Identifying and Analyzing Traits Associated with High Performers

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Executive Summary

Glentel is a mobile phone retailer that operates 350+ wireless outlets across Canada. The primary issue they are facing is high employee churn, which is costly. We propose to use natural language processing techniques to extract information from employees' resumes such as education, employment history and job hopping. The Master of Data Science (MDS) team will extract such features and provide an analysis of the extent to which these features contribute to employee performance. This will provide valuable insight to help Glentel decrease employee churn and optimize their hiring process.

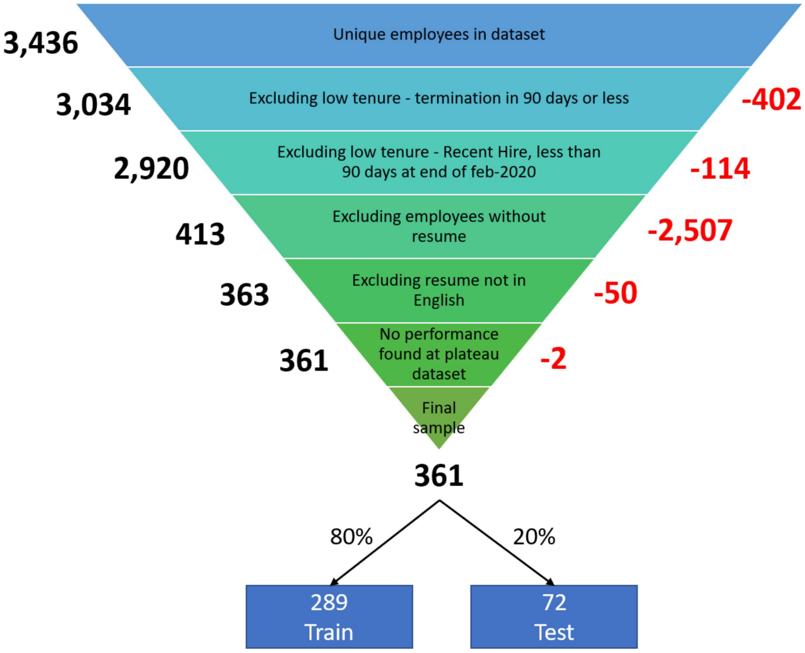
Data Science Problem

Glentel has requested tools to introduce evidence-based procedure to their hiring process. In addition to current COVID 19 crisis, it is critical that retail organizations have a deep understanding of their workforce. The question our team would like to help Glentel answer is **"What are the traits that are associated with employees who become high performers?"** We want to provide Glentel with a quantitative data analysis about their staff to make relevant and timely decisions that could help them decrease employee churn and optimize their workforce.

Data

Glentel has provided our team with unstructured data of 413 resumes and structured tabular data such as activations, compensation tier and termination reasons. Our team has several data challenges that we will need to overcome. First, due to no universal resume standards each resume is unique with information spread across the document. Additionally, we have documents in PDF, doc, docx, rtf and txt forms. The solution we are working on is creating a resume scanner which will transform the resumes into plain text.

Second, some of the resumes are blank or in an unreadable form. Based off of a sample size of 150 resumes we estimate that 5%-8% of the total resumes might be unusable and need to be discarded. Third, due to Canada being a bilingual nation some of the resumes are in French. We have asked our partner, Glentel, to prioritize the English ones. Our model will only consider English resumes for now; however, further into the project we can look into translating the French resumes into English time permitting if need be. Finally, after discussing this with the partner, we have narrowed down our study to employees who worked at Glentel for at least 3 months, have a resume on file and performance data. Moreover, during modeling, we will be splitting the data into train and test splits in order to examine to what extent the patterns we identify in the training set generalize on the test set. So, the final training size we are left with is 289, as shown in Figure 1. Due to a lack of resumes' attributes in tabular form, a good portion of the MDS team's time and resources will be utilized on data cleaning and feature extracting.

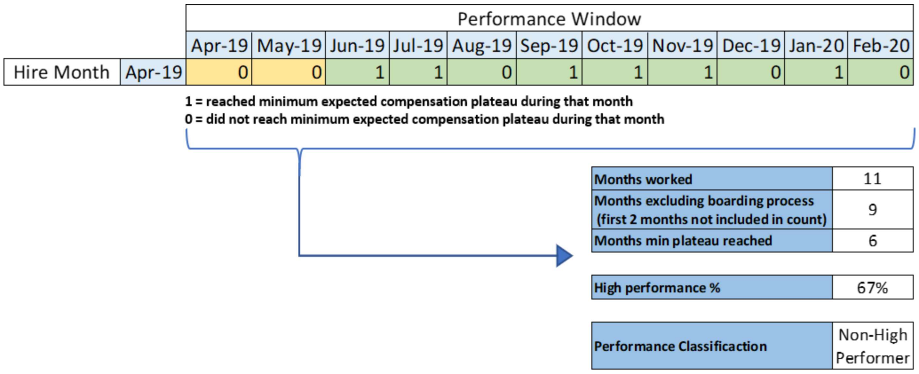


3,436
Unique employees in dataset
3,034
Excluding low tenure - termination in 90 days or less
-402
2,920
Excluding low tenure - Recent Hire, less than 90 days at end of feb-2020
-114
413
Excluding employees without resume
-2,507
363
Excluding resume not in English
-50
361
No performance found at plateau dataset
-2
Final sample
361
80%
20%
289 Train
72 Test

Figure 1. Granularity of sample size

Target

The main target for our model's outcome is to predict employee performance in binary form: a high performer (1) or a non-high performer (0). Glentel has recommended that we use pay achievement levels as a proxy for performance. Each month, an employee can achieve a pay level between 0 and 4 depending on how many customer phone activations they attain. In Jan, Feb, Apr, May, Jul and Oct, a pay achievement level of at least 2 must be achieved and Mar, Jun, Aug, Sept, Nov and Dec a pay achievement level of at least 3 must be accomplished for an employee to gain a binary high performer flag for that month. Additionally, an employee must achieve at least an average of 75% of their monthly high-performance flags in order to reach an overall target of high performer. The first two months of employee performance data will be removed from their average as this is considered an “adjustment” period.



		Performance Window										
		Apr-19	May-19	Jun-19	Jul-19	Aug-19	Sep-19	Oct-19	Nov-19	Dec-19	Jan-20	Feb-20
Hire Month	Apr-19	0	0	1	1	0	1	1	1	0	1	0

1 = reached minimum expected compensation plateau during that month
0 = did not reach minimum expected compensation plateau during that month

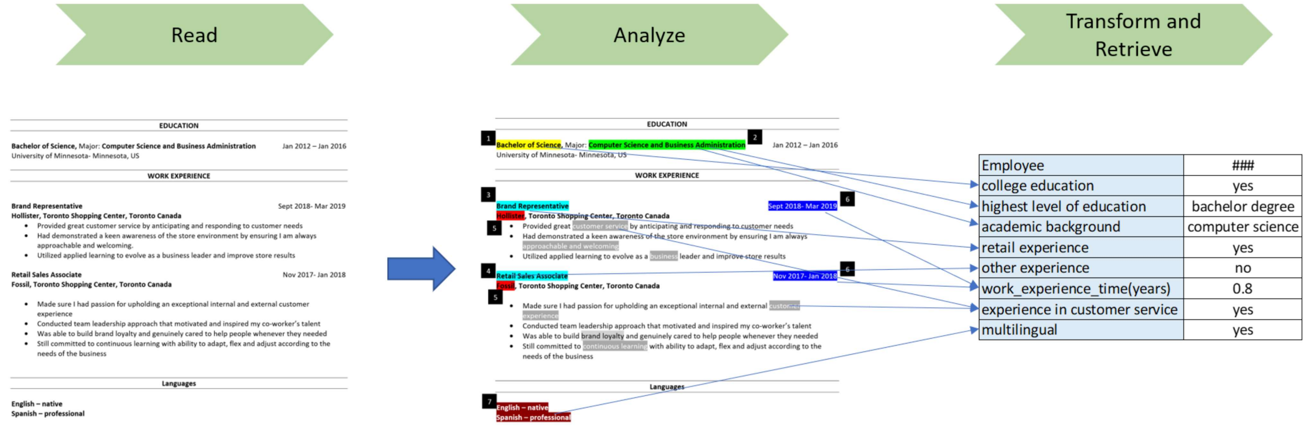
Months worked	11
Months excluding boarding process (first 2 months not included in count)	9
Months min plateau reached	6
High performance %	67%
Performance Classificaction	Non-High Performer

Figure 2. Example target calculation

Figure 2 shows a sample calculation of a fictitious Glentel employee and how it was determined if that employee was considered high performer or non-high performer. The fictitious employee worked 11 months; the first two months will be excluded which narrows the performance window to 9 months. They received a high performance flag in 6 of those 9 months which results in a 67% high performance average and because their average is below 75% their final performance classification is non high performed.

Our Approach

We propose to use natural language processing (NLP) techniques to extract information and find patterns in resumes. Our proposed approach has five major components: plain text extraction, preprocessing and exploratory data analysis (EDA), feature engineering, modeling, evaluation and interpretation. Since not all resumes are in plain text format the first step is to extract plain text from resumes to create a corpus of plain text resumes. The second step is text preprocessing and EDA. In this step we preprocess the text (e.g., removing commonly occurring uninformative words such as ‘the’). Moreover, we also carry out exploratory data analysis to examine obvious patterns occurring in the resumes. Additionally, we will also use topic modelling to extract key words, potential features and insights in addition to retrieving information from the resumes and count vectorizing the plain text. In the third step, we will extract other features from these resumes such as education level, experience, job hopping, and language along with supplementary tabular date such as re-hire or referral. This will allow our model to take into consideration key features other than word occurrences in the resumes. In the fourth step, we will build models utilizing the resumes plain text plus the extracted features starting with our base model of logistic regression and then expanding into an ensemble of models such as support vector machine (SVM), Random Forest and Multilayer perceptron(simple neural network) to gain insight about the features of our models. In the final step after selecting the final model or models, we would like to make our models into "white box" models instead of "black box" models using tools such as "eil5" and "SHAP". We expect to use a mixture of bag-of-words features as well as features we engineered from the insights of the topic modeling, Glentel's expertise and data science team's creativity.



EDUCATION

Bachelor of Science, Major: **Computer Science and Business Administration** Jan 2012 – Jan 2016
University of Minnesota- Minnesota, US

WORK EXPERIENCE

Brand Representative Sept 2018- Mar 2019
Hollister, Toronto Shopping Center, Toronto Canada

- Provided great customer service by anticipating and responding to customer needs
- Had demonstrated a keen awareness of the store environment by ensuring I am always approachable and welcoming.
- Utilized applied learning to evolve as a business leader and improve store results

Retail Sales Associate Nov 2017- Jan 2018
Fossil, Toronto Shopping Center, Toronto Canada

- Made sure I had passion for upholding an exceptional internal and external customer experience
- Conducted team leadership approach that motivated and inspired my co-worker's talent
- Was able to build brand loyalty and genuinely cared to help people whenever they needed
- Still committed to continuous learning with ability to adapt, flex and adjust according to the needs of the business

Languages

English – native
Spanish – professional

Employee	###
college education	yes
highest level of education	bachelor degree
academic background	computer science
retail experience	yes
other experience	no
work_experience_time(years)	0.8
experience in customer service	yes
multilingual	yes

Figure 3. Example resume feature extraction

Figure 3 shows an example of potential feature extraction the MDS team could perform on the Glentel resumes.

Data Product

Our group will provide Glentel with the MDS GitHub repository that contains all reports, models and scripts. The final report will consist of qualitative recommendations on the traits of high performing employees that Glentel might want to consider when hiring future employees. The models will include the models, outputs, and interpretations that the MDS team used to develop those insight in the final report. The scripts will clean and wrangle the resume data into machine learning ready spreadsheets.

Machine Learning Pipeline

The machine learning pipeline will be as follows:

1. Feature scaling (massaging our features to fit uniformly into our model)

2. Cross validation (better generalization)
3. Hyperparameter (tuning how the model interprets data)
4. Feature selection (selecting the attributes of employees)
5. Model training (prediction)
6. Model interpretation (drawing insights from the model and jugging performance)

our model:

- **Baseline**: logistic regression
- Ensemble of additional classifiers such as:
  - SVM
  - Random Forest
  - Multilayer perceptron

Timeline

Figure 4 shows our proposed timeline for the lifecycle of the project.

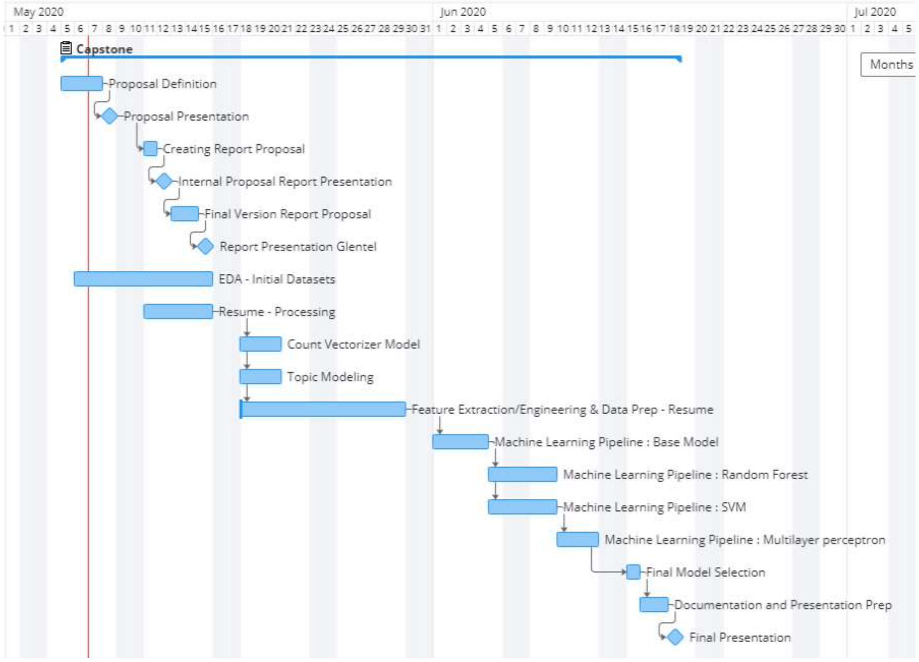


Figure 4. MDS team proposed gantt chart