Methods of Detecting Home Language Shift in Canadian Census Data

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***Abstract*—Canada is a nation composed of a highly diverse language population. This provides a unique opportunity to study the factors causing certain languages and language families to be lost over subsequent generations amongst allophones (people with a mother tongue other than English or French). This paper applies and compares the performance of Decision Tree Induction, Random Forest, and Gaussian Naive Bayesian algorithm to census microdata to analyze the influence of various social and economic factors on the probability that allophones adopt official languages as their language spoken at home.**

***Keywords*-component; language cohorts; allophones; mother tongue; language persistence**

I. Introduction

Canada is a nation composed of a highly diverse language population. Immigration and migration has risen both in numbers and as culturally relevant components of modern communities, especially in diverse countries such as Canada.

This provides a unique opportunity to study the rates at which certain languages and language families are lost over subsequent generations as allophones (people with a mother tongue other than English or French) adopt English or French as their primary language. Certain factors such as sex, age, educational status and economic success may prove to be a key indicator of how quickly an individual adopts a language other than their mother tongue in everyday life.

A language shift occurs when an allophone adopts an official language as their primary language and ceases to use their mother tongue. Several studies have aimed to measure language shift rates through linear regression on various cohorts of the population. Ultimately, it is impossible to ascertain precisely when a language shift occurs, so the insights offered by linear regression are limited in accuracy.

This paper proposes an application of various data mining algorithms and compares their accuracy and speed when used on census data, namely the Random Forest algorithm, the Decision Tree algorithm, and the Gaussian Naive Bayesian algorithm.

Some challenges working with census microdata include the fact that the Public Use Microdata Files (PUMF) have been downsampled from the census population size. In order to perform an analysis that would take into account the population distribution, we needed to multiply records by a corresponding weight included in the PUMF datasets. Additionally, the PUMF datasets contain over 100 potential features, some of which contain largely invalid/unavailable data. As a result, some level of feature selection is required.

The Canadian census is conducted every five years. As a result, changes that occur between census periods may not be captured at the exact time of their occurrence.

II. Related Work

Over the past several years, researchers have come up with multiple approaches to analyze census microdata to determine the rates at which allophones express a language shift. Several authors has focused on identifying whether a shift towards official languages (English and French) have occurred by determining if the mother tongue is the same as the language spoken at home. This is typically accomplished by performing linear regression.

A. Linear Regression of Language Cohorts

1) Fictitious Cohorts: Patrick Sabourin and Alain Bélanger use the concept of a 'fictitious cohort', in which groups separated by age or time since immigration are compared across a single census. They define language persistence as the proportion of each cohort that has kept their mother tongue as the language most often spoken at home. The authors analyze language shift using linear regression and polynomial regression. They then construct a survival curve which determines the probability that each subsection of a cohort (such as a specific age group) will undergo a language shift. They make the assumption that the rate of language shift is constant among several censuses. [1]

One limitation to this method is that members of a cohort are defined in binary terms as having lost a language if they no longer speak it at home, while this process might occur gradually in real time. Additionally, certain language groups may experience different rates of language shift. [1]

2) Synthetic Cohorts: Marie T Mora, Daniel J Villa and Alberto Davila use an alternative method known as 'synthetic cohort' analysis on census data in the United States. Their paper aims to better understand the recent dynamic of language loss and intergenerational maintenance of Spanish in the U.S., and compare this understanding to other non-English languages. In other words, exploring the

retention or loss of Spanish in the U.S., particularly among foreign-born and U.S.-born children with immigrant parents. [2]

The technique for analysis, synthetic cohort analysis, is based on data drawn from 1980, 1990, and 2000 United States Censuses. It creates a temporal representation of a population, over ten-year intervals. The authors track the reported language use of individuals starting at ages 5-7 and ending at ages 15-17 across two United States census. [2]

This is in contrast to cross-sectional methods like the synthetic cohort method which uses data from only one Census period to analyze language shifts. Combining this method with the synthetic cohort, the paper argues that the dynamic in language shift is better predicted, as supported by what has been observed in the U.S. [2]

There are still some difficulties with this approach. For example, 1980 and 1990 samples could have emigrations before 1990 and 2000, and from this the "true" cohorts of the foreign-born may not be entirely reflected.[2]

3) Limitations of Linear Regression: As seen above, multiple approaches to analyzing language cohorts temporally run into limitations in how census data is collected. Sampling errors and poorly worded census questions make it difficult to capture whether emigration has occurred between censuses. Even within a census, it is tempting to view language shift within a cohort as binary when this process occurs gradually.

Populations are dynamic, and multiple categorical variables influence whether a language that is the mother tongue is spoken at home. A decision tree can reveal which categorical variables determine whether mother tongue is retained as the language spoken at home. Conversely, linear regression is poorly suited for finding insights from categorical data.

B. Decision Tree Performance in Other Areas

1) Decision Trees in Student Performance Prediction: Decision trees have also been compared and applied in other fields. Osmanbegovic and Suljic compared the performance of an implementation of a decision tree algorithm, Naive Bayes algorithm, and a Multilayer Perceptron algorithm in predicting student performance by the prediction accuracy, learning time, and error rate. [3]

Osmanbegovic and Suljic used 12 input features such as gender, GPA, and whether or not the student had scholarships, and outputted whether or not the student would pass or fail. The output could also be classified by letter grades, but due to the disparity in the amount of data for each class, was not used. [3]

They found that the Naive Bayes algorithm managed to outperform the C4.5 decision tree algorithm implementation, J48, in both prediction accuracy, and error rate. Additionally, it was found that the Naive Bayes algorithm and the decision tree algorithm created prediction models that were both accurate, and user-friendly enough for the stakeholders. [3]

2) Improvements: Similarly to Osmanbegovic and Suljic's data, some classes in census data are going to have differing amounts of data, and will affect prediction accuracy. Instead of changing the class groupings to get more equal representation, weights could be added to the training data to account for these differences. In the case of the Canadian Census data, these weights are already added to the data for use.

C. An Alternative Approach to Census Data Mining

In their paper, Klösgen and May took a different approach to mining census data. Klösgen and May used the United Kingdom's census data, which was only available in an aggregated form. The census data was available aggregated across various wards within the region, along with a detailed set of geographic layers. Thus, Klösgen and May decided to use those wards as the focus of their examination, and propose an application of SubgroupMiner, an advanced subgroup mining system. [4]

D. An Improved Decision Tree Algorithm

Hulten, Spencer, and Domingos' CVFDT algorithm improves on the VFDT decision tree learner by accounting for data changing over time. [5] Their CVFDT algorithm works by maintaining a decision tree with respect to a sliding window of data and grows an alternative subtree to replace an old one if it becomes out of date. This allows for it to learn a similar model to one from the VFDT algorithm but in constant time [5].

Applying the algorithm to census data seems like a natural fit, and can be used to improve the performance of any decision tree learners in use. The addition of the time aspect could also be used to improve the accuracy in cases where the data from only one period of time is used, instead of multiple.

III. Main Body

A. Data Collection

Data was collected from the 2016 Canadian census public use microdata file (PUMF), which contains around 930,421 (or 2.7% of the target population) individual, anonymized records, with 123 features. Additionally, there's an individual weight attached to each record, and 16 estimate weights for sampling variability.

1) Privacy: While the PUMF does give individual records, some of the data was aggregated to preserve confidentiality (e.g. categories being combined together), and some records had some of their variables changed to 'Not Available' for similar reasons. Furthermore, only the largest of the census metropolitan areas and provinces were covered.

2) Data Weighting and Sample Universe: Since the PUMF data is only a sample of the target population, each record includes an individual weight to indicate how much of the target population that the record represents. In addition to the weights, 31 of the features are drawn from the universe of family, household, and dwelling universes, and the remaining 92 features are from the individual universe.

3) Data Cleaning: Since some values in the PUMF data are marked as invalid or unavailable, some preprocessing on the data is required. Due to each record having an individual weight attached to it, rather than impute a value for the missing/invalid values, those rows were dropped instead.

In general, some features had a high rate of invalid data and were not used for any of the classifiers.

B. Methodology

data imputation
import pandas
feature selection
create dictionaries for mother tongue and home language classifier languages and language groups
remap mother tongue language groups that are not in the home language dict to 'All other languages'
remove mother tongue and home language from features that are used for classification, since we are attempting to classify mother tongue != home language
If mother tongue == home language, then no language shift has occurred (language shift is false).
If mother tongue != home language, then a language shift has occured (language shift is true)
save weights for each record in dataset

C. Random Forest

Split data into training and testing data for weights, features, and language shift variable
fit random forest classifier on training features, language shift variable to classify, and weights
predict language shift using classifier
print confusion matrix for language shift variable
print classification report detailing precision, recall, and f1-score
print accuracy of classifier
print feature importances
export sample dot file as decision tree

D. Decision Tree

Split data into training and testing data for weights, features, and language shift variable
fit decision tree classifier on training features, language shift variable to classify, and weights
predict language shift using classifier
print confusion matrix for language shift variable
print classification report detailing precision, recall, and f1-score
print accuracy of classifier
print feature importances
export sample dot file as decision tree

E. Naive Bayesian

Split data into training and testing data for weights, features, and language shift variable
fit naive bayesian classifier on training features, language shift variable to classify, and weights
predict language shift using classifier
print confusion matrix for language shift variable
print classification report detailing precision, recall, and f1-score
print accuracy of classifier

IV. Analytic Evaluation

V. Conclusion

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Acknowledgment

The authors would like to thank the staff at the Elizabeth Dafoe library for giving direction on locating census microdata, and Dr. Carson Leung of the Databases and Data Mining Laboratory at the University of Manitoba for support of this project.

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