**Background**

* Employee attrition is the departure of an employee(s) from employment, for whatever reason, be it voluntary or involuntary. Some of the major causes of attrition includes resignation due to dissatisfaction, lack of opportunities for growth and discrimination, followed by terminations, lack of skills and retirement. Presently as shown, attrition stands for 16.8% in UK while the accepted maximum threshold is 20%. Once it touches the maximum threshold, it would see a gradual decrease in economy and overall development of the country. We have chosen Logistic Regression as our model, as an employee of a company resigning his workplace would be a binomial answer.

**Data Source**

* For our project, we used IBM’s HR analytics and employee attrition csv, sourced via Kaggle.
* We liked this dataset as it had a range of metrics for us to analyze.

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**Data Import**

PostgreSQL

* Since we were required to import our data source from either SQL or Spark, we opted to use SQL.
* Firstly, we created a table in postgres to house our csv data (see table schema).
* We then imported the csv file into SQL and verified the import.

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Psycopg2

* In order for us to execute SQL commands in python (including visualizing the table), we needed to install the psycopg2 module.
* First, we establish a connection to the database.
  + We needed to provide details such as the database name, postgres username, and postgres password.
* A SQL query was executed to view the whole table, while pandas was used to convert this into a DataFrame.
* And at the end, the connection was closed to disconnect it from the database.

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Gitignore

* Since we had used a confidential password for the postgres database, we included it in out gitignore.

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**Data Pre-processing**

*Next slide*

Input data

* Our input data had 35 columns, each measuring different metrics relating to job employment and work. Some were personal details such as age, marital status, gender, while some were different facets of work life, such as salary, satisfaction, training, etc.
* Initially, we identified all these columns as features for our model, except for attrition, which we designated as our target. Most of the data were integers, with a few categorical columns

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Dropping columns

* For our first step in pre-processing, we identified 4 columns that we could remove straight away: employee count, over 18, and standard hours were the same for all employees, while employee number was just an identifier number that was not necessary for analysis.

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Encoding

* We used get dummies to encode any categorical data, and we created a function to encode columns that contained Boolean data (e.g. we changed all the “Yes” and “Male” to 1, and “No” and “Female” to 0).

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**LR Model**

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* After obtaining our new features from the target, we split the data into testing and training set then fit the training data into our Logistic regression model.
* We then made predictions on the training data and measured it up against the actual outcomes.

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**Evaluation**

* To evaluate our model, we generated a classification report and a confusion matrix generated with seaborn, as shown here.
* Our model has an accuracy of 83%, which is acceptable.
* Our model has an almost perfect recall when it comes to attrition; of the 309 cases of attrition in the testing data set, the model was accurately able to predict 304 of them as attrition.

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**Optimization**

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Optimization methods

* In order to optimize our model, we looked at a range of methods:
* We looked at pre-processing our input data further, to remove and reduce columns e.g. removing columns outright.
* We also looked at reducing the number of features so that only the most important ones are used in the model i.e. the features that have the greatest impact on attrition. We investigated 4 methods to discern the most important features, which we will explore later:
  + Comparing model coefficients
  + Permutation importance.
  + Recursive feature elimination (RFE)
  + Correlation Analysis.
* We had generated confusion matrices for all the methods but in the interest of time, we are just showing the accuracy scores at the end.

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Further pre-processing

* We looked at pre-processing the data further; from the source data, we noticed that there were 3 “rate” columns – hourly rate, daily rate, and monthly rate, as well as monthly income. We dropped these 3 columns as they were a source of redundancy. We kept the monthly income column as a signifier for salary.

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Model coefficients

* Comparing model coefficients by looking at the weights of model coefficients for each feature.
* We obtained the coefficients for our model in an array, before converting it into a dataframe, and exporting it as a bar plot.
* *Next slide*
* The bar plot shows that the most important features, by model weight, are: number of companies worked, years since last promotion, environment satisfaction, job satisfaction, and years with current manager.
* So we recreated our model, and ran it with only these 5 columns as features. We will discuss the evaluation of this later.

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Permutations

* We repeated this process but this time, we used permutation importance to obtain our most important features.
* Permutation Importance shuffles the values in a certain feature, and tests the model. If the performance of the model drops significantly, then that feature is important. However, if shuffling random values in a feature has minimal impact on performance, we can ignore that feature.
* *Next slide*
* We can see from the bar plot that the most important features are distance from home, years in current role, years with current manager, number of companies worked, and monthly income.
  + A lot of the features had an importance of 0, hence they do not appear on the plot.
* Again, we re-fitted our model with only these 5 features.

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Correlation analysis

* Correlation analysis identifies the variables that have a strong correlation with our target. (e.g. correlation of >0.8 signifies that 2 variables are strongly linked)
* For this, we created a correlation matrix, which is a table detailing how strongly 2 features are linked to each other
* *Next slide*
* We converted the matrix to a heatmap, as well as isolating the “attrition” column to identify the features that are strongly linked to attrition.
* Again, we ran our Logistic regression model with only the 5 most important features.

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Recursive feature elimination

* RFE ranks all the features in terms of importance and removes the least important feature. This process repeats until we are left with a desired number of features (we chose to look at the 5 most important features).
* *Next slide*
* RFE identified these features as being important, so we re-ran our model with these features.

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**Evaluation**

* Our base model had an accuracy score of 83%; the table shows the accuracy scores after we applied our various techniques.
* We evaluated the accuracy scores of our different optimization methods and discovered that RFE performed best, with an accuracy of 85%.

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**Summary**

* Feature importance did not seem to have a profound impact on accuracy, as the methods we used resulted in closely similar accuracies, despite their strengths and weaknesses.
  + However we did notice that the accuracy and precision scores for identifying “no attrition” were low across the board. In fact, the coefficient analysis model had a score of 0% in both precision and recall for “no attrition” but high scores for “yes” attrition, but it misidentifies the “no attrition” employees.
  + Correlation analysis performed fairly well, but correlation does not necessarily signify causation; we would be getting an accurate result but trying to apply the model in real life and use the highlighted features to address employee attrition may not be successful.
* Further methods we could use could involve grouping data into “bin”, to reduce the number of records, selecting more important features; we used 5 for our project as an arbitrary number.
* Permutation importance and RFE both use iterative methods when they run. We set the number of iterations to 100 as a standard. More iterations could provide more accurate results, but would take up more time.
* We attempted to combine further pre-processing with RFE but the result ended up with the same accuracy; combining other methods to reduce the number of features may also be a potential future target.

‘’’At the conclusion of our analysis, we realized that we have achieved 85% accuracy after a optimisation based on Recursive Feature Elimination (RFE), which is based on the idea to repeatedly construct a model and choose either the best or worst performing feature, setting the feature aside and then repeating the process with the rest of the features. This process is applied until all features in the dataset are exhausted. Some of further analysis includes:

1. Binning data – Although used to reduce errors, it may get complicated based on the dataset we have got
2. Feature Selection – This would help us in known irrelevant features and picks the best set of features for better dimensionality
3. Closer look at pre-processing
4. Combining methods

Whether an employee is going to stay or leave a company, his or her answer is just binomial i.e. it can be “YES” or “NO”. So, we can see our dependent variable Employee Attrition is just a categorical variable. In the case of a dependent categorical variable, we can not use linear regression, in that case, we have to use “LOGISTIC REGRESSION“.’’’