzzy



(a) Mamdani Surface (b) Neuro-Fuzzy Surface

Fig. 3. Mamdani and Neuro fuzzy surface's comparison (Color figure online)

approach can be put in place of Mamdani, whenever an HR human expert is not available, thus representing a good automation of his way of reasoning when assessing profiles.



(a) Mamdani Rules (b) Sugeno Rules

Fig. 4. Comparative example between Mamdani and Sugeno rules.

As also shown by the triangular rules, in Fig. 4a and b it is possible to see how the Sugeno model follows the trend of the human expert supported by the evaluation of the machine learning approach. Such a trend assumes, however, an attitude that takes into account both the assessments made by the human expert and those obtained from the machine learning.

Anyway, as reported in Table 1, the evaluations carried out on the skills leaving the Neuro Fuzzy system show a cautious and prudent attitude, especially in cases that report opposite assessments between the human expert and the machine learning approach.

Table 1. Example of the skill values obtained from the rules application.

ML input	HR input	Output skill value	
		Mamdani	Sugeno
0.0028	0.45	0.2500	0.2620
0.0028	−0.45	−0.1960	−0.1920
0.0028	0.0028	0.0042	−0.0007
0.45	0.45	0.3870	0.4230
0.45	−0.45	7.17e−4	1.84e−05
0.45	0.0028	0.1100	0.1000
−0.45	0.45	0.2240	0.2620
−0.45	−0.45	−0.3240	−0.3460
−0.45	0.0028	−0.1930	−0.230

8 Conclusions

In this paper a framework to represent the soft skills profile of a PhD by means of a 2-tuple fuzzy linguistic approach is presented. The framework can be used in many contexts: in this work it has been applied for designing a recommender system of candidates for recruiting purposes. The recommender system is defined through the implementation of a Neuro fuzzy controller that aims to simulate the decision of a HR team in evaluating the soft skills profile of a candidate. Among all the profiles assessed by the HR team with the support of the ML soft skills classifier, the system proposes to the HR manager only the profiles evaluated as the best w.r.t. a set of preferences representing the Company vision in terms of employees soft skills. The approach is capable of calculating a set of inference rules that are shown to be very similar to those that an HR human expert should otherwise calculate each time for each selected profile and for each individual skill.

Since the outcome of the framework is a vector representation of a profile, any matching function derived from the vector space model can be easily applied. The overall model behavior will be fully personalized since computed on a training dataset of pairs (profile, set of soft skills) that represents the decisional behavior of a certain HR Manager rather than another. Future work will investigate the application of the implemented Neuro Fuzzy recommender system in other contexts, like those regarding the human resources or recruitment areas of big companies, thus collecting more datasets to better test the hypothesis of creating a good “HR manager bot”.

References

1. Allen, J., van der Velden, R.: The Flexible Professional in the Knowledge Society: New Challenges for Higher Education. Springer, Dordrecht (2011). https://doi.org/10.1007/978-94-007-1353-6
2. Azzini, A., Galimberti, A., Marrara, S., Ratti, E.: A taxonomy of researchers soft skills. Internal Report, Consortium for the Technology Transfer, C2T (2017)
3. Azzini, A., Galimberti, A., Marrara, S., Ratti, E.: A classifier to identify soft skills in a researcher textual description. In: Sim, K., Kaufmann, P. (eds.) EvoApplications 2018. LNCS, vol. 10784, pp. 538–546. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-77538-8_37
4. Azzini, A., Galimberti, A., Marrara, S., Ratti, E.: SOON: supporting the evaluation of researchers' profiles. In: Uden, L., Hadzima, B., Ting, I.-H. (eds.) KMO 2018. CCIS, vol. 877, pp. 3–14. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-95204-8_1
5. Box, S.: Transferable skills training for researchers supporting career development and research: supporting career development and research. OECD Publishing (2012)
6. Buga, A., Freudenthaler, B., Martinez-Gil, J., Nemes, S.T., Paoletti, L.: Management of accurate profile matching using multi-cloud service interaction. In: Proceedings of the 19th International Conference on Information Integration and Web-based Applications & Services, pp. 161–165. ACM, New York (2017)
7. Herrera, F., Herrera-Viedma, E., Verdegay, J.: Direct approach processes in group decision making using linguistic OWA operators. Fuzzy Sets Syst. **79**(2), 175–190 (1996)
8. Herrera, F., Martínez, L.: A 2-tuple fuzzy linguistic representation model for computing with words. IEEE Trans. Fuzzy Syst. **8**(6), 746–752 (2000)
9. Herrera-Viedma, E.: Modeling the retrieval process for an information retrieval system using an ordinal fuzzy linguistic approach. J. Assoc. Inf. Sci. Technol. **52**(6), 460–475 (2001)
10. Hong, W., Zheng, S., Wang, H.: Dynamic user profile-based job recommender system. In: 2013 8th International Conference on Computer Science & Education (ICCSE), pp. 1499–1503. IEEE (2013)
11. Jang, J.: ANFIS adaptive-network-based fuzzy inference system **23**, 665–685 (1993)
12. Kumar, S., Kumari, R., Sharma, V.: Adaptive neural fuzzy inference system for employability assessment. In: Int. J. Comput. Appl. Technol. Res
13. Lafferty, J., McCallum, A., Pereira, F.: Conditional random fields: probabilistic models for segmenting and labeling sequence data. In: Proceedings of the Eighteenth International Conference on Machine Learning, ICML, vol. 1, pp. 282–289 (2001)
14. Lee, I.: Modeling the benefit of e-recruiting process integration. Decis. Support Syst. **51**(1), 230–239 (2011)
15. Mamdani, E., Assilian, S.: An experiment in linguistic synthesis with a fuzzy logic controller. Int. J. Man Mach. Stud. **7**(1), 1–13 (1975)
16. Pfister, M., Rojas, R.: Hybrid learning algorithms for feed-forward neural networks. In: Reusch, B. (ed.) Fuzzy Logik, pp. 61–68. Springer, Berlin, Heidelberg (1994). https://doi.org/10.1007/978-3-642-79386-8_8
17. Poch, M., Bel, N., Espeja, S., Navıo, F.: Ranking job offers for candidates: learning hidden knowledge from big data. In: Language Resources and Evaluation Conference (2014)

18. Porcel, C., Herrera-Viedma, E.: Dealing with incomplete information in a fuzzy linguistic recommender system to disseminate information in university digital libraries. Knowl.-Based Syst. **23**(1), 32–39 (2010)
19. Rumelhart, D.E., Hinton, G.E., Williams, R.J.: Parallel distributed processing: explorations in the microstructure of cognition. In: Learning Internal Representations by Error Propagation, vol. 1, pp. 318–362. MIT Press, Cambridge, MA, USA (1986)
20. Singh, A., Rose, C., Visweswariah, K., Chenthamarakshan, V., Kambhatla, N.: PROSPECT: a system for screening candidates for recruitment. In: Proceedings of the 19th ACM International Conference on Information and Knowledge Management, pp. 659–668. ACM (2010)
21. Takagi, T., Sugeno, M.: Fuzzy identification of systems and its applications to modeling and control. IEEE Trans. Syst. Man Cybern. **SMC–15**(1), 116–132 (1985)
22. Topor, D.J., Colarelli, S.M., Han, K.: Influences of traits and assessment methods on human resource practitioners' evaluations of job applicants. J. Bus. Psychol. **21**(3), 361–376 (2007)
23. Yi, X., Allan, J., Croft, W.B.: Matching resumes and jobs based on relevance models. In: Proceedings of the 30th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, pp. 809–810. ACM (2007)
24. Zadeh, L.A.: The concept of a linguistic variable and its application to approximate reasoningi. Inf. Sci. **8**(3), 199–249 (1975)
25. Zaheeruddin, Garima: A neuro-fuzzy approach for prediction of human work efficiency in noisy environment. Appl. Soft Comput. **6**, 283–294 (2006)