Explainable Career Path Predictions using Neural Models

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1 Introduction

With the rise of the modern gig economy, it has become more difficult for job seekers to find stable positions of employment [6]. As a result, deep learning has been on the come up for *career path prediction*. This task aims to predict a person's next position of employment, given their career up until this point. We attempt to answer the following research question: *To what degree can career path predictions done by deep learning models be made explainable?* This is done by means of the following sub-questions:

RQ1: How well do state-of-the-art deep learning models perform career path prediction on Randstad's dataset?

RQ2: How do different ways of making model predictions explainable impact performance?

RQ3: Which explainable model is the most useful for recommending jobs to candidates?

2 Methodology

The data for this research was provided by Randstad NV (Randstad). Randstad's dataset consists of over two million jobs relating to more than five hundred thousand individuals. After cleaning and balancing the data, our final dataset consisted of the careers of 113724 candidates, each being limited to the 25 most recent jobs they had. For each candidate we used the profile-specific features (such as previous work experience, education, and skills) as input for the models, after which the models would predict their next job in the form of its ISCO job type.

2.1 Baselines and Models

Three non-deep learning baselines were used for comparison: a majority class baseline, a majority *switch* (most common job following the current job) baseline, and k-nearest neighbors based on the dynamic time warping distance between candidates that had the same previous job (KNN-DTW).

RQ1 To study the impact of explainability mechanisms on model performance, three state-of-the-art, non-explainable models made up a second baseline. The LSTM-based model used in this paper is based on the HCPNN by Meng et al. [5]. The CNN-based model is that of He et al. [3]. Lastly, the CNN-LSTM-based model is based on the model created by Livieris et al. [4].

RQ2 The explainable LSTM-based model (eLSTM) used in this paper is based on Ding et al. [1]. The explainable CNN-based model (eCNN) is based on the XCM by Fauvel et al. [2]. Finally, the explainable CNN-LSTM-based model (eCNN-LSTM) is based on that of Schockaert et al. [8].

RQ3 To measure the adequacy of the explanations generated by the models, six recruiters were tasked to determine which variables were most relevant for predictions made by the three models. For each prediction, they were tasked to distribute 100 'relevance points' over the features used by the models, after which their distribution was compared to that of the models. Furthermore, the recruiters were presented with the explanations generated by each model and tasked to judge them.

3 Results

Of the three simple baselines, the majority switch baseline performed the best, reaching over 19.1% accuracy @ 1, 46.6% accuracy @ 5, and 61.3% accuracy @ 10. As a result, the performance of the deep learning models was compared against the scores achieved by the majority switch baseline.

3.1 RQ1 & RQ2 - Model performance

Out of all the models, the CNN-LSTMs performed the best. Unlike what was hypothesized, the explainable models were not inferior to their non-explainable counterparts, as they achieved comparable scores at all values of k (Table 1).

3.2 RQ3 - Real-world utility

To measure the sensibility of each model's explanations (Figure 1), three metrics were calculated based on the recruiters' distributions: RMSE, MAE, and Pearson correlation. The results can be seen in Table 2. The results indicate that the models' explanations were positively correlated with those made by the recruiters.

Additionally, the recruiters were asked how sensible they found the models' explanations, as well as how useful they considered the models to be in general. The recruiters showed a preference for feature explanations, and to a lesser extent for feature/time interaction explanations. All three models were determined to be useful for recommending a job to a candidate, as every model was rated above a 6/10 for general usability by the recruiters.

4 Conclusion

In the span of this paper, it was shown that career path predictions made by deep learning models can be made explainable to a high degree. While different types of explanations made by the models can differ in terms of how understandable they are to humans, all of them turned out to be useful for recruiters nonetheless. Due to the fact that these explainability mechanisms do not lead to a decrease in performance, they form a good addition to existing career path prediction models. This goes especially for CNN-LSTMs, as those perform the best as explainable and non-explainable models, while also providing the best explanations according to recruiters.

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Appendix 1.A

Model	Acc@1 ⇑	Acc@5 ⇑	Acc@10 ⇑
Majority switch	19.1%	46.6%	61.3%
CNN	20.8%	50.8%	63.7%
LSTM	21.9%	49.3%	62.9%
CNN-LSTM	**26.4%**	**56.5%**	**68.6%**
eCNN	20.1%	47.7%	61.5%
eLSTM	22.2%	47.6%	60.8%
eCNN-LSTM	**26.0%**	**55.7%**	**67.5%**

Table 1. Test set performance of each model at different values of k ($\mathbf{N = 11372}$).

	r ⇑	**RMSE** ⇓	**MAE** ⇓
eLSTM	0.142	4.661	4.094
eCNN-LSTM	0.436	6.014	4.847
eCNN	0.152	5.594	4.518

Table 2. The Pearson correlation, RMSE, and MAE of each model compared to the scores given by the recruiters ($\mathbf{N = 6}$).

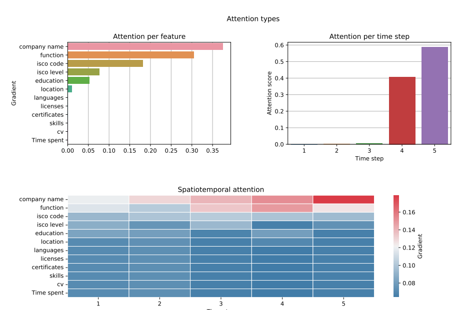

Fig. 1. An example of an explanation generated by the explainable CNN-LSTM.

This abstract is a summary of Schellingerhout et al. [7].