Mirror, Mirror on the Wall, Who is Leaving of Them All - Predictions for Employee Turnover with Gated Recurrent Neural Networks

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Abstract Employee turnover is a serious issue for organizations and disrupts the organizational behavior in several ways. Hence, predicting employee turnover might help organizations to react to these mostly negative events with e.g. improved employee retention strategies. Current studies use a “standard analysis approach” (Steel 2002) to predict employee turnover, accuracy in predicting turnover by this approach is only low to moderate. To address this shortcoming, we conduct a deep learning experiment to predict employee turnover. Based on a unique dataset containing twelve months of time series of e-mail communication from 3952 managers our model reached an accuracy of 80,0%, a precision of 74.5%, a recall of 84.4%, and a Matthews correlation coefficient value of 60.4%. This paper contributes to turnover literature by providing a novel analytical perspective on key elements of turnover models.

1 Introduction

Employees or so-called human resources are as important as other resources involved in the production of goods and services. They have a major effect on the productivity of a firm and are responsible for the creation of new knowledge – which may have a significant impact on firm growth. It is not surprising, therefore, that organizations seek to gain benefits by investing in human resources. These benefits, though, diminish when highly skilled employees voluntarily leave an organization for, say, a better position or higher wages at another organization. Further, while losing a highly skilled employee to a competitor may lead to access to external knowledge for the former employer, it also increases the risk that the former employer's knowledge will be leaked to the competitor (Somaya et al. 2008; Aime et al. 2010). Further, employee turnover reduces human capital of the former employer (Shaw et al. 2005) and is generally found to negatively impact company performance (Hancock et al. 2013). Hence, the competition for highly skilled personnel and their retention is critical to organizations. Such competition was dubbed the "war for talent" (Chambers et al. 1998) back in 1998 and later extended to the "war for Internet talent" (Efrati and Tam 2010), considering developments after the dot-com bubble burst in 2001.

Consequently, the turnover of highly skilled employees is a topic of interest for practitioners and scholars alike. It is a well-studied phenomenon in the applied psychology, human resource, and general management literatures (for an overview of turnover research history, see Holtom et al. 2008). Especially, the causes of actual turnover behavior are focused by research communities, since March and Simon (1958) proposed a first turnover model that takes the reasons for participating in organizations into account. They suggest that employees who are happy with their job and who do not have a job alternative will not leave their employer. Over thousands of scientific articles about employee turnover later, job dissatisfaction became and still is an important proximal cause for employee turnover (Lee and Mitchell 1994). Job dissatisfaction leads to thoughts of quitting and culminates in actual turnover behavior. Hence, it is important to know why and when highly skilled employees become dissatisfied with their current job.

To predict such changes and thus turnover behavior, researchers follow a "standard research design" (Steel 2002): Data on turnover predictors are collected via a survey and the information on the actual leaving is collected later. Then, the analysis is conducted with ordinary least squares (OLS) regression, survival and hazard functions or structural equation modeling (SEM). The accuracy in predicting turnover by this approach is only low to moderate (Lee et al. 2017), slightly higher using turnover intention as a proxy for actual turnover behavior. Novel approaches are necessary that take the trajectories of turnover determinants over time into account, because changes over a specific period time in distal precursors affect turnover through changes in proximal antecedents (Hom et al. 2017; Lee et al. 2017).

In this paper, we follow the call for novel approaches for employee turnover prediction applying a gated recurrent neural network model (Chung et al. 2013), a variation of long short-term memory (LSTM) networks (Hochreiter and Schmidhuber 1997; Gers 2001) on longitudinal turnover data. Our goal is to predict turnover of highly skilled employees. Our research questions are:

- Is a deep learning model suitable for employee turnover prediction?
- How does the model perform in the prediction of employee turnover?

The remainder of this paper is structured as follows. The next section provides the theoretical grounding. This section contains an overview of related works regarding employee turnover, the role of job (dis-)satisfaction on employee turnover and the importance of the relational perspective of employee turnover. The subsequent section describes this study's setting, data, and methodology. The paper concludes with a discussion of the results and implications for future research.

2 Related Work

This section begins with a brief overview of employee turnover literature, the role of job satisfaction and communication behavior of employees on turnover. We then provide an overview of the idea behind recurrent neural networks (RNNs), long short-term memory (LSTM) and gated recurrent units (GRUs), all deep learning architectures that are important for understanding our study's experimental settings.

2.1 Employee Turnover

The investigation of employee turnover has a long history. March and Simon were the first who define a formal theory of turnover focused on participation in organizations (March and Simon 1958; Lee et al. 2017). Further research focuses on antecedents of individual employee turnover (Mobley 1982). Other research considers external factors such as promotional opportunities and kinship responsibility influencing employee turnover (Price and Mueller 1981). Moreover, studies focus on the negative and positive effects of employee turnover (Dalton and Todor 1979; Mobley 1982). In addition to the obvious negative effect on company performance, turnover can have some other negative effects. These can be differentiated into direct costs (e.g., for recruiting and training the successor) and indirect costs. The latter include loss of firm-specific human capital, demoralization of remaining employees, and loss of social capital embedded in the employees' relationships (Ton and Huckman 2008). Not surprisingly, loss of social capital from employee turnover negatively impacts company performance (Shaw et al. 2005). But, the opposite can also be the case: employee turnover can potentially lead to the creation of a business tie between the former and new employer, resulting in increased social capital for both firms (Somaya et al. 2008; Corredoira and Rosenkopf 2010).

More recent research on turnover analyzes the reasons for staying with a company and not the reasons for leaving (Lee et al., 2017). This shift in research objectives is based on the idea of job embeddedness, which incorporates off-the-job and on-the-job factors that embed employees in their job positions (Mitchell et al. 2001). Links to other colleagues, fit within the organization, and potential sacrifices in case of a turnover were found to influence intentions to leave an organization (Mitchell et al. 2001). Especially, relationships with other colleagues and groups are important for high job embeddedness and thus negatively related to turnover intention (Maertz and Griffeth 2004). The analysis of such relations between employees is mostly conducted by a social network analysis approach using centrality measures (c.f. Feeley 2000; Mossholder et al. 2005; Oldroyd and Morris 2012). Brass (1981) found no relationship between being central to an organization's workflow network and job satisfaction. However, more recent studies show that strong and positive social intra-organizational networks reduce employee turnover (Mossholder et al. 2005; Moynihan and Pandey 2007; Hom and Xiao 2011). Mossholder et al. (2005) found that network centrality might even predict employee turnover. However, the predictive power of past studies of employee turnover that follow the "standard research design" (Steel 2002) is low (Lee et al. 2017). Hom et al. (2017) and Lee et al. (2017) call for research that considers the dynamic nature of antecedents of employee turnover and conduct additional network-based investigations. Gloor et al. (2017) follow this call and analyze the relational view of employee turnover in a detailed manner. Therefore, they analyze e-mail communication of 866 managers with the largest set of network and text analysis metrics so far and show that managers who quit have lower closeness centrality, less engaged conversations, shift their communication behavior starting from 5 months before leaving by increasing their degree and closeness centrality, the complexity of their language, as well as their oscillations in betweenness centrality and the number of nudges they need to send to peers before getting an answer. They show that intra-organizational e-mail communication analyzed with social network and text analysis metrics might be a promising predictor for turnover from the relational perspective.

Our study follows the call of Lee et al. (2017) and is influenced by the study Gloor et al. (2017). However, we want to go one step further in turnover prediction by using recurrent neural networks (RNNs) that might enhance the predictive power of the relational perspective of employee turnover.

2.2 Recurrent Neural Networks (RNN) & Gated Recurrent Units (GRU)

Recurrent neural networks (RNNs) are artificial neural networks that encode knowledge dependencies learned over past events, and use this knowledge to reason about current events. RNNs achieve this by using cycles in a network, which allows past knowledge to persist in the form of inputs to the next network. RNNs can be thought of as a directed graph where each node passes the knowledge on to the next node after applying set of weights and transformations. Hence, RNNs are appropriate for data in the form of sequence or data with temporal attributes.

In recent years, RNNs have been used successfully in a variety of contexts, like object detection (Szegedy et al. 2013), speech recognition (Graves et al. 2013) or classification problems (Krizhevsky et al. 2012). Standard RNNs have a few limitations: They cannot process inputs with varying length because long-term knowledge of too long input sequences cannot be stored (vanishing gradient problem). To process long-range sequences and identify relevant reasons for employee turnover, we need a model that can remember long-term knowledge. Long short-term memory (LSTM) is a RNN architecture that avoids the vanishing gradient problem (Hochreiter and Schmidhuber 1997; Gers 2001) and learns tasks that require knowledge of events that happened lots of time series earlier (Schmidhuber 2015). Therefore, we use a LSTM architecture with a simpler gating mechanism called gated recurrent units (GRU). GRUs are comparable to LSTM in terms of performance and exhibit better performance on smaller datasets (Chung et al. 2014).

3 Experiments

In this section, we present a brief description of our data, describe the data preprocessing steps, continue with the experimental settings, and conclude this section by presenting the results of our experiments.

3.1 Data Pre-Processing

This study is based on employees' e-mail communication data that is provided by a global professional services firm with more than 70,000 employees in over 20 countries. The e-mail data contain 845,208 actors (employees[1] and external stakeholders), ~138 million edges representing the communication that took place from 1st January 2017 till 29th January 2018.

We filtered the 845,208 actors by employees in managerial positions, which led to e-mail data of 3,952 managers containing 35% (48 million of 138 million edges) of the provided e-mail communication data. After collecting the mailboxes of the 3,952 managers, we prepared the data for the deep learning experiments. Therefore, we split the data in time frames (15 days time window with three days separation for the next window) and calculated network metrics (see Table 1) for each time frame with Condor[2], a social network and text analysis software. Each time frame was exported in a separate CSV file. The calculated network metrics are capable to show the changes in communication patterns of employees (c.f. Gloor et al. 2017) and hence serve as input variables for the deep learning models.

[1] Some employees had more than one e-mail account in this company. In these cases, we merged the multiple e-mail accounts of an employee into one.

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Table 1. Calculated network metrics that are considered as input variables for the machine learning models

Metric	Definition
Messages sent	# of e-mails sent by an employee.
Messages received	# of e-mails received by an employee.
Messages total	Sum of e-mails sent and received by an employee.
Words total	# unique words an employee used in her e-mails.
Degree Centrality	# of colleagues each employee is directly connected within the communication network (Freeman, 1979).
Betweenness Centrality	Likelihood to be on the shortest path between any two actors in the network. Indicates the extent to which each employee acts as an information hub and controls the information flow (Freeman, 1979).
Betweenness Centrality Oscillation	# of local maxima and minima in the betweenness curve of an actor. Indicates how frequently employees change their network position in the team, from central to peripheral, and back.
Closeness Centrality	Inverse of distance of an actor from all other actors in the network, considering the shortest paths that connect each pair of actors. Indicates the efficiency of transmitting information and independence from other peripheral actors (Friedkin, 1991).
Reach 2	# of colleagues each employee can reach by the distance of two.
Contribution Index	# messages sent - # messages received / (# messages sent + # messages received). Indicates how balanced a communication is in terms of sent and received messages.
Contribution Index Oscillation	# of local maxima and minima in the contribution index curve of an actor.
Ego ART	Avg # of hours sender takes to respond to emails. Time until a frame is closed for the receiver after she has sent an e-mail. Indicates the respect the receiver has for the sender.
Ego Nudges	Avg # of follow-ups that the sender needs to send to receive a response from the receiver.
Alter ART	Avg # of hours receiver takes to respond to emails. Time until a frame is closed for the sender, after she has sent an email. Indicates the respect the receiver has for the sender.
Alter Nudges	Avg # of follow-ups that the receiver needs to send to receive a response from the sender.

Metric	Definition
Avg. influence per message	Avg # of terms per message that has been introduced into the network.
Total influence	# new terms which a sender has introduced into the network and which are subsequently used by other members of the network. Indicates the extent to which someone causes the other person's pattern of speaking to match their own pattern.
Avg. Sentiment	Uses automatically generated bag of word, based on a dictionary trained for language/subject area. Indicates positivity and negativity of communication.
Avg. Emotionality	Standard deviation of sentiment. It represents the deviation from neutral sentiment.
Avg. Complexity	Information distribution using TF/IDF, independent of single words. Indicates the complexity of word usage. The more diverse words, which are all used evenly, a sender uses, the higher the complexity.

For the machine learning experiments, we consider each CSV file as a single data point, meaning we combine 30 CSV files to have network metrics related to 3 months of e-mail communication as the input. Depending on the date an employee left the company, we consider her as a leaver or not. The last three months of work of employees who left the company are not considered in the model, because employees in this company are asked to send the resignation letter three months before leaving. Following Gloor et al. (2017), we assume that the closer employees get to the final decision of quitting, the higher the likelihood to exhibit divergent communication behaviors. Hence, we define five to seven months prior turnover as the period, where an employee is thinking about leaving the company. This means that 150 days before the actual turnover job satisfaction might turn to job dissatisfaction (see Figure 1).

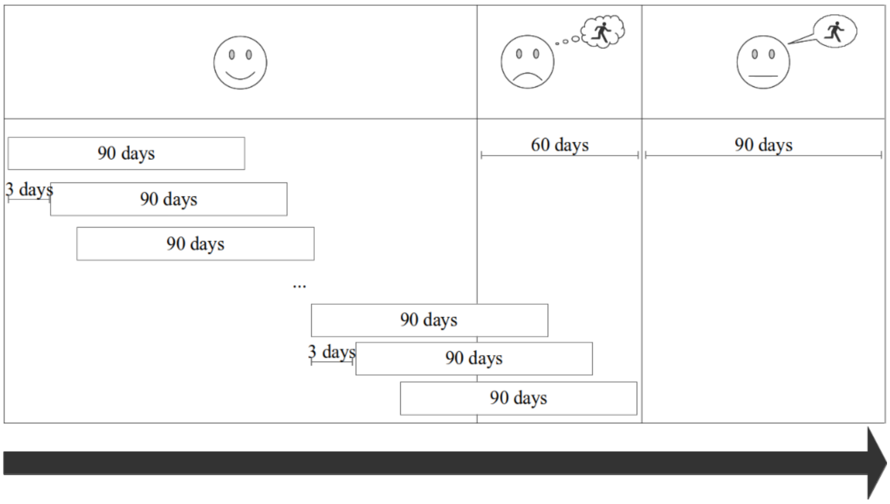

Fig. 1. Employee satisfaction timeline

3.2 Experiment Setup

We built a RNN with GRU. We trained our model on 2898 employees and tested on the remaining 954 employees. Further, we apply 4-fold cross-validation to provide a robust estimate of the performance of our model. Therefore, we split the training data into four equal sized subsets, each subset has a similar number of employees who left (leavers). One of the four subsets are retained as the validation data for testing and the remaining three subsets are used for training. Since our dataset contains only a small number of actual employees who left the company (78 leavers), we had to preprocess the data with Synthetic Minority Over-Sampling Technique (SMOTE) to handle the imbalanced dataset (see Table 2 for dataset statistics). SMOTE is an over-sampling approach in which the minority class, in our case the leavers, is over-sampled. But instead of over-sampling with replacements, synthetic instances are created by joining any of the k minority class nearest neighbors of a minority class. These synthetic instances lead to more sensitivity regarding a minority class without too severe minority over-sampling.

We evaluate the results using precision, recall, accuracy, area-under-curve (AUC) and Matthews correlation coefficient (MCC) score, a discretization of the Pearson correlation value. We chose MMC as an additional performance measure, because our model represents a binary classification problem (leavers / stayers) and MCC is more informative than other confusion matrix measures (such as F1 score and accuracy) in evaluating binary classification problems. MCC takes the balance ratios of the four confusion matrix categories (true positives, true negatives, false positives, false negatives) into account (Chicco 2017).

Table 2. Statistics of the dataset

	Training	Test
# of actors	2898	954
# of leavers	59	19
# of stayers' time series	238438	78468
# of leavers' time series	832	262
# of stayers' SMOTE time series	238438	78468
# of leavers' SMOTE time series	238438	78468

3.3 Results

Table 3 (training set) and Table 4 (test set) show four fold cross validation results of our dataset. We conducted the GRU experiment with a keep probability of 0.1, one LSTM layer, eight neurons and a learning rate of 0.001. All folds perform well, the average fold has an ACC of 0.933 and a MCC of 0.872. The test set's performance is good. The ACC is 0.800 and MCC (0.604) shows a strong positive predictive power.
Table 5 shows the performance of the two GRUs with different configurations. Model 1 with eight neurons performs slightly better (MCC = 0.604) than Model 2 with 16 neurons (MCC = 0.552).

Table 3. Model results, training set

Fold #	ACC	P	R	AUC	MCC
0	0.903	0.924	0.883	0.903	0.807
1	0.934	0.987	0.894	0.940	0.873
2	0.936	1.000	0.884	0.942	0.879
3	0.947	1.000	0.906	0.953	0.899
1.5 (avg)	0.933	0.998	0.886	0.942	0.872

ACC=Accuracy, P=Precision, R=Recall, AUC=Area under curve, MCC=Matthews correlation coefficient

Table 4. Model results, test set

Fold #	ACC	P	R	AUC	MCC
0	0.790	0.698	0.855	0.800	0.589
1	0.787	0.666	0.878	0.804	0.590
2	0.795	0.748	0.825	0.797	0.592
3	0.703	0.501	0.840	0.742	0.443
1.5 (avg)	0.800	0.745	0.844	0.816	0.604

ACC=Accuracy, P=Precision, R=Recall, AUC=Area under curve, MCC=Matthews correlation coefficient

Table 5. Model results based on different configuration (test set, 1.5 fold)

	Configuration parameters	ACC	P	R	AUC	MCC
Model 1	Keep Probability: 0.1 Layers: 1 Size: 8 Learning Rate: 0.001 Type:'GRU'	0.800	0.745	0.844	0.816	0.604
Model 2	Keep Probability: 0.1 Layers: 1 Size: 16 Learning Rate: 0.001 Type:'GRU'	0.768	0.653	0.849	0.786	0.552

4 Discussion and Implications

The results of the experiments revealed that applying a deep learning approach has potential to conduct a binary classification of employees in stayers or leavers by analyzing their e-mail communication behavior.

What are the implications from this study’s findings for future RNN experiments and research on employee turnover? First, our study provides a novel approach to analyze longitudinal employee turnover data. This study is among the first to apply a RNN besides the usual applications of RNNs, such as object or speech recognition. As such, this paper may provide an insightful account for researchers interested in the context of employee turnover and provide an example of how deep learning methodology can be meaningful integrated in management research studies in general. We found it encouraging that the experiments went well in regard of performance. Further, we address the call by Hom et al. (2017) as well as Lee et al. (2017) by considering the dynamic nature of antecedents of employee turnover and conducting a network-based analysis in comparison to earlier research that primarily used a standard research approach (Steel 2002).

For organizations, the findings suggest the critical importance of human resource (HR) data analytics. We provide a possibility to predict employee turnover. HR managers can use our experiment setup as an 'early warning system' for employee turnover. Since employee turnover might be dysfunctional and has serious impact on company performance, HR managers could counteract with retention strategies when an important and highly skilled employee intend to leave the company. Nevertheless, ethical issues should be considered before applying this methodology in an organization.

5 Limitations and Future Research

One limitation of this work pertains to the generalizability of our proposed approach. It is plausible that the insights from this study might not directly apply to other companies or occupational groups. However, that would be a practical concern caused by insufficient data, which should be manageable.

Second, the premise of this study is that dissatisfaction derived from e-mail communication behavior culminates in leaving. Other options or paths of dissatisfied employees are ignored. Employees may lower job inputs or improve their circumstances (via promotion) rather than leave (with or without job offers) (Hulin et al. 1985). Thus, leaving is only one option among many ways to cope with job dissatisfaction.

Third, employee turnover data is an imbalanced dataset by nature. The number of leavers is always much lower than the number of stayers. Our dataset is extremely imbalanced, but we overcome this issue with SMOTE. However, a higher sample of leavers might improve the predictive performance of our models.

Fourth, this paper takes the relational perspective on employee turnover. However, traditional antecedents like organizational commitment were not considered.

Future research should conduct a classifier performance comparison by including several configurations of LSTMs, GRUs and other classifier models like Support Vector Machines (SVMs). Additionally, a comparison with models that are based on the mentioned standard research approach is necessary. Further, this study should be replicated with employee turnover data from other organizations, other occupational groups and with additional input variables.

6 Conclusion

In this paper, we applied a GRU RNN classifier that classifies employees in two states (leaver or stayer) by taking their e-mail communication behavior into account. The classifier's performance is measured in terms of confusion matrix with accuracy, recall, precision, AUC and MCC values. The developed GRU RNN model provides promising performance. Here, GRU can strongly benefit from the fact that it can look back in time and learn to correlate the calculated network metrics. GRU can learn these correlations, although it might require further training or different variables to be added to the data. In the future, we will continue to improve the performance of our model and conduct in depth error analysis.

We finally conclude that GRU is very suitable for classifying employees' turnover behavior. This is the first reported demonstration of a successful application of GRU neural networks to data from an organizational management context, namely employee turnover.

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