Employee Attrition: What makes an employee leave?

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**Abstract.**  In this paper, we present a model for employee attrition prediction and discuss the ethical impacts of using such a model within private and public sector organizations. As it is in Human Resource personnel’s best interest to improve retention, implementing statistical and machine learning techniques is the most viable means to attrition abatement. To this end, we examine Office of Personnel Management public sector, Bureau of Labor Statistics public sector, and IBM anonymized private sector employee separation data. Three classification models (Methodologies include Logistic Regression, Random Forest, and K Nearest Neighbor) are trained and tested on these data before selecting our best fit model for attrition prediction. We finally use metrics such as Gini and Permutation Importance to identify the most impactful variables in determining prediction outcome before presenting the ethical ramifications of using such outputs in HR planning. [WILL ADD SENTENCE FOR MAIN RESULT AND SENTENCE FOR MAIN CONCLUSION ONCE THESE DEVELOPMENTS ARE COMPLETE].

1 Introduction

How much does it really cost to lose an employee? Studies such as the Center’s for American Progress analysis (November, 2012) indicate a separated employee may cost anywhere between 16 percent to 213 percent depending on the position [1]. Precisely quantifying this may seem out of reach depending on the complexity of a particular role, but areas of impact that one may foresee at many organizations are: 1) determining if the employee’s vacancy should be replaced or duties handed off to others; 2) posting the job opportunity to various outlets; 3) interviewing, hiring, and training a replacement; 4) enduring lowered employee morale / possible lower productivity from remaining employees; and 5) tolerating a lower skill set from an underdeveloped replacement [2].

Corporations are keenly aware of the downsides to losing employees and exert great effort to maintain retention levels. In their efforts to not only attract talented workers but retain them as well, businesses provide substantial benefits [3]. With industry competitiveness the norm, many employers may still face retention challenges as their employees have alternate employment options. To become even more proactive in attrition prevention, companies must gain a solid understanding for the reasons their employees separate. Foresight into attrition development and contributing factors empowers Human Resource departments to improve retention efforts through improved planning and intervention. While such insights are available to organizations that store employee data, these understandings are not within reach without sufficient analysis.

The first step in gaining foresight into employee attrition is obtaining pertinent data. Companies are understandably reluctant to release the methods, proprietary or purchased, that use even anonymous data to help them in their management of human resources. Various articles allude to this challenge [4, 5, 6]. However, we identified three valid sources of Human Resources data in the forms of Office of Personnel Management data, Bureau of Labor Statistics data, and the “IBM HR Analytics Employee Attrition” dataset. All three forms were analyzed in unison to complement one another in insight and model validity.

During analysis, dimensionality reduction was performed on the datasets. This was essential to reduce numerous correlating and covariant relationships present between dataset variables. Only after these relationships were addressed and the datasets simplified were the data prepared for modelling.

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2 Attrition as Seen in Civil Service Workers

The U.S. Office of Personnel Management (OPM) serves as the central Human Resources department for all Federal agencies, including the management of federal agency health insurance and retirement benefits. Their oversight of policy implementation as well as being a general resource for all agency Human Resource departments makes their employment data of particular interest for this paper. OPM regularly captures a wide range of data on the millions of federal civil service workers, and we used several of their data sources that focus on attrition. These data [7], include variables such as job level, locality, salary, length of service, and basic reason for termination of employment. Important for understanding our findings in the correct context are the following points:

* **October 2014 – September 2015:** The date range used to filter the final dataset (one full calendar year).
* **General Schedule Pay Scale (GS)**: This is the centralized pay scale used by many civil service agencies which covers the majority of white collar professionals. Whether or not a person is paid under the GS, the OPM converts the level he or she is paid under to the GS for data collection purposes. The scale numbers 1-15 and there are ten “steps” within each of those levels.
* **Locality adjustments:** To remain competitive with industry salaries, the GS operates a locality adjustment scale that adds a particular percentage to a person’s salary, based on city of occupation alone.
* **Federal Employees Retirement System (FERS):** Beginning on January 1, 1987, new civil employees are paid under FERS. This mix of Social Security, a Basic Benefit Plan, and a Thrift Savings Plan helps make civil service positions stand out from many current private sector jobs. We account for this factor in our research, taking into consideration the confounding effect this has on length of service (LOS). At the time of this paper, the pension is based on salary and length of service.
* **Reasons for separation:** OPM captures termination information as "Transfer Out – Individual," "Transfer Out – Mass," "Quit," "Retirement – Voluntary,” and "Retirement – Early Out."

3 OPM Data Consolidation, Sampling, & Creation of New Attributes

Worth mentioning are a few measures taken to consolidate, sample, and enhance the OPM dataset from its original form. Firstly, observations for locations outside the United States were removed as our intent is to model domestic jobs only. In addition, records with no specified occupation, no specified salary, no specified length of service level, and no specified age level were removed from the dataset. Age level *A* employees were also removed as this category includes employees age 20 to as young as age 14, and, therefore, may not reflect relevant work schedules, share common benefits, or separate for valid reasons as compared to the remaining age level categories. These actions reduced the dataset from 8,423,336 to 8,223,193 observations. In addition to observation removal, the second and third measures include new attribute derivation and proper sample design as described in sections 3.1 through 3.3 below.  
  
**3.1 OPM Computed Attributes**

Within the original OPM data, six new attributes were created through aggregation or calculation amongst various attributes: 1) SEP Count by Date & Occupation – Total number of separations (of any type) for a given Date and Occupation; 2) SEP Count by Date & Location – Total number of separations (of any type) for a given Date and Location; 3) Industry Average Salary – Average salary amongst non-separated employees, grouped by quarter, occupation, pay grade, and work schedule; 4) Lower Limit Age – Youngest age within each age level category; 5) Years to Retirement – Based on FERS retirement eligibility baseline of 57 years of age [8]; and 6) Salary Over/Under Industry Average – Difference between computed average salary of non-separated employees and actual salary for each observation. Note also another 1,293 observations were removed after calculating industry average salary as they had no matching non-separation observations (matched on quarter, occupation type, pay plan /grade, and work schedule), which were utilized to ensure realistic salary averages.  
  
**3.2. Bureau of Labor Statistics Derived Attributes**

In addition to the OPM data, we merged 10 attributes from the Bureau of Labor Statistics (BLS). Data were sourced from Federal Government industry codes across all regions. Although assumed to be highly correlated, we sourced both Level (Total number) and Rate (Percentage of Level to total employment and / or job openings) for the following statistics: 1) Job Openings, 2) Layoffs, 3) Quits, 4) Total Separations, and 5) Other Separations. While Rate paints an aggregated, holistic picture for job market trends, Level provides a raw count for total separations alone. Both these statistics were captured by a monthly aggregate and merged to the OPM data by their respective months.  
  
**3.3 Sample Design**

Of the 8,221,900 observations present in the reduced OPM dataset, only 214,282 contained actual separation data and all other observations were considered non-separation. This state of data was inoperable for analysis; therefore, a sample design was determined to mitigate sample size constraints and high variance amongst frequencies of separation types.

Data were divided into groups based on separation type, allowing a maximum of 50,000 observations per type to persist forward during analysis. In so doing, the following retirement separation types were combined: 1) SD Retirement – Voluntary, 2) SE Retirement – Early Out, 3) SF Retirement – Disability, and 4) SG Retirement – Other. Next, the following separation types were dropped completely: 1) SB Transfer Out – Mass Transfer, 2) SK Death, and 3) SL Other Separation. Within each separation group (including non-separation), proportional allocation was performed on a combination of date and age level strata to ensure a sample demographic which, as closely as possible, represents that of the original strata-level populations. After sampling was complete, we were left with 229,826 observations.  
  
**4 Data Visualization**

5 Modeling and Evaluation   
5.1 Dimensionality Reduction  
  
5.2 Classification Model Training  
  
5.3 Classification Model Comparison  
  
  
6 Ethical Considerations

7 Conclusion

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