Exploring Lawyer Relationships in Litigation Scenario

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Abstract. As important participants in court proceedings, litigation lawyers bear the responsibility of securing the best possible outcome for their clients. In the majority of cases, clients have their cases handled by legal representatives; consequently, court proceedings typically involve multiple lawyers presenting their arguments. There exists a relationship of both cooperation and competition between our counsel and the opposing counsel. To explore the relationships between lawyers within the same case, we propose lawyer relationship network. Specifically, we first model the characteristics of the lawyers, then use the Elo rating system to model the interactions between them during courtroom proceedings, and finally predict the outcome of the case for each lawyer. On this basis, we visualise and analyse the relationships between the lawyers. We have validated the effectiveness and interpretability of our proposed method using real-world datasets.

Keywords: lawyer · relationship · user modeling.

1 Introduction

2 Related works

2.1 Contextual User Modeling

Contextual User Modeling is widely used in the e-commerce sector, for example, to uncover user preferences for products, and collaborative filtering algorithms are extensively applied. With the advancement of recommendation systems, Contextual User Modeling has been applied to fields such as social media platforms, smart education, and workplace analytics. For example, on social media platforms, user attributes and social networks are constructed based on social behaviors such as likes and comments; in education, students' mastery of specific concepts is assessed through their test records [2]; and in the workplace, talent information is used to match employees with job roles and predict employee turnover. Generally speaking, the standard approach involves using user interaction data from a specific scenario to represent user features as vectors, followed by user modeling, ultimately achieving the goal of personalized recommendations.

2.2 Relationship Modeling

Modeling relationships among users in various contexts has been extensively studied. For example, whether two people are successfully matched in a dating context; team members with different skills collaborating in the workplace; matching in games and cooperation versus competition in competitive settings; similar purchasing behaviors among users in recommendation systems; and the connections formed between people in social networks.

3 Method

In this section, we describe the process we propose for modeling the lawyer relationship network. Specifically, we first represent lawyers as different contextual factors and integrate them into lawyer features; then, we use the ELO method to model the defense process; and finally, we predict the outcome of the lawyer's case. Fig. **??** illustrates our framework.

3.1 Factor Embeddings

We have incorporated interpretable representations, including:

- expectation
- effort
- mobility
- pattern
- attractive
- growth
- conflict
- death
- environment
- selection
- flow
- cognitive

3.2 Representing

We integrate various factors to represent the characteristics of lawyers. Inspired by IRT, the representation of lawyers is as follows:

$$characteristic = expectation*(effort+mobility+pattern+attractive+growth+conflict+death)*(environment+ \tag{1}$$

We add similar characteristics and multiply attributes that are less closely related; this ensures that each feature has a proportional influence on the prediction results.

3.3 Defence Modeling

We use the original ELO modeling defense process.

$$x = \frac{1}{1 + 10^{(R_B - R_A)/400}} \tag{2}$$

3.4 Predicting and Learning

To adaptively integrate characteristics and defense information, we use full connection layers and predict the final result of the case:

$$\boldsymbol{o}_1 = tanh\left(\boldsymbol{W}_1 x\right), \tag{3a}$$

$$\boldsymbol{o}_2 = tanh\left(\boldsymbol{W}_2 \boldsymbol{o}_1\right), \tag{3b}$$

$$\boldsymbol{y} = sigmoid\left(\boldsymbol{W}_3 \boldsymbol{o}_2\right), \tag{3c}$$

where W_* are trainable parameters.

To satisfy the positively correlation between the probability x and prediction result $\boldsymbol{y}$, we adopt a strategy which restricts each weights of fully connection layer (e.g., $\mathbf{W}_1$, $\mathbf{W}_2$ and $\mathbf{W}_3$) to be positive [2]. It can be easily proved that $\frac{\partial y}{\partial R_{A,i}}$ is positive for each entry $R_{A,i}$ in R_A. Thus the positively correlation is always satisfied during training.

The loss function of LRN is cross entropy between the ground truth y and prediction probability of $\hat{y}$:

$$\mathcal{L} = -\sum_i \left(y_i \log \hat{y}_i + (1 - y_i) \log\left(1 - \hat{y}_i\right)\right). \tag{4}$$

in this way, we can learn LRN by directly minimizing the objective function using Adam optimization.

4 Experiments

4.1 Datasets

LCHR [1]

4.2 Overall Performance

Table 1

4.3 Ablation Study

4.4 Visualization of cooperation and competition

5 Conclusion

In this paper, we model lawyer characteristics in courtroom debate and defence scenarios. Specifically, we represent lawyer factors, integrate lawyer representations through defence modelling, and predict case outcomes. We have validated the effectiveness and validity of our proposed method on a real-world dataset.

Table 1. Predictions of lawyers' effect on cases. The values in brackets of LawyerPAN indicate relative increase over NeuralCDM-BERT. The values in brackets of variants of LawyerPAN indicate relative decrease compared to LawyerPAN.

Methods	LCHR-small			
	Accuracy	RMSE	AUC	F1
AVG	0.706	0.443	0.663	0.810
NeuralCDM	0.695	0.461	0.492	0.820
LRN	0.695	0.461	0.492	0.820

Table 2. Predictions of lawyers' effect on cases. The values in brackets of LawyerPAN indicate relative increase over NeuralCDM-BERT. The values in brackets of variants of LawyerPAN indicate relative decrease compared to LawyerPAN.

Methods	LCHR-small			
	Accuracy	RMSE	AUC	F1
LRN	0.695	0.461	0.492	0.820
w/o pattern	0.695	0.461	0.492	0.820

References

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