**Canadian Wages and Social Change**

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**Table of Contents**

[Abstract 2](#_Toc168938966)

[Literature Review 3](#_Toc168938967)

[Introduction 3](#_Toc168938968)

[Articles 4](#_Toc168938969)

[1 4](#_Toc168938970)

[2 5](#_Toc168938971)

[3 6](#_Toc168938972)

[Conclusion 7](#_Toc168938973)

[Methodology 7](#_Toc168938974)

[GitHub 7](#_Toc168938975)

[Understanding the Dataset 7](#_Toc168938976)

[Preparing the Dataset 10](#_Toc168938977)

[Exploratory Data Analysis (EDA) 11](#_Toc168938978)

[Feature Selection Techniques 13](#_Toc168938979)

[Missing Data 13](#_Toc168938980)

[Low Variance 13](#_Toc168938981)

[Correlation 14](#_Toc168938982)

[Random Forest Dimensionality Reduction 18](#_Toc168938983)

[Selected Features 20](#_Toc168938984)

[Outliers 21](#_Toc168938985)

[Approach 23](#_Toc168938986)

[Assumptions of Linear Regression 24](#_Toc168938987)

[Knowledge Induction 26](#_Toc168938988)

[References 29](#_Toc168938989)

# Abstract

According to the 2021 Census, it is estimated that 21% of Canadians earn at least $100, 000 per year (Statista, 2024). In comparison, 9.9% of the population in Canada lives in poverty, with 5% in deep poverty as of 2022 (Government of Canada, Statistics Canada, 2024). With the Consumer Price Index increasing to 2.9% in March 2024 (Government of Canada, Statistics Canada, 2024), many Canadians may experience increased challenges with the cost of living as their spending power declines. With a national average hourly wage of $33.55 in 2023 (Government of Canada, Statistics Canada, 2024), earning power is a conversation of mutual interest to both the government and its labor force. For governments, it drives strategic planning that can create gender equality, lower poverty, and stimulate economic development. For employees, these factors can be used to retrain, transition, or navigate into a second career. Overall, it is imperative to the betterment of both parties that they comprehend these variables. The goal of this paper is to identify the most important features that likely contribute to an hourly wage that is greater than the national average.

This research paper will use the Labour Force Survey: Public Use Micro File (Government of Canada, Statistics Canada, 2024) dataset between January and April 2024 to identify key factors that can be used to predict an employee’s hourly wage. The data is filtered for employees who have one single full-time permanent job, and do not attend school. The factors can be classified as either human capital, social capital, or labour market (Wang, Liao, & Miu 2022). Limitations of the sample are that the hourly wage is only available for employees – emitting those that are self-employed, and some columns contain missing values. Regarding the latter, feature selection techniques are used to reduce the dimensions, include filtering for low variance, high correlation, missing values, and Random Forest dimensionality reduction.

Non-linear regression supervised machine learning models will be used because the assumptions of linearity were not met to use the linear regression models. These models, Regression Trees, Random Forest Regressor, Support Vector Regression, KNN, and XGBoost, will be facilitated using the Python programming language to conduct analyses and computations. Data science packages within Python, such as pandas, numpy, sklearn, scipy, xgboost, statsmodels, mlxtend, ydata\_profiling, matplotlib, and seaborn will be used to understand and explore the data, conduct predictive modelling, validation, and generate visualizations. Statistical techniques such as parametric and non-parametric tests will be used to identify any significant differences between the machine learning models.

The research questions that will be explored are:

1. What are the top ten variables that contribute to an hourly wage?
2. What do data mining techniques, specifically association rules, reveal about the data?
3. Which machine learning model, with tuned hyper parameters, will have strong a ?

# Literature Review

## Introduction

The freedom to choose your own destiny is the essence of the human spirit. The ability to recognize and change the trajectory of your future based on labour force statistics is a powerful concept. This might be the first study in Canada that uses machine learning to predict a general hourly wage based on data presented in the Labour Force Survey: Public Use Micro File (Government of Canada, Statistics Canada, 2024) (LFS) between January and April 2024. Thus, it is important to draw insights from similar research, and acknowledge the work of others that could potentially be used in answering the following research questions:

1. What are the top ten variables that contribute to an hourly wage?
2. What do data mining techniques, specifically association rules, reveal about the data?
3. Which machine learning model, with tuned hyper parameters, will have strong a ?

The three classes of variables of most important to this research are based on the ideas of human and social capital, and the labour market. Human capital circles around education and training (Matbouli, Y. T., & Alghamdi, S. M. 2022), social capital places emphasis on an individual’s social relationships (Putnam 1995), and the labour market ultimately embraces economic cycles.

## Articles

### 1

In this peer reviewed scholarly study, “Statistical Machine Learning Regression Models for Salary Prediction Featuring Economy Wide Activities and Occupations” (Matbouli, Y. T., & Alghamdi, S. M. 2022), five machine learning regression techniques were used to predict annual salaries based on many limited surveys from the Saudi labour market, in 2020, that are mapped to the International Standard Classification of Occupations (ISCO-08). The objective was to find the best algorithm for predictions across job titles. A striking difference between this survey and the LFS is that the Saudi survey is aggregated and thus the dependent variable, salary, is given as a mean, whereas the LFS provides the hourly wage on an individual level. Furthermore, the LFS dataset is more robust, as no mappings need to be done with other datasets. The Saudi paper distinguishes between its independent variables as organizational characteristic and occupational features and touches on theories on human capital (merits of an individual) and the labour market (features of an organization). One interesting note on the Saudi paper was that the researchers assumed that high skilled workers have more education, and less skilled workers have less education, and thus eliminating the education feature. In terms of machine learning, both linear and non-linear regression models were used, in the R programming language, such as Multiple Linear Regression, Artificial Neural Networks (ANN), Tree Regression, Support Vector Regression, and Bayesian-based machine learning using the Gaussian Process Regression. The performance evaluation metrics used were root-mean-square error (RMSE), R-squared () and mean absolute error (MAE). The finding of the paper was that non-linear models worked the best, and ANN was one such model with a of 94%.

### 2

In this second peer reviewed scholarly article, “Prediction of Factors Influencing the Starting Salary of College Graduates Based on Machine Learning” (Wang, Liao, & Miu 2022), looks to uncover the factors that influence salaries of college graduates in China. The data comes from Sichuan, a financial college, between October 2019 and December 31st, 2020. A key discussion in this paper was how certain attributes were classified. The features were categorized either as being associated with human capital, social capital, or the labour market. These groupings allow one to more easily understand how certain factors can have an impact on salary, and to have a broader discussion without worrying about the specificities of a particular attribute. As discussed previously, human capital is discussed in terms of as high academic achievements, social capital is discussed as a social network where resources can be exchanged, and the labour market is discussed as the segmentation between public and private firms. In contrast to the Saudi paper, this paper uses classification techniques to predict whether a starting salary for a college graduate is high or low. The interaction recorded between the three categories was executed in R by five machine learning models: Logistic Regression, Support Vector Machine (SVM), Naïve Bayes, Regression Tree, Random Forest (RF), and XGBoost. The latter of these models proved to be the best at determining the starting salary of a college graduate with an accuracy of 92.5%. The metrics for validation were precession, recall, accuracy and F1 score. One interesting observation was that the dependent variable was not balanced so the sampling method was divided into under sampling, oversampling and combined sampling. From the paper’s correlation analysis, backward stepwise logistic regression, and p-value calculations, the key findings on what the impacts on salary were: high education levels in fields like engineering, gender, employment characteristics such as in geographical areas, and industries like finance.

### 3

In this third peer reviewed scholarly article, “Machine Learning Based Method for Deciding Internal Value of Talent” (Loyarte-López & García-Olaizola 2022). This paper looks at predicting salary using artificial intelligence to help HR in making decisions regarding equitable pay based on historical metrics. The dataset used in this research is of roughly a few hundred rows from a European research organization, from January 2021, that has characteristics of its employees, the researchers. Most notably that dataset contains 40% of researchers holding a doctoral degree. The goal of the paper was to identify the key factors that led to the influence of salary. This information would then be used at the time of hiring, and at the time of possible salary increases. The variables in the dataset are all related to personal characteristics such as gender, work, education, and experience. Again, a common theme with the other two articles above is that the independent variables can be categorized into human capital, social capital and the labour market. Regression machine learning models were used in this analysis, and they were: Linear, Ridge, Lasso, SVM, Gradient Boosting Regressor (GBR), RF, Neural Networks, Bayesian Ridge, Ada Boost, and KNN. In addition, K-Folds folds was utilized with 10 folds for cross-validation to overcome the small sample size. The model that performed the best was the GBR to predict salary increases, and RF was a better model used at the time of recruitment. The evaluation metrics that were used were the coefficient of determination and absolute mean square. Both winning models had an of greater than 90%. The features that were important were education and professional experience. Interestingly, gender was below a certain threshold to be considered as important. Overall, this paper provides valuable insights in terms of its methodologies used and the features it found to be important.

## 4

In this fourth peer reviewed scholarly article, “The influence of computer network technology on national income distribution under the background of social economy” (2021 Zhu and Luo), it uses association rules and k-means to mine the national income dataset, which contains approximately 30, 000 records, from China between 1952 to 2015. The study had ten features, such as salary, education, sex, marital status, occupation, and other variables related to work, to conduct data mining. The support and confidence levels were set at 25% and 80% respectively, and along with the upper antecedent limit set at 5. The paper used two induction algorithms, but the one of interest is the Apriori one. It determined that marital status and education had the strongest correlation, respectively, via the association rules.

## Conclusion

After completing the literature review of past work, this paper will use many of the same machine learning models to tackle the research questions outlined above. In addition, common metrics to assess the validity of the models will be used in this research will be , AIC, and RMSE. The first three articles identify features such as education, industry, and experience, and sex that may be important in predicting salary. In addition, all articles identified that non-linear regression was the best approach in terms of evaluation metrics, and there was some overlap in the supervised machine learning models deployed such as Support Vector Regression, Regression Tree, Random Forest Regressor, and XGBoost. Also, from conducting this literature review it has become abundantly clear that not much research exists in this field, especially in Canada, and thus a very naturally compelling argument to conduct this research and present its findings. Therefore, given the past research, the methodology below was developed to tackle the research questions outlined above.

# Methodology

# GitHub

<https://github.com/harpkang/CIND820_CAPSTONE/tree/main>

# Understanding the Dataset

The “Labour Force Survey: Public Use Microdata File” (LFS) dataset can be found via the Statistic Canada’s website <https://doi.org/10.25318/71M0001X-eng>. The complete dataset is comprised of concatenating 4 files representing 4 months (January, February, March, and April) of 2024. The unprocessed multivariate dataset contains 442, 576 records made up of 60 features. Please see Figure 1 below for a complete list of all the features. The LFS, which is an observational study conducted each month across Canada, is vital as it the basis for determining important economic indicators such as the unemployment rate. This rich dataset is constructed by compiling survey information of individual Canadians each month. The information contains demographic characteristics such as age, gender, employment status, and labour market characteristics such as the employment status, profession, and industry to name a few. The survey is randomly taken of 56, 000 households across Canada of all household members over the age of 15 (Government of Canada, Statistics Canada, 2024). It is mandatory by law, the Statistic Act, to complete the LFS in good faith (Government of Canada, Statistics Canada, 2024). The random and independent sampling design is a combination of stratified sampling, where the provinces are the strata, and then clustering, where geographic areas are further granularized to reduce bias and error (Government of Canada, Statistics Canada, 2024). Stratifying ensures that the diversity of the population is representative, and clustering allows for cost efficiency.

**Figure 1 – Variable Descriptions (descriptions were collected from the data dictionary)**

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable** | **Description** | **Data** | **Data Type** |
| AGE\_12 | Five-year age group of respondent | Qualitative | Ordinal |
| AHRSMAIN | Actual hours worked per week at main job | Quantitative | Continuous |
| ATOTHRS | Actual hours worked per week at all jobs | Quantitative | Continuous |
| CMA | Nine largest CMAs | Qualitative | Nominal |
| COWMAIN | Class of worker, main job | Qualitative | Nominal |
| EDUC | Highest educational attainment | Qualitative | Ordinal |
| EFAMTYPE | Type of economic family | Qualitative | Nominal |
| ESTSIZE | Establishment size | Qualitative | Ordinal |
| FINALWT | Standard final weight | Quantitative | Continuous |
| FIRMSIZE | Firm size | Qualitative | Ordinal |
| FTPTMAIN | Full- or part-time status at main or only job | Qualitative | Nominal |
| HRLYEARN | Usual hourly wages | Quantitative | Continuous |
| IMMIG | Immigrant status | Qualitative | Nominal |
| LFSSTAT | Labour force status | Qualitative | Nominal |
| MARSTAT | Marital status of respondent | Qualitative | Nominal |
| MJH | Single or multiple jobholder | Qualitative | Nominal |
| NAICS\_21 | Industry of main job | Qualitative | Nominal |
| NOC\_10 | Occupation at main job (noc\_10) | Qualitative | Nominal |
| NOC\_43 | Occupation at main job (noc\_43) | Qualitative | Nominal |
| PERMTEMP | Job permanency | Qualitative | Nominal |
| PROV | Province of Residence | Qualitative | Nominal |
| REC\_NUM | Order of record in file | Qualitative | Nominal |
| SCHOOLN | Current student status | Qualitative | Nominal |
| SEX | Sex of respondent | Qualitative | Nominal |
| SURVMNTH | Survey month | Qualitative | Ordinal |
| SURVYEAR | Survey year | Qualitative | Ordinal |
| TENURE | Job tenure with current employer | Quantitative | Discrete |
| UHRSMAIN | Usual hours worked per week at main job | Quantitative | Continuous |
| UNION | Union status | Qualitative | Nominal |
| UTOTHRS | Usual hours worked per week at all jobs | Quantitative | Continuous |
| HRSAWAY | Hours away from work, part-week absence only | Quantitative | Continuous |
| PAIDOT | Paid overtime hours in reference week | Quantitative | Continuous |
| UNPAIDOT | Unpaid overtime hours in reference week | Quantitative | Continuous |
| XTRAHRS | Number of overtime or extra hours worked | Quantitative | Continuous |
| AGYOWNK | Age of youngest child | Qualitative | Ordinal |
| AGE\_6 | Age in 2 and 3 year groups, 15 to 29 | Qualitative | Ordinal |
| YAWAY | Reason for part-week absence | Qualitative | Nominal |
| PAYAWAY | Paid for time off, full-week absence only | Qualitative | Nominal |
| WKSAWAY | Number of weeks absent from work | Qualitative | Nominal |
| YABSENT | Reason of absence, full week | Qualitative | Nominal |
| AVAILABL | Availability during the reference week | Qualitative | Nominal |
| DURJLESS | Duration of joblessness | Qualitative | Discrete |
| DURUNEMP | Duration of unemployment | Qualitative | Discrete |
| EVERWORK | Identifies if a person has worked in the last year | Qualitative | Nominal |
| FLOWUNEM | Flows into unemployment | Qualitative | Nominal |
| FTPTLAST | Full- or part-time status of last job | Qualitative | Nominal |
| LKANSADS | Unemployed, placed or answered ads | Qualitative | Nominal |
| LKATADS | Unemployed, looked at job ads | Qualitative | Nominal |
| LKEMPLOY | Unemployed, checked with employers directly | Qualitative | Nominal |
| LKOTHERN | Unemployed, other methods | Qualitative | Nominal |
| LKPUBAG | Unemployed, used public employment agency | Qualitative | Nominal |
| LKRELS | Unemployed, checked with friends or relatives | Qualitative | Nominal |
| PREVTEN | Job tenure with previous employer | Quantitative | Discrete |
| PRIORACT | Main activity before started looking for work | Qualitative | Nominal |
| TLOLOOK | Temporary layoff, looked for work during the last four weeks | Qualitative | Nominal |
| UNEMFTPT | Job seekers by type of work sought and temporary layoffs by work status of last job | Qualitative | Nominal |
| WHYLEFTN | Reason for leaving job during previous year (whyleftn) | Qualitative | Nominal |
| WHYLEFTO | Reason for leaving job during previous year (whylefto) | Qualitative | Nominal |
| WHYPT | Reason for part-time work | Qualitative | Nominal |
| YNOLOOK | Reason for not looking for work during the reference week | Qualitative | Nominal |

# Preparing the Dataset

The dataset was filtered by using 4 independent variables and then eliminating them to achieve the desired working dataset. First, the dependent variable ‘HRLYEARN’ was filtered to have all the null values removed. Second, the data set was filtered for individuals that only held one job, which is measured by the variable ‘MJH’. Third, the dataset was filtered to only include non-students by using the ‘SCHOOLN’ variable. Fourth, the variable ‘FTPTMAIN’ was used to filter for full-time employees. Finally, the variable ‘PERMTEMP’ was filtered so that the dataset would only have permanent positions. Ultimately, what was achieved was a dataset that represented full-time employees who had one main job, were working full-time on a permanent basis, and were not in school. The employee’s main job refers to the job where the usual hours worked far exceeds any other hours worked at one or more other jobs. Furthermore, usual hours refer to what the employee is contractually obligated to work not including overtime. This contrasts with actual hours, which adjusts the usual hours with any absences from work. Working full-time reflects the fact that the employee was working at least thirty hours a week. These steps reduced the number of records in the working dataset to 155, 250. In any type of regression modelling, there is a rule of thumb that states that the number of samples in a dataset should be greater than or equal to 50 + (8 x Independent Variables), which is the case in this paper.

## Exploratory Data Analysis (EDA)

The ydata\_profiling library in python, generates a report that gives a quick synopsis of the features in the dataset with visuals. A summary below was prepared to highlight the descriptive statistics of the 60 features ranked by the missing values in Figure 2.

**Figure 2 – Descriptive Summary**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **Mean** | **Median** | **Min** | **Max** | **Standard Deviation** | **Missing Values %** |
| AGE\_12 |  | 6 | 1 | 10 | 2.35 | 0 |
| AHRSMAIN | 36.22 | 40 | 0 | 99 | 13.46 | 0 |
| ATOTHRS | 36.22 | 40 | 0 | 99 | 13.47 | 0 |
| CMA |  |  | 0 | 9 | 2.8 | 0 |
| COWMAIN |  |  | 1 | 2 | 0.45 | 0 |
| EDUC |  | 4 | 0 | 6 | 1.38 | 0 |
| EFAMTYPE |  |  | 1 | 18 | 4.95 | 0 |
| ESTSIZE |  | 2 | 1 | 4 | 1.05 | 0 |
| FINALWT | 315.26 | 220 | 1 | 2795 | 289.2 | 0 |
| FIRMSIZE |  | 4 | 1 | 4 | 1.12 | 0 |
| FTPTMAIN |  |  | 1 | 1 | 0 | 0 |
| HRLYEARN | 37.21 | 32.79 | 5.77 | 208.33 | 18.55 | 0 |
| IMMIG |  |  | 1 | 3 | 0.61 | 0 |
| LFSSTAT |  |  | 1 | 2 | 0.27 | 0 |
| MARSTAT |  |  | 1 | 6 | 2.11 | 0 |
| MJH |  |  | 1 | 1 | 0 | 0 |
| NAICS\_21 |  |  | 1 | 21 | 5.01 | 0 |
| NOC\_10 |  |  | 1 | 10 | 2.75 | 0 |
| NOC\_43 |  |  | 1 | 43 | 13.01 | 0 |
| PERMTEMP |  |  | 1 | 1 | 0 | 0 |
| PROV |  |  | 10 | 59 | 14.36 | 0 |
| REC\_NUM |  |  | 2 | 112082 | 31965.5 | 0 |
| SCHOOLN |  |  | 1 | 1 | 0 | 0 |
| SEX |  |  | 1 | 2 | 0.5 | 0 |
| SURVMNTH |  | 3 | 1 | 4 | 1.12 | 0 |
| SURVYEAR |  | 2024 | 2024 | 2024 | 0 | 0 |
| TENURE | 100.13 | 73 | 1 | 240 | 82.95 | 0 |
| UHRSMAIN | 39.38 | 40 | 30 | 99 | 5.79 | 0 |
| UNION |  |  | 1 | 3 | 0.93 | 0 |
| UTOTHRS | 39.38 | 40 | 30 | 99 | 5.79 | 0 |
| HRSAWAY | 1.54 | 0 | 0 | 99 | 4.83 | 7.8 |
| PAIDOT | 0.89 | 0 | 0 | 80 | 3.7 | 7.8 |
| UNPAIDOT | 0.76 | 0 | 0 | 98 | 3.05 | 7.8 |
| XTRAHRS | 1.64 | 0 | 0 | 98 | 4.71 | 7.8 |
| AGYOWNK |  | 2 | 1 | 4 | 1.08 | 56.75 |
| AGE\_6 |  | 5 | 1 | 6 | 1.2 | 84.04 |
| YAWAY |  |  | 0 | 4 | 1.04 | 86.93 |
| PAYAWAY |  |  | 1 | 2 | 0.5 | 92.2 |
| WKSAWAY |  |  | 1 | 99 | 24.74 | 92.2 |
| YABSENT |  |  | 0 | 3 | 0.96 | 92.2 |
| AVAILABL |  |  |  |  |  | 100 |
| DURJLESS |  |  |  |  |  | 100 |
| DURUNEMP |  |  |  |  |  | 100 |
| EVERWORK |  |  |  |  |  | 100 |
| FLOWUNEM |  |  |  |  |  | 100 |
| FTPTLAST |  |  |  |  |  | 100 |
| LKANSADS |  |  |  |  |  | 100 |
| LKATADS |  |  |  |  |  | 100 |
| LKEMPLOY |  |  |  |  |  | 100 |
| LKOTHERN |  |  |  |  |  | 100 |
| LKPUBAG |  |  |  |  |  | 100 |
| LKRELS |  |  |  |  |  | 100 |
| PREVTEN |  |  |  |  |  | 100 |
| PRIORACT |  |  |  |  |  | 100 |
| TLOLOOK |  |  |  |  |  | 100 |
| UNEMFTPT |  |  |  |  |  | 100 |
| WHYLEFTN |  |  |  |  |  | 100 |
| WHYLEFTO |  |  |  |  |  | 100 |
| WHYPT |  |  |  |  |  | 100 |
| YNOLOOK |  |  |  |  |  | 100 |

There are 4 variables that can be binarized to simplify the working dataset. First is the marital status (‘MARSTAT’), which is a categorical variable with six levels. It is best to binarize this feature as married or not because the working dataset as is contains 47% married, 30% single, 15% Common-law, with the percentages dwindling downwards in the remaining classifications. Keeping this variable either at 0 or 1 will simplify the algorithm. Secondly, the immigrant status variable (‘IMMIG’) currently has three categories. Categories 1 and 2 describe immigrants who landed less than and more than 10 years ago, and the third category is for non-immigrants. Since this research is not focusing on distinguishing between classes of immigrants, this feature can be mapped to either 1 meaning an individual is an immigrant or 0 meaning otherwise. Finally, the variable ‘CMA’, which indicates on the survey whether an individual is from a major metropolitan area, has 9 categories that represent major cities in Canada such as Toronto, Vancouver, and Montreal. For efficiency these 9 categories will be marked by 1, if an individual resides in these cities or 0 otherwise.

## Feature Selection Techniques

### Missing Data

One anomaly that stands out is that there are twenty variables that contain no values at all, five variables that have 80% of its values missing, and one variable that has over 50% of its values missing. In total there are 26 variables that can be eliminated from this dataset (the bottom 26 variables in Figure 2 above).

### Low Variance

Furthermore, variables record number, survey month, survey year, and standard final weight (‘REC\_NUM’, ‘SURVMNTH’, ‘SURVYEAR’, ‘FINALWT’) can also be eliminated because they do not provide any information towards the prediction of the target variable. The four variables that were used to filter the dataset, ‘MJH’, ‘SCHOOLN’, ‘FTPTMAIN’, and ‘PERMTEMP’, naturally have an imbalance and will be eliminated from the dataset. These imbalances can be seen in the last four rows of Figure 3 below. In the same figure, the first five variables show a high imbalance and therefore, those variables will be removed from the dataset. In addition, continuous variables ‘PAIDOT’ and ‘UNPAIDOT’, which represent paid and unpaid overtime hours, show a low variance because both have zero hours worked as 79% of their respective distributions. Thus, these two variables can be eliminated from the working dataset. The labour force status (‘LFSSTAT’) nominal variable, in the working dataset, contains two categories, which are employed and not absent from work, and employed and absent from work. This research paper will assume that everyone is employed, and disregard whether or not an employee is absent or not because it does not provide any valuable information.

**Figure 3 – Variable Imbalances**

|  |  |
| --- | --- |
| **Variables** | **Imbalance** |
| XTRAHRS | 80% |
| HRSAWAY | 86% |
| PAIDOT | 90% |
| UNPAIDOT | 90% |
| LFSSTAT | 92% |
| FTPTMAIN | 100% |
| MJH | 100% |
| PERMTEMP | 100% |
| SCHOOLN | 100% |

### Correlation

Multicollinearity in machine learning models, such as regression, can have varying degrees of effects on the outcome of the analysis. The risk of overfitting the model is one of these concerns, which can lead to the model not being able to perform well on unseen data. In addition, the sum of squares for new features will be small because they will contribute little to no information. Thus, it is important to identify and eliminate highly correlated features.

The code to generate the profiling report mentioned above has a default value that auto detects data types to apply different correlation methods. Spearman Correlation is used when two numerical features are assessed, and Cramer’s V association coefficient is used for both when two categorical features are assessed, and when numerical and categorical features are assessed together. From analyzing the correlation table generated by the profile report, a correlation warning appears, if the correlation coefficient is greater than the default value of 0.50. This research paper will continue to adhere to this 0.50 default threshold. Please see the correlation matrix below in Figure 4. The matrix was generated, after removing the variables that contained low variance from above. The heat map makes it easy to identify visually how strong the correlations are between multiple variables at a single glance. Dark blue indicates a strong positive correlation and dark red demonstrates a strong negative correlation.

**Figure 4 – Correlation Matrix**

A diagram of a number of men and women

Description automatically generated with medium confidence

As we can see in Figure 5 below, there are few variables that were highly correlated. All the variables in the left column of table are the variables that were selected to remain in the dataset, and in the right column to be eliminated. The first two ordinal features that are correlated are firm size (‘FIRMSIZE’) and establishment size (‘ESTSIZE’). The difference between the two features is that the variable firm size documents the total number of employees at all locations of the organization, whereas the measure establishment size records the total number of employees at only the individual’s location of employment regardless of whether the employer has other locations. The nominal variables ‘EFAMTYPE’, which is made up of various classifications of family members working or not along with ages of children, and ‘MARSTAT’ classifying marital status are also correlated. The nominal variables ‘COWMAIN’ and ‘NAICS\_21’, are correlated, and their respective classifications identify whether the firm is either public or private, and the North American Industry Classification System. Furthermore, variables ‘NOC\_10’ and ‘NOC\_43’ are nominal variables, with many categories breaking down industries further by profession, that are correlated with the nominal variable ‘SEX’, which represents gender as either male or female. The five other correlated continuous variables expressed in hours were ‘UTOTHRS’, ‘ATOTHRS’, ‘UHRSMAIN’, and ‘AHRMAIN’ represent usual and actual overtime, usual and hours worked at the main job, and any extra hours worked. From utilizing this feature selection technique, the number of variables can be reduced to what is presented in Figure 6 below.

**Figure 5 – Correlations**

|  |  |  |
| --- | --- | --- |
| **Variables Kept** | **Variables Removed** | **Correlation** |
| FIRMSIZE | ESTSIZE | 0.514 |
| MARSTAT | EFAMTYPE | 0.566 |
| NAICS\_21 | COWMAIN | 0.818 |
| SEX | NOC\_10 | 0.507 |
| SEX | NOC\_43 | 0.540 |
| UHRSMAIN | AHRSMAIN | 0.547 |
| UHRSMAIN | UTOTHRS | 0.547 |
| UHRSMAIN | ATOTHRS | 0.547 |

**Figure 6 – Variable Unique Values**

|  |  |
| --- | --- |
| **Variables** | **Unique Values** |
| HRLYEARN | - |
| TENURE | - |
| UHRSMAIN | - |
| NAICS\_21 | 21 |
| PROV | 10 |
| AGE\_12 | 10 |
| EDUC | 6 |
| FIRMSIZE | 4 |
| UNION | 3 |
| CMA | 2 |
| SEX | 2 |
| MARSTAT | 2 |
| IMMIG | 2 |

### Random Forest Dimensionality Reduction

Before any machine learning model can be utilized within the sklearn library, it is mandatory that all values be numeric and non-null. Thus, all the qualitative variables must be converted into a 0 or 1. The number of classifications of all the categorical variables combined in the working dataset is 62, as shown in Figure 6 above. The number of dummy variables that are needed are , where k is the number of levels for each qualitative variable. Since, there are 9 of these variables, then the total amount of extra features in the dataset would amount to 52, ). Adding the three remaining quantitative features, the grand total becomes 55, which means that the total number of combination of subsets that a regression model could be fitted with is . Since this is an extremely large value, further dimensionality reduction is needed to reduce computational complexity.

RF is an ensemble of many decision trees that can be used as feature selection technique by utilizing its feature importance method. The parameters of this model were set so that they were the least computationally expensive. The parameter that contributed to one of the longest run times in the algorithm was n\_estimators, which determined the number of trees in the forest, and was subsequently set to 10 trees. In addition, there was no hyper parameter tuning done for this feature selection technique because the run time of the algorithm was too long, which made it inefficient to tune the parameters. After running the RF model, Figure 7 was generated below to show all the features in the working dataset with their respective importance, and Figure 8 below to show this in a visual representation.

It is important to note that the feature importance of all the variables will always add up to one. Thus, making it possible to select the attributes that cumulatively add up to 95%. In doing so, the first 41 variables in Figure 7 can be selected. This algorithm helps to remove 14 more additional features that were created by dummy variables. There is the argument that reducing features will ultimately mean in the loss of information, and ultimately the loss of accuracy, however it is far easier to understand fewer significant variables than many. Fewer independent variables allow for easier decision making without getting fixated on the granular items. Secondly, it becomes less computationally intensive to hyper tune models with a larger dataset, and thus more efficient. Finally, it helps with generalizing the model and avoid over fitting.

**Figure 7 – Feature Importance**

|  |  |  |
| --- | --- | --- |
| **Feature** | **Importance** | **Cumulative Importance** |
| TENURE | 21.36% | 21.36% |
| EDUC\_Bachelor's degree | 6.20% | 27.56% |
| EDUC\_Above bachelor's degree | 6.00% | 33.56% |
| UHRSMAIN | 4.69% | 38.25% |
| SEX\_1 | 3.35% | 41.60% |
| CMA\_1 | 2.63% | 44.23% |
| MARSTAT\_1 | 2.38% | 46.61% |
| EDUC\_Post-secondary certificate or diploma | 2.36% | 48.97% |
| FIRMSIZE\_More than 500 employees | 2.35% | 51.32% |
| PROV\_ON | 2.27% | 53.59% |
| IMMIG\_1 | 2.17% | 55.76% |
| UNION\_Union member | 2.03% | 57.79% |
| NAICS\_Public administration | 1.89% | 59.69% |
| NAICS\_Mining, quarrying, and oil and gas extraction | 1.82% | 61.51% |
| NAICS\_Professional, scientific and technical services | 1.70% | 63.21% |
| NAICS\_Retail trade | 1.67% | 64.88% |
| PROV\_QC | 1.62% | 66.50% |
| AGE\_45-49 | 1.60% | 68.10% |
| FIRMSIZE\_Less than 20 employees | 1.60% | 69.70% |
| PROV\_BC | 1.58% | 71.29% |
| AGE\_40-44 | 1.52% | 72.81% |
| AGE\_50-54 | 1.49% | 74.29% |
| AGE\_55-59 | 1.46% | 75.75% |
| AGE\_35-39 | 1.37% | 77.12% |
| AGE\_60-64 | 1.23% | 78.35% |
| PROV\_MB | 1.21% | 79.56% |
| AGE\_30-34 | 1.20% | 80.76% |
| NAICS\_Finance and insurance | 1.19% | 81.95% |
| FIRMSIZE\_20-99 employees | 1.18% | 83.12% |
| AGE\_25-29 | 1.07% | 84.20% |
| PROV\_SK | 1.03% | 85.23% |
| NAICS\_Health care and social assistance | 1.00% | 86.22% |
| NAICS\_Construction | 0.97% | 87.19% |
| NAICS\_Utilities | 0.97% | 88.16% |
| PROV\_NS | 0.90% | 89.07% |
| NAICS\_Manufacturing - non-durable goods | 0.89% | 89.96% |
| NAICS\_Wholesale trade | 0.88% | 90.83% |
| PROV\_NB | 0.87% | 91.70% |
| AGE\_20-24 | 0.86% | 92.56% |
| NAICS\_Manufacturing - durable goods | 0.85% | 93.41% |
| NAICS\_Educational services | 0.83% | 94.24% |
| PROV\_NL | 0.79% | 95.03% |
| NAICS\_Transportation and warehousing | 0.78% | 95.81% |
| NAICS\_Information, culture and recreation | 0.73% | 96.54% |
| NAICS\_Business, building and other support services | 0.62% | 97.16% |
| NAICS\_Other services (except public administration) | 0.55% | 97.71% |
| PROV\_PE | 0.51% | 98.22% |
| NAICS\_Real estate and rental and leasing | 0.45% | 98.67% |
| UNION\_Not a member but covered by a union contract or collective agreement | 0.38% | 99.05% |
| EDUC\_Some post-secondary | 0.27% | 99.32% |
| EDUC\_High school graduate | 0.24% | 99.56% |
| EDUC\_Some high school | 0.20% | 99.77% |
| NAICS\_Agriculture | 0.14% | 99.91% |
| NAICS\_Forestry and logging and support activities for forestry | 0.09% | 100.00% |
| NAICS\_Fishing, hunting and trapping | 0.00% | 100.00% |

**Figure 8 – Feature Importance Visualization**

A graph showing the number of the same number

Description automatically generated with medium confidence

### Selected Features

Figure 9 below categorizes the 12 features that were selected from above into Human Capital, Social Capital, or the Labour Market. Armed with this information, modelling can now be done to understand what category contributes the most to an hourly wage that is higher than the national average.

**Figure 9 – Features Categorized**

|  |  |
| --- | --- |
| **Feature** | **Category** |
| EDUC | Human Capital |
| TENURE | Human Capital |
| UHRSMAIN | Human Capital |
| NAICS\_21 | Labour Market |
| FIRMSIZE | Labour Market |
| UNION | Labour Market |
| SEX | Social Capital |
| PROV | Social Capital |
| AGE\_12 | Social Capital |
| CMA | Social Capital |
| MARSTAT | Social Capital |
| IMMIG | Social Capital |

## Outliers

The response variable ‘HRLYEARN’ is a continuous label that has a precision level of two, is skewed to the right, and is not normally distributed according to the Shapiro-Wilk test. The first histogram on the left below in Figure 10, shows the relative frequency distribution for this variable and reinforces the findings of the statistical test. Furthermore, this distribution resembles an exponential distribution because all the random variables are positive and continuous. Figure 10 also shows the distributions of the quantitative variables ‘UHRSMAIN’, and ‘TENURE’, the two histograms from the right respectfully. According to the Shaprio-Wilk test, and a quick visual observation, it is safe to conclude that both features are not normally distributed.

**Figure 10 - Histograms**

A graph with blue bars

Description automatically generated

The two boxplots in Figure 11from the left show the outliers highlighted in red, for hourly earnings and usual hours worked respectfully. Interestingly, there appear to be no outliers in the Tenure variable, the right most boxplot in Figure 11. To remove the outliers in each of these features, a non-parametric statical technique is needed to first identify and then remove them. The Interquartile Range method will be used in this research to remove the outliers in both hourly earnings and usual hours worked variables. It is imperative to remove outliers from the dependent variable because they inevitably reduce the accuracy of the overall model. Out of 155, 250 records, the number of outliers is 4, 685 and 18, 344, respectfully for both hourly earnings and usual hours worked. The combined outliers are less than 15% of the dataset, and thus can be eliminated from the working dataset. To understand the effect of removing the outliers from the two variables, the before and after statistics are shown in Figure 12 and 13 respectively. A keen observation is that the mean and median of the ‘HRLYEARN’ variable are both much closer to the national average of $33.55.

**Figure 11 - Boxplots**

A graph of a line with numbers

Description automatically generated with medium confidence

**Figure 12 - Before Removing Outliers**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **Data** | **Data Type** | **Mean** | **Median** | **Min** | **Max** | **Standard Deviation** |
| HRLYEARN | Quantitative | Continuous | 37.21 | 32.79 | 5.77 | 208.33 | 18.55 |
| UHRSMAIN | Quantitative | Continuous | 39.38 | 40 | 30 | 99 | 5.79 |
| TENURE | Quantitative | Discrete | 100.13 | 73 | 1 | 240 | 82.95 |

**Figure 13 - After Removing Outliers**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **Data** | **Data Type** | **Mean** | **Median** | **Min** | **Max** | **Standard Deviation** |
| HRLYEARN | Quantitative | Continuous | 35.63 | 32.69 | 5.77 | 79.37 | 14.32 |
| UHRSMAIN | Quantitative | Continuous | 38.96 | 40 | 33.8 | 47.5 | 2.16 |
| TENURE | Quantitative | Discrete | 100.17 | 73 | 1 | 240 | 82.82 |

# Approach

There is no doubt that supervised machine learning must be implemented because the data contains a quantitative label on which it can be trained and tested on. From the sklearn library, the following modules will be used on all the machine learning models presented in this research paper. These are RandomizedSearchCV, KFolds, OneHotEncoder, MinMax Scaler, ColumnTransformer, and Pipeline. RandomizedSearchCV will be used tune hyper parameters, KFolds will be used to measure performance by 10 folds cross validation, OneHotEncoder will be used to convert all the qualitative variables into dummy ones, MinMaxScaler will be used to scale the quantitative features, ColumnTransformer will be used to store the procedures to initiate OneHotEncoder and MinMaxScaler, and Pipeline will be used to execute the stored procedures along with the machine learning model.

To increase the performance of the algorithm, the randomize grid search will test only 10 random values in the respective hyperparameters in each fold. Furthermore, the number of folds for every iteration will be set to 10 due to the same reasons. K-Folds was picked over the traditional train, test, split validation technique because firstly it is integrated into the grid search algorithm, and secondly, it uses the entire dataset to train and test the model 10 times, thus making it very efficient for hyperparameter tuning. Pipelines will help avoid any potential data leakage because the preprocessing steps are replicated identically in each of the training and testing folds of the cross validation. Finally, MinMaxScaler will be used to normalize the numeric values as opposed to other methods because the quantitative variables, in this paper, are not normally distributed. The bonus of using this method is that every feature will be between the values of 0 and 1, hence on the same scale.

# Assumptions of Linear Regression

Multiple Linear Regression can be presented by the following formula:

, where alpha is the y-intercept, beta is the partial regression coefficient and x is the independent variable. In addition, there is a random error term with four assumptions that must be met to use the linear regression models. The assumptions are firstly, that all the error terms must be independent and normally distributed, and secondly, have a common variance and mean equal to zero. The main goal of regression is to minimize the deviations between the predicted and original values, thus optimizing the sum of squares for errors, by using the least squares method. The Durbin-Watson test will be used to check for independence, Shapiro-Wilk test will be used to check for normality, mean of the residuals will be checked to see whether they are equal to zero, and a scatter plot will be used to visualize whether there is a constant variance among the residuals. The research found that the Durbin-Watson test result is 2.01, which means the residuals are independent. The mean of the residuals is 1.71, which indicates that it is very close to 0, thus unbiased. Figure 14 below shows that the residuals are not perfectly normally distributed and shows a slight skewness towards the right. In addition, the Shaprio-Wilk test confirms this non-normality. Finally, Figure 15 below indicates that there is no common variance among the residuals. An attempt at a log transformation of dependent variable did address the normality issue but did not fix the common variance issue. Even using a weighed least square model did not help in solving this last problem. Therefore, there will be no need to do a t-test to assess whether there is linearity between the response variable and its features because the assumptions of linearity are not met. As a result, this research paper will implement non-linear regression models to predict the dependent variable. The models that will be used are the Regression Tree, Random Forest Regressor, Support Vector Regression, KNN, and XGBoost. Two other fundamental concepts to remember about the predictions made by the models are that only dependent values, which are within the range of the dataset can be extrapolated and to do so otherwise would be incorrect, and that correlation is not causation.

**Figure 14 – Histogram of Residuals**

A graph of a person with a bar graph

Description automatically generated with medium confidence

**Figure 15 – Scatter Plot of Residuals**

**A blue doted chart

Description automatically generated with medium confidence**

# Knowledge Induction

This part of the research paper will focus on the Apriori algorithm in Python to uncover any hidden patterns among the top 10 features selected above with the response variable. The algorithm only works with categorical variables, thus the two numeric independent variables will need to be transformed along with the dependent variable. All three of these variables will be categorized into five classes each as shown in Figure 16 below. Apriori is a rule-based algorithm that is looking for associations between sets of items. This research is interested in data mining what independent variables (‘left hand side’ or antecedent) lead to one of the hourly earning classifications (‘right hand side’ or consequent), . Furthermore, there are three important components to this model that will be discussed. First, ‘support’ measures how many times the LHS variable is present with a particular RHS classification over the entire dataset. Thus, a higher support percentage indicates that there is strong evidence that the variables occur together. Second, ‘confidence’ is the conditional probability of the RHS occurring given that the LHS has occurred. In other words, this is the ‘support’ divided by the occurrence of the LHS in the dataset. Lastly, ‘lift’ is a measure how many times both the LHS and RHS occur together versus how many times the RHS simply occurs on its own in the dataset. As one can imagine, there is a combinatorial explosion even with a small set of variables in any given dataset. To limit the scope of the item sets, two additional principals will be discussed. First, “downward closure” is the minimum support level an item or an itemset needs to continue through the iterative process to be considered as a rule. The iterative process is where first a single item is evaluated against the support threshold, then a combination of two items is evaluated against threshold, and so on until the support threshold cannot be met any further with higher combinatorial spaces. Second, “antimontonicity” is the principal where a subset of items has not met the support threshold, and ultimately that subset cannot continue forward through the iterative process to become a combination of a larger subset.

**Figure 16 – Numeric values classified**

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable** | **Categories** | **Bin Start** | **Bin End** |
| UHRSMAIN | 0 | 33.8 | 35.78 |
| UHRSMAIN | 1 | 35.78 | 37.76 |
| UHRSMAIN | 2 | 37.76 | 39.74 |
| UHRSMAIN | 3 | 39.74 | 41.72 |
| UHRSMAIN | 4 | 41.72 | 43.7 |
| TENURE | 0 | 1 | 48.8 |
| TENURE | 1 | 48.8 | 96.6 |
| TENURE | 2 | 96.6 | 144.4 |
| TENURE | 3 | 144.4 | 192.2 |
| TENURE | 4 | 192.2 | 240 |
| HRLYEARN | 0 | 5.77 | 20.49 |
| HRLYEARN | 1 | 20.49 | 35.21 |
| HRLYEARN | 2 | 35.21 | 49.93 |
| HRLYEARN | 3 | 49.93 | 64.65 |
| HRLYEARN | 4 | 64.65 | 79.37 |

# References

1. Canada: income distribution (2024 March 11). Statista, Retrieved May 14, 2024, from [https://www.statista.com/statistics/464262/percentage-distribution-of-earnings-in-canada-by-level-of-income/ - :~:text=In 2021, 21.2 percent of, representing the second largest group](https://www.statista.com/statistics/464262/percentage-distribution-of-earnings-in-canada-by-level-of-income/#:~:text=In%202021%2C%2021.2%20percent%20of,representing%20the%20second%20largest%20group)
2. Consumer price index portal (2024 May 10). Government of Canada, Statistics Canada Retrieved May 14, 2024, from <https://www.statcan.gc.ca/en/subjects-start/prices_and_price_indexes/consumer_price_indexes>
3. Dimensions of Poverty Hub (2024 April 26). Government of Canada, Statistics Canada, Retrieved May 16, 2024, from <https://www.statcan.gc.ca/en/topics-start/poverty>.
4. Employee wages by industry, annual (January 2024 05). Government of Canada, Statistics Canada Retrieved, Retrieved May 19, 2024, from <https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1410006401&pickMembers%5B0%5D=1.1&pickMembers%5B1%5D=2.2&pickMembers%5B2%5D=3.1&pickMembers%5B3%5D=5.1&pickMembers%5B4%5D=6.1&cubeTimeFrame.startYear=2023&cubeTimeFrame.endYear=2023&referencePeriods=20230101%2C20230101>
5. <https://docs.profiling.ydata.ai/4.5/advanced_settings/available_settings/#correlations>
6. Labour Force Survey: Public Use Micro File. (2024 May 10). Government of Canada, Statistics Canada, Retrieved May 9, 2024, from <https://doi.org/10.25318/71M0001X-eng>
7. Labour Force Survey (LFS). (2024 May 31). Government of Canada, Statistics Canada, Retrieved May 31, 2024 from <https://www.statcan.gc.ca/en/survey/household/3701>
8. Labour Force Survey (LFS). (2024 May 31). Government of Canada, Statistics Canada, Retrieved May 31, 2024 from <https://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getSurvey&Id=1541308>
9. Loyarte-López, E., & García-Olaizola, I. (2022). Machine Learning Based Method for Deciding Internal Value of Talent. Applied Artificial Intelligence, 36(1). <https://doi.org/10.1080/08839514.2022.2151160>
10. Matbouli, Y. T., & Alghamdi, S. M. (2022). Statistical Machine Learning Regression Models for Salary Prediction Featuring Economy Wide Activities and Occupations.Information, 13(10), 495. <https://doi.org/10.3390/info13100495>
11. Putnam, R. D. (1995). Tuning In, Tuning Out: The Strange Disappearance of Social Capital in America. PS: Political Science and Politics, 28(4), 664–683. <https://doi.org/10.2307/420517>
12. Wang, P., Liao, W., Zhao, Z., & Miu, F. (2022). Prediction of Factors Influencing the Starting Salary of College Graduates Based on Machine Learning. Wireless Communications & Mobile Computing (Online), 2022. <https://doi.org/10.1155/2022/7845545>
13. Xiaoyun Zhu, Shuping Luo, The influence of computer network technology on national income distribution under the background of social economy, Computer Communications, Volume 177, 2021, Pages 166-175, ISSN 0140-3664, https://doi.org/10.1016/j.comcom.2021.06.025.