Week 2: Literature Review

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Paper Information

Title: Predicting Employee Attrition Using Machine Learning Techniques **Authors:** Francesca Fallucchi, Marco Coladangelo, Romeo Giuliano, and Ernesto William De Luca **Year:** 2020 **Journal:** Computers (MDPI)

1. Background and Motivation

Enterprise turnover costs have long hampered organizations in translating their human capital into profitability and performance. This is more apparent the higher up the value chain an employee is situated or the more specialized an occupation the employee works in. The authors stipulate that this is due to the recruitment and retraining costs involved in the succession process for departing employees [1].

The authors' observations are borne out by industry organizations like SHRM which aver that the total replacement costs can often range between 0.5 – 2 times the annual salary of the departing employee [2].

It is also widely acknowledged by scholars and academics in the realm of Human Resources and Organizational Behaviour that motivated and engaged employees who already demonstrate positive behavioural intent to the firms that they belong to demonstrate better task performance and experience higher levels of creativity which in tandem lead them to being comparatively more productive [3].

Having then defined the scope of the problem, the authors reveal a lapse of understanding in conventional wisdom of the motivational and/or relational reasons that influence an employee's decision to depart an organization. To ameliorate this understanding the authors of this paper set out to explore and determine the casual factors and influences behind attrition via categorical data exploration and machine learning techniques on the IBM dataset consisting of 1400 observations of IBM employees that either stayed with or departed IBM based on 35 features that were recorded about them [1].

2. Methods Used

Fallucchi et al. [1] adopt a 5 step framework in conducting their study called **TDSP** or the **Team Data Science Process**, this methodology involves Data Acquisition, Data Cleaning, Exploratory Data Analysis using Descriptive Statistics, Testing and Training of Classification models and finally the compilation and interpretation of results to pick the best performing model.

This methodology is in line with industry standards in training and provisioning machine learning models and the authors aim to use the feature importances of their trained best performing model to identify the features (or reasons) most correlated with Employee attrition.

The Authors use the **Attrition** variable of the IBM Dataset (which tracks if an employee departs IBM with a "Yes" or "No") as the target column for descriptive analysis and machine learning and perform a correlation analysis on all variables to determine which variables are correlated with each other. This is a sound preventative approach in machine learning as correlated and/or collinear features often result in unstable models that are often overfit to training data and violate the assumptions of models like linear regression models for instance.

The authors also use **categorical variable encoding** to translate all non numerical columns to numerical ones, this is often standard practice when training ML models using scripting languages like R, Python or Scala since the machine learning extensions or pages used by these technologies often necessitate arrays of numerical variables for input.

3. Significance of the Work

The study offers a glimpse into the performance of various models on structured human resources data for the purposes of predicting employee attrition. Prioritized here were a small ensemble of classification models with key metrics like precision and recall being used to adjudicate the best model.

Fallucchi et al. [1] place a noteworthy emphasis on **Recall** (true positive rate) over precision (the proportion of a models positive predictions that are truly positive) which underscores the importance enterprises place in detecting exits before they happen.

The choice of Recall as the key discerning metric here allows for the minimization of false negatives (which in an enterprise context would translate to the model not predicting an employee's impending exit before they indeed do exit).

Methodologically, the authors use a correlation matrix to find dependencies between variables. Shrestha [4] mentions this is a normal way to handle **multicollinearity**, which can mess with model coefficients and raise variance. The findings show that **MonthlyIncome**, **OverTime**, and **Age** are the big predictors. This lines up with Kushwaha et al. [5], who say that fixing "Deficiency Needs" like low pay or too much work is a necessary step for retention.

4. Connection to Other Work

This paper follows the turnover research by Griffeth et al. [6]. That work used **demographics (like age and tenure)** as the main way to predict attrition. But Fallucchi et al. [1] change things up. They use **machine learning classifiers** to predict when someone will leave, rather than just looking at it after it happened.

4.1 The Shift from Explanation to Prediction Old papers looked at linear correlations to find out "who leaves." Fallucchi et al. deal with the class imbalance problem in turnover data. Their tests show **Naive Bayes** had the best **Recall**. In HR analytics, finding the people actually leaving is way more important than just high overall accuracy. This moves the field from simple heuristics to actual risk mitigation.

4.2 Addressing the "Black Box" Dilemma People in Organizational Behavior often complain that algorithms are hard to understand. Griffeth had clear risk coefficients. Fallucchi's work shows there is a trade-off between sensitivity and how easy a model is to interpret. By picking "At-Risk" employees (High Recall) over variable transparency, this paper acts as a bridge between Data Science and HR management.

5. Relevance to Capstone Project

This paper is a technical benchmark for my Capstone, **"Drivers of Attrition: An Application of the MARS Model."** Since I am also using the **IBM HR Analytics** dataset, I'm going to adopt Fallucchi's preprocessing pipeline. Specifically, I'll use their method for encoding categorical variables and normalizing salary data.

5.1 Operationalizing the MARS Model The paper validates variables that map to the **MARS Model** (Motivation, Ability, Role Perceptions, Situational Factors) from McShane and Von Glinow [3]. I will use these pillars for my own feature selection:

- **Motivation (M):** The authors' finding that **JobInvolvement** is a top predictor lets me use it as a proxy for Motivation. I'll also add **RelationshipSatisfaction**, which is a known driver of engagement even though it wasn't the main focus of Fallucchi's paper.
- **Ability (A):** For the Ability pillar, I will use **Education**, **JobLevel**, and **TrainingTimesLastYear** to track technical competency.
- **Role Perceptions (R):** The authors didn't really focus on this, but it's a big part of MARS. I will use **YearsInCurrentRole** and **YearsWithCurrManager** to look at role clarity.
- **Situational Factors (S): OverTime** and **DistanceFromHome** were big factors in the study. This justifies putting them under "Situational Factors"—external things that force an employee to leave [1]. I'll also use **EnvironmentSatisfaction** to see how they feel about the physical workplace.

- **Distributive Justice:** Since **MonthlyIncome** was so dominant, I'll include "Distributive Justice" theory. This explains turnover as a rational response to wage issues [3].

5.2 Methodological Divergence Fallucchi et al. prioritized **Recall**. My Capstone is going to prioritize **Interpretability** using Decision Trees and Logistic Regression. I don't just want to flag "Flight Risks," I want to explain *why* they are leaving by looking at odds ratios. This helps create actual organizational interventions.

References

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[2] SHRM Executive Network, “The myth of replaceability: Preparing for the loss of key employees.” [Online]. Available: https://www.shrm.org/executive-network/insights/myth-replaceability-preparing-loss-key-employees

[3] S. L. McShane and M. A. Von Glinow, *Organizational behavior: Emerging knowledge, global reality*, 10th ed. McGraw Hill, 2024.

[4] N. Shrestha, “Detecting multicollinearity in regression analysis,” *American Journal of Applied Mathematics and Statistics*, vol. 8, no. 2, pp. 39–42, 2020.

[5] B. P. Kushwaha, V. Tyagi, P. B. Sharma, and R. K. Singh, “Mediating role of growth needs and job satisfaction on talent sustainability in BPOs and call centres: An evidence from india,” *Journal of Public Affairs*, vol. 22, no. e2400, 2020.

[6] 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,” *Journal of Management*, vol. 26, no. 3, pp. 463–488, 2000.