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An Analytics Approach for Proactively Combating Voluntary Attrition of Employees

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***Abstract*—We describe a framework for using analytics to proactively tackle voluntary attrition of employees. This is especially important in organizations with large services arms where unplanned departures of key employees can lead to big losses by way of lost productivity, delayed or missed deadlines, and hiring costs of replacements. By proactively identifying top talent at a high risk of voluntarily leaving, an organization can take appropriate action in time to actually affect such employee departures, thereby avoiding financial and knowledge losses. The main retention action we study in this paper is that of proactive salary raises to at-risk employees. Our approach uses data mining for identifying employees at risk of attrition and balances the cost of attrition/replacement of an employee against the cost of retaining that employee (by way of increased salary) to enable the optimal use of limited funds that may be available for this purpose, thereby allowing the action to be targeted towards employees with the highest potential returns on investment. This approach has been used to do a proactive retention action for several thousand employees across several geographies and business units for a large, Fortune 500 multinational company. We discuss this action and discuss the results to date that show a significant reduction in voluntary resignations of the targeted groups.**

***Keywords*-Predictive modeling; Clustering; Attrition; Proactive retention**

I. Introduction

High voluntary employee attrition has a significant negative effect on an organization by virtue of lost productivity, increased training and recruitment costs. By taking proactive action to retain its top employees, a company can thus reap substantial benefits, thereby increasing its top and bottom line. Employees voluntarily leave an organization for various reasons, such as new opportunities, limited or no professional growth in current position, unhappiness with compensation, personal reasons, etc. Not all voluntary departures can be prevented by an organization since the reasons an employee leaves may be totally outside the control of the company. For example, an employee who resigns due to the fact that his/her spouse is relocating can likely not be influenced to stay by the company. On the other hand, a valued employee leaving due to compensation reasons could potentially be retained by an increase in salary.

The problem of voluntary employee turnover and retention has been studied in the management and organizational behavior literatures for several decades, starting with the model of March and Simon [1]. Several factors have been identified and empirically validated as contributors to the propensity of an employee voluntarily resigning, including job satisfaction, perceived ease of movement, intraorganizational movement possibilities, salary growth, and promotion ([2], [3], [4]). Similarly, various factors contributing to employees staying have also been identified and studied empirically [5]. These include advancement opportunities, extrinsic rewards, flexible work arrangements, job satisfaction, lack of alternatives, non-work influences and organizational factors such as prestige.

Although the prior work in the management and organizational behavior fields has included substantial empirical validation of individual factors, the problem of predicting individual employees at risk of voluntary attrition has not been approached through a data mining or machine learning perspective. Specifically, holistic predictive models have not been learned from historical training data and applied to current employees to identify those at risk of voluntarily leaving. Moreover, in this literature, there has been no suggestion of data- and analytics-driven proactive retention programs that identify individuals to receive extrinsic rewards (the third of the twelve factors of retention) in order to enhance an organization's cost-benefit outlook. While various retention actions (both compensation as well as non-compensation based) are often carried out by organizations in order to reduce voluntary employee attrition, the increasing collection and availability of historical data on active/attrited employees allows for data mining to be used to build models to identify those employees at the most risk of attrition and optimize the distribution of such actions amongst these employees so as to maximize the return on investment.

It is important to note that not all voluntary attrition is bad, and it does not make good business sense for an organization to try to retain all employees expected to attrit voluntarily. This is especially true when the retention lever to be used is a salary increase (or a one time bonus) since the available investment bucket is often quite limited and a decision needs to be made about the number of people who much be incentivized as well as the size of the actual incentive that each individual employee receives. As such, employees with low or declining performance are generally

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not good candidates for a retention action. Moreover, even top employees who are engaged in jobs that require common skills that can be easily replaced are not good candidates for retention actions. Often, these employees are being paid higher salaries (by virtue of getting regular raises) than the going market rate which is governed by the availability of the skills, tightness of the labor market, economic factors, etc., and if such an employee departs, the company can replace him/her without much financial cost. Although the departure of such an employee may result in short term losses, trying to retain someone else who has some core skills that are very difficult to find, and hence is very expensive to replace, makes better business sense for an organization.

In this paper, we describe an analytics based framework for tackling voluntary employee attrition using a one-time proactive salary increase as the retention lever. The approach involves the identification of individual employees at a high risk of voluntary resignation, and optimally choosing that set of such employees for retention action for whom the total cost of retention action (by virtue of a salary increase) is the least compared to the total cost of replacing them in the event they depart. Note that, as discussed earlier, compensation is only one of several levers that may be used to affect voluntary attrition, and may not be the best approach for each employee. Other approaches, such as promotions, may be better suited for some employees. While the framework described in this paper is focused solely on salary increases as the sole retention lever, the framework can be easily extended to include other retention actions as long as the cost of such actions can be quantified. In Section II, we describe the analytics based framework in detail. We then discuss a retention action (Section III) involving several thousand employees that has been recently carried out using this framework in a large Fortune 500 multinational and describe the results of the action achieved so far. Finally, we offer some concluding remarks and discuss future steps in Section IV.

II. Framework for Proactive Retention

The proposed framework consists of a number of steps as we discuss below.

A. Understanding reasons for attrition and identifying potential attriters

First, a company has to understand the reasons for voluntary attrition. This has to be done in terms of actionable attributes so that appropriate retention actions can be formulated. While it may be interesting to note that attrition in a certain business area is high, it is not particularly useful unless the root cause of such attrition is identified and that too in actionable terms. Mining historical employee data can help build models to understand factors that affect voluntary attrition as well as identify employees likely to attrit in the future based on such factors. A very important consideration in such a mining exercise is that the models must be easily interpretable and understandable so that reasons for identifying employees as potential attriters (as well as appropriate retention actions for each such individual) can be explained and supported by fact. This is imperative to ensure executive support as well as make sure that retention action decisions abide by company policy as well as legal guidelines. Various retention actions that can potentially be taken by a company include cash/non-cash rewards, one-time bonus payments, salary increase, promotion, etc. By carefully constructing features around such actions and mining historical data to build attrition models, it is possible to understand how such actions may affect attrition. For example, directly modeling the salary of employees may not show any relationship with attrition (due to the potentially wide range of salaries in an organization); however, identifying the appropriate peer group of employees for each individual against which his/her salary can be compared and building a feature to reflect that may help model any relationship that may exist between salaries and voluntary attrition.

B. Understanding the cost of attrition

1) Salary Premium: Typically, market salaries often increase at a faster rate (e.g. for jobs requiring hot skills) than inside a company. Hence, the market salary for hiring a new employee to replace an existing, attriting employee for such a job is often higher than what was being paid to the current employee. However, jobs requiring common skills may actually have a lower prevailing market rate than what a company is paying to an existing employee. In such a case, such an employee can be replaced at a lower cost than what is currently incurred by the company. Note that this assumes that both employees (existing as well as potential) will do the exact same job and have the same skills that are needed for the position; it does not mean that the new employee has to have the same attributes as the existing employee (such as years of experience) if such attributes are not needed to do the job properly.

The salary premium for an employee, thus, is an important factor in determining whether it is financially viable for a company to try to retain an employee or not by way of financial retention actions. The higher the salary premium, the more expensive it is to replace the employee and probably cheaper to try to retain instead.

2) Hiring Costs: In addition to salary premiums, another potential cost which may be incurred by an employee if a valued employee departs is the cost of hiring a replacement. Based on the tightness of the labor market, the kinds of skills needed and the availability of such skills, economic conditions, etc., these costs may vary widely. These include recruiting costs (such as agency or headhunter fees) and bonuses (referral, sign-on, etc.), as well as various costs incurred in training the new employee and bringing him/her up-to-speed with regards to the company culture as well as job requirements. Once again, hiring costs are an important financial consideration in deciding whether to invest in trying to retain a potential attriter.

3) Productivity Losses: While salary premiums and hiring costs are tangible costs (the company has to spend a measurable amount of money), a intangible but significant cost of employee attrition is productivity loss. This is especially true in services where deals may fall through or contractual obligations may be missed or delayed due to unexpected departures. Moreover, new hires often have little or no productivity for a significant amount of time after joining as they get up to speed in terms of various products and processes of their new employer.

C. Determining optimal compensation investments

In addition to costs, a company also has to decide appropriate investment levels (what sizes of raises to give and to whom) and the population to target. This includes deciding on whether to target employees already being paid above or near market (or those who would reach that level after getting a raise) if it will be beneficial to try to retain such employees, or to focus on those employees who are significantly underpaid and where the impact of a salary raise will perhaps be most strongly felt. Similarly, a decision has to be made regarding the skills, performance levels, job roles etc. that are most critical for the company so that retention actions can be focused in that direction.

D. Choosing employees for proactive retention action

Once attrition reasons have been understood and employees at risk of voluntary attrition identified, costs have been quantified and compensation decisions made, a subset of those employees have to be chosen for retention action such that the maximum possible savings are generated subject to the constraints imposed by financial limits. This can be posed as an optimization problem.

Assume that benefit of doing a retention action is evaluated over a certain time horizon (say 1 year). Let this time horizon be h months.

Consider employee i who is identified to be at risk of voluntary attrition with a probability pb_{im} of attrition (before any retention action is taken) in month $m, 1 \leq m \leq h$. Let HC_i be the cost of hiring a new employee to replace the employee if s(he) resigns, SP_i be the *annual* salary premium for the employee, and SI_i be the *a*nnual salary investment (equal to $R_i * B_i$) due to the retention action.

Then, if no action is done and the employee leaves, the cost to the company will include the hiring cost as well as the salary premium that the company will have to pay in order to replace the employee. If the employee leaves in month m month, the company will pay a salary premium for $h-m+0.5$ months (assuming, on average, half a month of salary premium for the departure month), and the expected attrition cost before (EACB) the retention action (over the horizon period h) will be given by

$$EACB_i = \sum_{m=1}^{h} (pb_{im} * (HC_i + SP_i/12 * (h - m + 0.5)))$$

If a retention action is taken, the employee is given a raise of $R_i\%$ over the existing salary of B_i, and there is still a pa_{in} probability that the employee will leave in month $n, 1 \leq n \leq h$. If the employee does leave, then the company has to pay the hiring cost, salary increase for the time the employee stays on, and then a salary premium for the rest of the time horizon. If the employee does not leave, then the only cost incurred is the increase in salary for h months. Thus, the expected cost after (EACA) a retention action is given by

$$EACA_i = \sum_{n=1}^{h}(pa_{in} * (HC_i + SP_i/12 * (h - n + 0.5) + SI_i/12 * (n - 0.5))) + (1 - \sum_{n=0}^{h} pa_{in}) * SI_i/12 * h$$

Again, the assumption is that for the month of employee departure, the cost will be 0.5 month of salary premium and 0.5 month of salary investment.

The total salary investment (TSI) over the horizon will be given by

$$TSI_i = \sum_{n=1}^{h}(pa_{in} * (SI_i/12 * (n - 0.5))) + (1 - \sum_{n=0}^{h} pa_{in}) * SI_i/12 * h$$

If the horizon being considered is 12 months ($h = 12$), and we assume that pb_i and pa_i are the probabilities that the employee will attrit over the next 12 months before and after action respectively, and assume that the employee attrition has a uniform distribution over the year, then $pb_{im} = 1/12 * pb_i \forall m$ and $pa_{in} = 1/12 * pa_i \forall n$.

Then,

$$EACB_i = pb_i * (HC_i + SP_i * 0.5)),$$

$$EACA_i = pa_i*(HC_i+SP_i*0.5+SI_i*0.5)+(1-pa_i)*SI_i$$

and

$$TSI_i = pa_i * (SI_i * 0.5)) + (1 - pa_i) * SI_i$$

In other words, if no action is taken, the cost will be, on average, the hiring cost and 6 months of salary premium multiplied by the annualized probability of attrition in the absence of any action. If action is taken, then it is hiring cost, 6 months of salary premium and 6 months of salary investment times annualized probability of attrition post action plus 12 months of salary investment times annualized probability of attrition post action.

The expected net benefit (savings) of taking an action to retain the employee is thus

$$NB_i = EACB_i - EACA_i - TSI_i$$

Let C be the total amount of money available to invest in the salary action. So, we want to choose the group of employees that maximize the total expected net benefit from the retention action. Then, we want to find the set of employees I that maximizes the expected net benefit which keeping the total salary investment less than C. That is, find I such that

$$\begin{aligned} \text{maximize} \sum_{i \in I} NB_i \\ \text{subject to} \sum_{i \in I} TSI_i \leq C. \end{aligned}$$

This optimization problem can be solved by a variety of standard methods.

III. Retention Action and Results

This methodology was used to identify top employees at risk of leaving a large, multinational within one year, and a retention action was carried out to try to retain them based on the net benefit of the action over a 1 year horizon. Due to the sensitivity of the data, we do not provide exact values for financial or attrition data; rather we present ranges, approximate values or relative values while trying not to distort the true picture. The investment bucket was in the low, double digit millions of US dollars, and the target population to be considered for retention action consisted of almost 200,000 employees across multiple business units and over two dozen countries. The retention lever used in this action was a one time, proactive salary increase which was provided to the employees as an off-cycle (outside the regular annual raise cycle) raise. The employees were also told that the raise was being given to them to show them that the company highly valued their services; however, they were not told that this was the result of a proactive retention action and that the company was expecting them to attrit in the near future (based on this study).

A. Data

The data consisted of monthly snapshots of HR data for all currently active employees (appx. 200,000) over a six year period. In addition, the data also included more than 125000 employees who had voluntarily resigned from the company any time in the past. For each employee, the data included salary and other compensation data, performance data, position data (level, skills, job role), dates of promotions, salary changes and performance evaluations, demographics (region, country, business unit), experience, education, etc. Note, however, that despite the fact that the data included monthly snapshots over a 6 year period, many of the attributes do not change quite often. For example, performance evaluations are done annually, and salary increases are also typically made only once a year. Other attributes change even less frequently (e.g. promotion). As such, the actual number of data points for each individual were very few.

B. Salary Premiums

As described earlier, the salary premium for an individual is the difference between the individual's salary and the salary that the company will have to pay in order to hire a replacement to do the same job as the attriting individual. Two different options were considered to get accurate salary premium data.

The first option was data maintained by the company itself about where each employee's salary is relative to the market for that employee's position. An advantage of this data is that it is available at the individual employee level. However, it is based on surveys as well as data from external vendors (such as Mercer) and the individual-level data is actually mapped from data at the job family level which is much higher than the level at which hiring/salary decisions are made. As such, the data may not be very accurate since there is not any differentiation at the job role level where different types of skills may have widely disparate market supply/demand and hence salaries. Moreover, this data is only updated once or twice a year, and as such can be fairly outdated, especially in regions where the job market is tight or there is high demand/competition for certain skills.

The second option was to obtain salary premiums by mining the historical data. By looking at the actual salaries at which new employees are being hired, it is possible to get a much more accurate view of current salary premiums. However, this approach too has some issues. First, the level at which new hire salaries have to be determined needs to be fixed. If it is too detailed, then enough new hire data is not available to accurately determine salaries. If it is too high, then the data is not very accurate as in the former case. Based on input from HR subject matter experts, peer groups (for determining salary premiums) were defined along four dimensions - country, business unit, position level and job role. For each employee in a given peer group, the salary premium was calculated as the difference between the peer group new hire salary and the employee's current salary. Moreover, one year of historical data was considered to provide a balance between too little data (small time period meant few new hires, especially at peer group levels) and too much data (long time period implied outdated new hire salaries, especially in rapidly growing regions). Moreover, to make sure that the peer group new hire salary was really representative of the market, and not just market noise, statistical significance testing was performed to make sure that the difference in new hire salaries was significantly different from recent attriter salaries. Only in cases where this was significant was the peer group salary premiums used. Thus, for each employee in a given peer group, the salary premium was based on the peer group salary premium only if enough number of new hires were found for the peer group and the difference in salaries between the new hires and recent attriters was statistically significant. For all other employees, the salary premium was based on the company maintained data explained previously.

The salary premium thus determined for every employee was then validated at the region/business unit level which were allowed to override the values determined from the data. The vast majority of the premiums were accepted as is; a very small number were changed.

C. Hiring Costs

Hiring costs for various positions were collected via interviews with subject matter experts. Since these costs can vary widely amongst different geographies, business areas and positions, we gathered recruiting and on-boarding costs for groups of positions defined along multiple dimensions, namely business unit, country, position level, experienced/non-experienced and seller/non-seller. The costs determined for each such group were then assigned to each employee that fell in that group.

D. Identifying potential attriters

Since attrition patterns could change over time (e.g. due to changes in the economy or changes in company performance, etc.), employees who had left longer than 3 years ago were not considered in the modeling. This was especially true in some fast growing regions where the company has been ramping up investment for only the last 2-3 years and hence the workforce needs have rapidly evolved over this period. However, looking at a shorter time period resulted in the not-so-desirable side-effect of limiting the amount of positive samples (attriters), especially in some small business units/geographies due to the highly skewed nature of the problem. The data was made somewhat less-skewed by also limiting the number of currently active employees that were included in the modeling data. An analysis of the data showed that the vast majority of attritions typically happen in the first few years of an employee's career; once the employee has been in the job for a few years, the propensity of voluntary attrition falls rapidly. As such, the active population was also restricted to only include those who had been with the company for 6 years or less. Finally, only employees who had received an above-average performance rating in the last performance evaluation cycle were considered for retention action.

Three factors influenced the actual approach taken for modeling employee attrition. First, an explicit requirement imposed by the company was that the results needed to be easily interpretable. This was due to several reasons. One, there was a need for a clear explanation of why a particular individual was being targeted, both for legal reasons as well as obtaining support of executives for carrying out the large financial investment. Interpretability was also important to understand the root causes of voluntary attrition in various regions/business units so that non-financial retention programs could also be set up in addition to the salary based retention action being carried out. Second, as explained earlier, despite the fact that data was available for individuals for multiple years, there were in fact few data points as most of the attributes change very infrequently. Hence, there was not enough data to carry out significant model training/testing/validation analysis. Thirdly, the data is extremely noisy. Individuals may leave for a whole variety of reasons (e.g. personal reasons) that are not captured in the data. As such, complex modeling techniques tended to over fit the data and did not result in much higher performance but did significantly degrade the interpretability of the results. Even decision tree techniques (such as C5.0) resulted in rules that were extremely deep (i.e. used a large number of attributes) and hence, although interpretable, too detailed and specific to be of much use. Attempts at reducing the depth of the trees resulted in a simultaneous decrease in performance.

Hence, the main focus of the approach was to build useful attributes that would capture some of the salient reasons for voluntary attrition and then use a simple modeling technique to build the actual models for prediction. The technique finally used was decision lists [6]. Decision lists allowed for the construction of easily interpretable rules that defined clusters of employees with high attrition rates. At the same time, appropriate settings of various parameters such as segment size, number of segments and number of attributes in a rule enabled overfitting to be kept in control. The simplicity and easy interpretability was well accepted by executives and HR even though it came at a price of lower accuracy in terms of correctly identifying attriters.

Several attributes were constructed based on the base variables, including deviation of salary from average salary of peers, time since last promotion, time since last salary increase, performance rating trend (weighted and un-weighted) over time, etc. Since the main retention action being considered was a salary increase, it was important to understand the effect of salary on attrition. To this end, the construction of the salary deviation attribute assumed a lot of importance. In order to do this correctly, peer groups were defined (as in the case of salary premiums) along 4 dimensions - country, business unit, position level and job role. In addition, a fifth dimension of years of service with the company was added to the peer group definition to adjust for salary differences due to the level of experience of an employee. Then, the average salary for each peer group was calculated for every month for which historical data was available. Finally, the

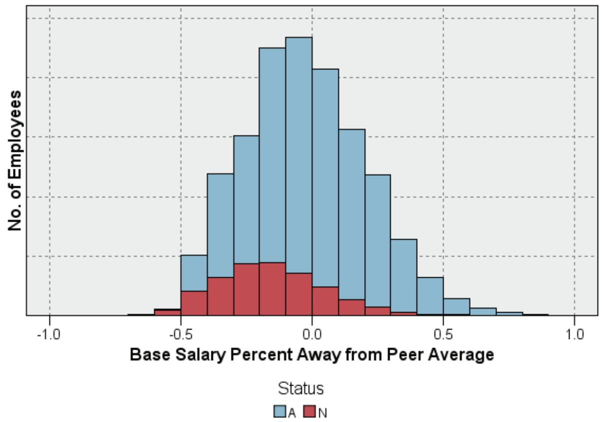

Figure 1. Effect of Salary on Voluntary Attrition.

salary of every active employee was compared to the current salary of the peer group to which the employee belonged while the salary of every attrited employee was compared to the peer group salary at the time of attrition. As can be seen in Figure 1, voluntary attrition is strongly impacted by salary relative to peer-group salary; the proportion of voluntary attriters (Status = 'N') to actives (Status = 'A') is much higher when salary is significant below peer group average, and is much lower amongst highly paid employees. This was also borne out in the modeling as one of the most important and frequently selected attributes that were found to affect voluntary attrition was deviation of salary from peer group average salary. However, other features such as time since last promotion and time since last salary change also showed up as strongly related to employee attrition. Most of the clusters of employees identified included one or more of these attributes in their definition (in addition to other less actionable attributes such as business unit, job roles and regions). Employees in clusters defined by the deviation from salary feature were considered for salary retention actions (e.g. employees in business unit 'X' and performance rating 'A' and paid less than 25% below peers had a 70% propensity to attrit). However, other clusters that were defined by non-salary features alone (e.g. employees in business unit 'Y' and band 'P' and country 'I' that had not been promoted in the last 2 years attrited at a 85% rate) were used to identify candidates for a separate, non-salary-based retention program that is being setup in certain fast growing economies where such attributes are found to be very important.

Four different decision list models were constructed with different sets of attributes; two of these were constructed based solely on compensation based attributes while the others were learned using other attributes as well. The predictions from the four models were combined using a majority rule to determine potential attriters. All employees whose predicted attrition probability was significantly higher than the mean were then considered for retention action on the basis of net savings ('benefits') that could be achieved by investing to retain the employees as opposed to the costs incurred in replacing them. A greedy formulation of the optimization step, as discussed in Section II was used wherein all potential attriters were sorted in decreasing order of net benefit, and the top set of employees was selected whose cumulative salary investment was just under the available investment bucket. While not guaranteed to be optimal, it provided us with a reasonable solution with very fast computational efficiency.

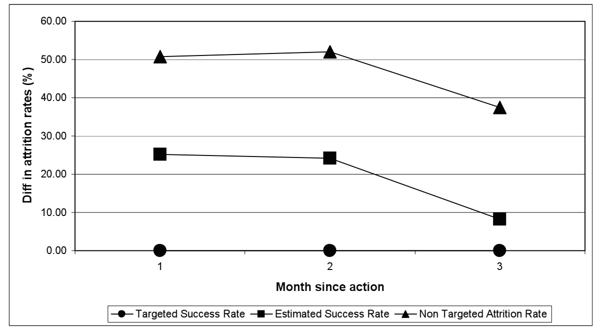

Figure 2. Retention Action Performance.

E. Results of the Proactive Retention Action

The retention action was carried out in two phases. The first phase involved around 7500 employees in all but one of the business areas considered. Due to logistical reasons, the second phase was carried out a couple of months later and involved roughly 12000 employees from the previously left out business area. Two different retention levers were used - a proactive salary raise in the high single digits (between 5 & 10%), or a proactive raise in the low double digits (between 10 & 15%). The exact levels of salary increases were fixed by the company's HR department a-priori. However, the level given to each employee was chosen based on the net benefit for that employee as discussed in Section II.

The total net benefit estimated by the company HR department is approximately 150% (over and above the salary investment made by increasing the salaries of the targeted employees) during the 2012 calendar year. This estimate is based on the assumption of a certain average 'success' attrition rate amongst the targeted employees, based on a limited (non data analytics based) retention action that had been carried out in a prior year. While data for the second phase is not yet available, three months of data is available for the initial action (targeting 7500 employees) and shows that attrition is significantly better than both the modeled success rate, as well as the rate of attrition amongst employees who were identified as being at high risk of attrition but were not targeted, either due to a low benefit/cost ratio or due to the available funds being exhausted (approximately 7000 additional employees). As can be seen from Figure 2, for the first two months post action, the attrition for the targeted population was lower by more than 25% as compared to the estimated 'success' rate and more than 50% lower than the attrition rate of the population of identified high-risk attriters who were not targeted by this action. In the third month, the difference was lower with the difference being just under 10% compared to the modeled rate and just under 40% compared to the non-targeted group. In the absence of additional data, it is not clear if it is a trend (i.e. the rates will converge over time) or if it is an aberration. As the performance of both phases is monitored over the coming months, this will become clearer; nevertheless, the performance difference is fairly large even at the third month mark and clearly shows the benefit of this retention strategy.

IV. Conclusions and Future Work

Retaining their best employees is one of the most important tasks faced by organizations In this work, we have focused on salary increase as the method or lever by which to proactively increase employee retention. We have described an analytics based approach to proactive retention and have discussed its implementation in a proactive retention action at a large multinational company with very good results over the initial months. As additional results get available, we intend to evaluate the action further, and also analyze the results further to identify what kind of employees are actually more likely to stay as a result of such action, and what kind are possibly better addressed by non-financial retention actions (e.g. promotions). Also, we would like to better model from data the causal effect of salary actions to see how these actions affect propensity to attrit over time post such actions.

Moreover, as discussed in the introduction, many other retention factors have been identified in the organizational psychology literature, some of which the organization can influence, e.g. advancement opportunities, organizational commitment, and organizational justice, as well as other forms of extrinsic rewards. In future work, we would like to consider some of these other levers for analytics-driven proactive retention.

Finally, we would like to explore/develop other techniques for better identifying employees at risk of voluntary attrition while maintaining the interpretability of the results.

References

[1] J. G. March and H. A. Simon, *Organizations*. New York, NY: Wiley, 1958.

[2] J. C. Anderson and G. T. Milkovich, *Propensity to leave: A preliminary examination of March and Simons model*, Relat. Ind., vol. 35, no. 2, pp. 279294, 1980.

[3] R. W. Griffeth, P. W. Hom, and S. Gaertner, *A meta-analysis of antecedents and correlates of employee turnover: Update, moderator tests, and research implications for the next millennium—*, J. Manage., vol. 26, no. 3, pp. 463488, 2000.

[4] C. O. Trevor, B. Gerhart, and J. W. Boudreau, *Voluntary turnover and job performance: Curvilinearity and the moderating influences of salary growth and promotions*, J. Appl. Psychol., vol. 82, no. 1, pp. 4461, 1997.

[5] J. P. Hausknecht, J. Rodda, and M. J. Howard, *Targeted employee retention: Preformance-based and job-related differences in reported reasons for staying*, Hum. Resour. Manage., vol. 48, no. 2, pp. 269288, 2009.

[6] R. Rivest R. *Learning decision lists*, Machine Learning, pp. 229-246, 1987.