CAREER PATH MODELING AND RECOMMENDATIONS WITH LINKEDIN CAREER DATA AND PREDICTED SALARY ESTIMATIONS

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ABSTRACT

Career planning involves devising a sequence of steps that build up an ideal career path for a person. However, career planning has become more complex in recent years. Given the limitations of existing works, we explored new variables and techniques that could help in predicting better career paths. We built a Long-Short Term Memory Network with Self Attention Layers called LSTM-ATT, that predicts a person's possible career path taking into account salary estimations and social networks or Linkedin Recommendations of a person. We measured the model's performance in terms of Mean Percentile Rank and Precision at 50 and 100. We found that LSTM and self-attention layers in themselves were able to show satisfactory predictive performance for multi-class classification with over 6000 classes. However, it can be seen that the predictive performance varies only slightly for all metrics in predicting jobs, companies, and skills. This leads us to conclude that the added variables did not help in predicting better career paths.

1 INTRODUCTION

We define a career path as a series of steps that allow individuals to achieve a specific goal or objective. There have been a few studies exploring predicting and recommending career paths (Wan & Ye, 2022; Natividad et al., 2019; Li et al., 2017b;a; Ghosh et al., 2020; Zhang et al., 2020).

However, choosing a career path has become more complex in recent years because of the following causes: (1) inaccessibility to career counseling, (2) the diversity of roles that an individual may partake in, and (3) career planning can lead to information overload (Wan & Ye, 2022). Given the limitations of existing works, we explored new variables and techniques that could help in predicting better career paths. We took into account unexplored variables from previous studies (Ghosh et al., 2020), namely social networks (better known as LinkedIn recommendations) and predicted salary estimations while adding Long-Short Term Memory Networks and Self-Attention Layers for improved accuracy.

2 METHODOLOGY

2.1 PROBLEM CONTEXT

Predicting a career path can be defined as two recommendation problems:

1. The first problem is defined as recommending the user's **latest** job and company as a relevant item.
2. The second problem is defined as recommending all the skills that an individual possesses in the given user or Linkedin Profile as all relevant items.

For both of these problems, we create different versions of our models with or without the added variables to test their effectiveness in recommendations. We then used the usual metrics in the domain of recommendation systems, namely the Mean Percentile Rank (MPR)and Precision @ K (at 10 and 100).

2.2 MODEL ARCHITECTURE

To train our model, we utilized scraped data obtained from LinkedIn and Payscale to predict career paths. For Linkedin, We extracted users' career histories (which consist of all the jobs and companies they transitioned to throughout their professional journey), set of skills, education history, and Linkedin recommendations posted by the user.

On the other hand, predicted salaries per job are derived by matching jobs from each job history of all users to the predicted salaries of each job taken from Payscale.

We then concatenated all of these features for all users and used the LSTM-ATT model to predict the latest career path.

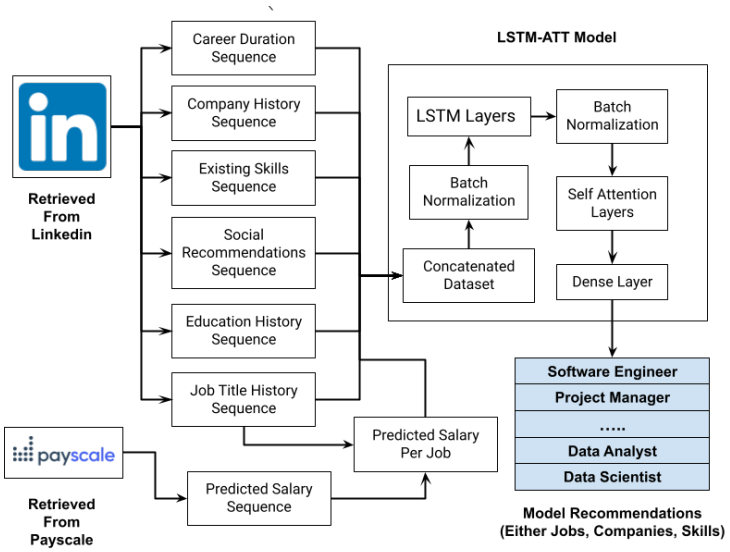

Figure 1: The Architecture of the LSTM-ATT Model

3 RESULTS AND DISCUSSIONS

Based on the predictive results of the base LSTM-ATT model below(See Table 1), We found that adding LSTM and self-attention layers in themselves was able to show satisfactory predictive performance for multi-class classification even with over 6000 classes for companies and skills. This leads us to conclude that LSTM and Attention Layers significantly helped in performance.

Using the same table, by checking versions of the model with or without added features, it can be seen that the predictive performance varies only slightly for all metrics in predicting jobs, companies, and skills. This leads us to conclude that the added variables did not help in predicting better career paths.

Table 1: Results on Model Predictions for Jobs, Companies, and Skills

	Jobs			Companies			Skills		
Methods	MPR	P@10	P@100	MPR	P@10	P@100	MPR	P@10	P@100
LSTM-ATT	0.011	0.107	0.134	0.118	0.747	0.952	0.059	0.293	0.402
LSTM-ATT-SAL	0.017	0.088	0.113	0.111	0.760	0.940	0.062	0.299	0.407
LSTM-ATT-SN	0.017	0.128	0.173	0.063	0.854	0.913	0.0612	0.286	0.395
LSTM-ATT-SAL-SN	0.021	0.105	0.163	0.063	0.0859	0.921	0.060	0.285	0.379

4 URM STATEMENT

The authors acknowledge that at least one key author of this work meets the URM criteria of ICLR 2023 Tiny Papers Track.

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