Predicting Ethnicity from Names with rethnicity: Methodology and Application

Fangzhou Xie¹

Department of Economics, Rutgers University

Abstract
In this study, a new R package, rethnicity¹ is provided for predicting ethnicity based on names. The Bidirectional LSTM and Florida Voter Registration were used as the model and training data, respectively. Special care was given for the accuracy of minority groups, by adjusting the imbalance in the dataset. The models were trained and exported to C++ and then integrated with R using Rcpp. Additionally, the availability, accuracy, and performance of the package were compared with other solutions.

Keywords: R, LSTM, Ethnicity Prediction

1. Introduction
The study on the differential effects of ethnicity requires researchers to have ethnic information available in a dataset. However, such information is usually not readily available.¹ When only names are available in the dataset, one naturally wants to predict people's ethnicity based on their names, as names are usually highly correlated with their races.

In fact, surname analysis has been used for many years to identify ethnicity but the application of deep learning can make it even simpler, as illustrated by Sood & Laohaprapanon (2018).

¹New Jersey Hall, Room 202, 75 Hamilton Street, New Brunswick, NJ 08901.
²https://github.com/fangzhou-xie/rethnicity It has also been published on CRAN.
³Health care is one of the areas that must be studied for ethnic disparities in insurance plans, and researchers in this field should deal with the missing ethnic information (Fiscella & Fremont 2006).
⁴See Fiscella & Fremont (2006) for a survey.
Herein, a novel approach to predict ethnicity from names is proposed and an R package is provided `rethnicity`\(^4\). The developed method achieves a good performance, is fast, and free.

The rest of the article is organized as follows. Section 2 describes the methodology of the package. Section 3 discusses some of the model’s implementation details. Section 4 highlights the notable features unique to the package. Section 5 compares its availability, accuracy, and performance against other solutions. Section 6 presents an example as a code snippet that can be used to analyze racial differences in political donations. Finally, Section 7 concludes the study.

2. Methodology

This section introduces the methodology of the prediction method provided by the R package and the procedures used to develop it.

2.1. Undersampling for the Imbalanced Racial Distribution

Most classification algorithms assume a relatively balanced dataset and equal misclassification cost (Sun et al., 2009). When applying them on imbalanced data, where the instances of some classes are significantly larger or smaller than other classes, the algorithm will mainly focus on the majority class and hence ignore the minority classes. One example is fraud detection, where most of the transactions are normal, but a few are fraudulent (Fawcett & Provost, 1997).

This is also a concern in our application. An attempt is made to predict ethnic groups from people’s names, which is a natural example of classifying imbalanced data\(^5\).

To overcome this problem, one important method is to oversample the minority class (Chawla et al., 2002; Fernandez et al., 2018). However, in this study, because abundant data points are available, the majority classes were undersampled to achieve a balanced dataset. This will also help reduce the training and testing time for the model owing to a large dataset\(^6\).

Furthermore, first names are not only associated with gender, but also with race (Fryer & Levitt, 2004). Hence, the dataset was grouped by both ethnicity and

---

\(^4\)https://github.com/fangzhou-xie/rethnicity

\(^5\)The dataset from Florida Voter Registration (Sood, 2017) was used in this study, and the predicted ethnic groups are defined in the U.S. context. The same methodology can be applied to build a classifier for another country or region if a proper dataset with both names and races is available.

\(^6\)Details in Section 3.1
gender, and all the groups except for the smallest one were undersampled. Two different models were trained for classifying ethnicity. One was trained using only last names, while the other was trained on first names. Therefore, it is crucial to adjust the dataset based on both gender and race to avoid disproportionate classification errors on minority classes.

2.2. Character-level Dictionary

Classic natural language processing (NLP) models consider “tokens” to be the building blocks of languages. This appears natural to humans because words and phrases are considered the smallest elements of language in our daily use. However, for algorithms to process sentences, there is a need to tokenize them, create a vocabulary, and then build a model based on the vocabulary. This process will become cumbersome as the size of the data increases and there is a need to retain an extremely large vocabulary, where some tokens are very common, while several are extremely infrequent (Zipf, 1936).

Moreover, the vocabulary is usually built during model training, and out-of-vocabulary (OOV) tokens may exist during inference once the model is deployed. The usual practice is to map OOV tokens to an “unknown” token and consider tokens that are not seen in the training process to be similar. This will inevitably lead to information loss, as some tokens are extremely informative but also infrequent (e.g., special words or abbreviations with domain knowledge).

To overcome this, efforts have been taken in the machine learning field to build models directly on characters, instead of tokens (Zhang et al., 2015; Sutskever et al., 2011). It is easier to enumerate all possible characters and maintain a dictionary of those characters, rather than a dictionary consisting of distinct tokens. Hence, in this study, OOV problems are not a concern because all the characters have been kept in the dictionary.

The other benefit of using a character-level dictionary is that it significantly reduces the size of the dictionary and the parameters needed in the model, as many, if not most, parameters in are needed in NLP for capturing the meaning of

---

7These character-level models only consider 26 English letters (and some symbols). Recently, Xue et al. (2021) proposed a byte-based model, which is fully compliant with the UTF-8 standard and can deal with non-English texts.

8In the case of English, only 26 letters are needed in addition to symbols when necessary. A larger dictionary could be used by including upper-case letters. It is more efficient to use lower-case letters for classifying names, as upper-case letters will be fewer and the model may not have enough opportunities to learn from the upper-case letters.
2.3 Bidirectional LSTM

Long short-term memory (Hochreiter & Schmidhuber, 1997; LSTM) has been widely used in sequence modeling since its proposal. Moreover, Graves & Schmidhuber (2005) proposed bidirectional LSTM (BiLSTM), which captures the context even better than the unidirectional LSTM model.

In this package, BiLSTM is used as the model architecture for predicting race from names. The model was built with 256 units of an embedding layer and four BiLSTM layers with 512 units each. The final output layer is a dense layer of four units (equal to the number of races for the classification problem) with softmax activation function.

The performance of the model in terms of accuracy is listed in Table 3.

2.4 Distillation of Knowledge

However, training models with a character-level dictionary might be more difficult than token-level dictionary models. This might be the only drawback of using a character-level dictionary. To overcome this difficulty, a large BiLSTM model with many parameters is trained for better accuracy. However, this trained model is extremely large and would be difficult to deploy in production. Therefore, “model distillation” is used to compress the information into a smaller model.

To compress a model, Hinton et al. (2015) proposed the “distillation” technique for extracting information from large models and teaching a smaller model to achieve a similar prediction. To be more precise, the “student” model is trained to match the “teacher” model, and the knowledge is transferred from the larger model to the smaller one.

---

9 Some of the most recent and exciting developments in LSTM include BERT (Devlin et al., 2019) and its variants.

10 BiLSTM uses both forward- and backward-passing LSTMs to capture the context of sequential data, which is one of the reasons it works well. Although BiLSTM cannot be used for real-time prediction, this is less of a concern for our name classification task.

11 The test accuracy is given in 5.2.

12 Last name and full name models have the same architecture but differ in terms of the dataset used for training.

13 For using the prediction of an ensemble of models to distill information into a single small model.
teacher to the student. In this way, the student will “learn” the interclass relationship better than directly learning from the data.

The distillation trick is applied on the trained large model to obtain a smaller model with the same architecture but fewer parameters and layers. The smaller model is compressed from the larger model and becomes the model used for inference in production.

Table 4 shows the test accuracy of the student (smaller) model.

2.5. Export to C++

After training the teacher and student models, the student model is exported to C++ via frugally-deep project. Hence, the model is no longer dependent on the installation of Keras (or tensorflow). Subsequently, the model is loaded directly in C++ with very few dependencies.

To make the model callable from R, an interface must be developed using Rcpp (Eddelbuettel & Francois, 2011). This will provide a wrapper around the underlying C++ code for loading the model and running the prediction for the names. Additionally, the prediction can be parallelly done by multi-threading. These features will enable the names to be processed rapidly for the prediction of ethnicity.

3. Data and Preprocessing

3.1. Name and Ethnicity Data

To train the ethnicity classification model using names, we need a dataset that includes names as well as individual-level racial information. Fortunately, the Florida Voter Registration Dataset (Sood, 2017) is an excellent candidate for this purpose.

However, the dataset contains names and races for almost 13 million people in Florida, and the racial distribution is naturally imbalanced. First, the names of Native Americans and multi-racial names were dropped because these groups

---

14The architecture of the student model includes dense, BiLSTM, and dense layers. However, there are only 32 units for dense, 64 units each for the two layers of BiLSTM.
15The accuracy comparison is shown in Section 5.2.
16https://github.com/Dobiasd/frugally-deep
17The frugally-deep is a lightweight header-only C++ project that depends only on FunctionalPlus, Eigen, and Json projects, which are all header-only projects.
18These names are defined in the Florida Voter Registration dataset as “American Indian or Alaskan Native.”
have little data. Furthermore, Asian or Pacific Islanders, Hispanic, Non-Hispanic Black, and Non-Hispanic White were defined as the four categories for the classification problem.\footnote{Henceforth, these groups will be referred to as Asian, Hispanic, Black, and White.}

Table 1 lists the frequency of names grouped by ethnicity and gender. The undersampling procedure discussed in Section 2.1 takes the smallest group, namely, Asian Male, and randomly selects samples for all other groups to eventually have the same group size. After undersampling, each race-gender group contains the same number (i.e., 104,632) of names.

| Race  | Gender | Count Before | Count After |
|-------|--------|--------------|-------------|
| Asian | Female | 131602       | 104632      |
| Asian | Male   | 104632       | 104632      |
| Black | Female | 989142       | 104632      |
| Black | Male   | 717118       | 104632      |
| Hispanic | Female | 1137594     | 104632      |
| Hispanic | Male   | 925623       | 104632      |
| White | Female | 4419030      | 104632      |
| White | Male   | 3963833      | 104632      |

Table 1: Count of Names, Grouped by Ethnicity and Gender.

3.2. Character Encoding

For the characters to be processed by the algorithm, characters must be encoded using numeric values. Because a character-level dictionary is the focus of this study,\footnote{The 26 lower-case English letters, a space character (“ ”), an empty character (“E”), and an unknown character (“U”) are considered. Hence, the size of the dictionary is 29} the dictionary is small and pre-defined. It is possible to map the characters from all names to a value in the dictionary.

In practice, first, upper-case letters are mapped to their lower-case counterparts, then all the punctuation symbols to space, and, finally, all other characters to “U” (Unknown). Furthermore, to ensure that all input data are of equal length, “E” (Empty) is inserted for names shorter than the threshold, and the additional characters in the names longer than the threshold are trimmed.\footnote{The threshold is ten for each name component. In other words, for the last name model, the} Subsequently,
the input name is transformed into a vector of integers according to the mapping described in Section 2.2.

3.3 Sequence Padding and Alignment

The number of characters in people’s names varies, as does their encoded numeric representation. However, the model will only accept input vectors of equal length. To achieve this, it is necessary to determine the expected length of a fixed number of input vectors and process the input data such that each string has the same length. Longer strings will be truncated and shorter ones will be padded.

Therefore, after padding the sequences at 10, all surnames will have the same length after the padding process. For example, consider the last name “Smith.” First, the last name is converted to lower case to obtain “smith,” and then five Empty (“E”) characters are added to get a vector of length ten. By contrast, for “Christensen,” the name is first converted into lower case, and then the last “n” is trimmed.

For the model that leverages both the first and last names, special care must be taken. Because first names also vary in length, if both the first and last names is considered as a single string, the starting point of the last name will also vary. The solution would be to pad the first and last names separately and then concatenate them into a single vector. This guarantees the same starting position for all last names across the sample. The first and last names are both padded with ten characters so that the total concatenated input for the full name model is 20, but the last name always starts at position 11.

The alignment method allows the model to recognize the difference between the first and last names, and the accuracy is higher compared with the models trained without the alignment process.

\[^{22}\text{This process is called “padding” and is the usual practice in the preprocessing of RNN models.}\]

\[^{23}\text{This fact makes the full-name model insensitive to the names with first and last names from different ethnic groups, for example, the descendants of immigrants. Early models trained without adjusting the position of the last names tend to focus more on the first names instead of the last names and tend to predict “Andrew Yang” as White instead of Asian. Hence, there is a need to introduce an alignment procedure.}\]
4. Features of the Package

In this section, several notable features of the package are presented.

4.1. Native in R

The R community has incorporated mature deep learning libraries from Python (Falbel et al., 2021a; Kalinowski et al., 2021) via reticulate package (Ushey et al., 2021). In essence, users need to install a separate Python environment with the required libraries (e.g., tensorflow), and then reticulate would provide the interface from R to Python so that neural networks can be developed in R.

In practice, this could be problematic for researchers, as this approach heavily relies on another language (Python) and may cause issues while replicating the studies. Moreover, in most applied research, researchers only need to make inferences on the dataset at hand. Installing and maintaining these libraries are usually problematic, even for veterans.

To ease the burden on users, the modeling processes and deployment are separated so that end-users would only need to install minimal dependencies on their machines. After training the teacher and distilling the student model, the student model is exported to C++ via frugally-deep. At this stage, the model is no longer dependent on any of the deep learning frameworks. Furthermore, to run the inference of this model in R, Rcpp is used to provide an interface to the C++ model and make it callable from R. The package is henceforth considered to be lightweight, without the need to refer to external languages (e.g., Python) by those who need to predict ethnicity from names.

4.2. Mature Dependencies

The torch package (Falbel et al., 2021b) aims to build the PyTorch package native to R, which is in sharp contrast to the approach of tensorflow and keras for R. However, this project is experimental and not ready for production. Additionally, this approach requires the installation of the massive torch package. Furthermore, such an installation might not be required for many people.

For the rethnicity package, there are only three dependencies: Rcpp (Eddelbuettel & Francois, 2011), RcppThread (Nagler, 2021), and RcppEigen (Bates & Eddelbuettel, 2013). They are all being well-tested, with mature packages published on CRAN and widely used by many other packages in the R community.

---

24The installation processes of these libraries and their dependencies are not trivial. Even after correct installation, they take up multiple gigabytes of storage.
4.3 High Performance

In particular, Rcpp provides an interface to C++, RcppThread provides the multi-threading support for fast inference, and RcppEigen provides a fast and efficient matrix computation of the neural network.25

4.3. High Performance

With the rise of empirical economics, economists often find themselves dealing with much larger datasets (Einav & Levin, 2014). Therefore, it is critical to have packages designed considering the performance requirements to process datasets as quickly as possible.

In terms of predicting ethnicity/nationality from names, some good API services26 exist. However, as is the case with most API services, they are rate-limited to make their service reliable and sustainable. This may create bottlenecks for researchers who have a large collection of names waiting to be predicted.

The rethnicity package is built with this concern in mind. By leveraging C++ and multi-threading27 the package could achieve extremely fast inference speeds. To illustrate this point, the inference speed between rethnicity and ethnicolr is compared in Section 5.3

5. Comparison with Existing Packages

5.1. Availability

Table 2 shows the differences between rethnicity and other solutions for predicting ethnicity from names. The comparison is made on four aspects: cost, rate limit, dependencies, and language.

NamePrism is free but is rate-limited to 60 requests per minute. nationalize.io offers 1000 free requests each day and requires a subscription to their services for more names to be processed in a day. ethnicolr might be the most similar in scope as rethnicity. However, it is written in Python and requires the installation of TensorFlow to run the inference. The installation of tensorflow might be daunting for many who only want to run the inference on a name dataset they have.

---

25 Apart from these three packages, it also depends on frugally-deep and its dependencies. But these header-only dependencies are included in the package during installation, and there is no need to link against external packages.

26 For example, nationalize.io (https://nationalize.io/) and NamePrism (https://www.name-prism.com/).

27 This is possible because the models exported by frugally-deep are thread-safe.
5.2 Accuracy

| Ethnicity       | Ethnicalr | NamePrism | nationalize.io |
|-----------------|-----------|-----------|----------------|
| Cost            | free      | free      | paid           |
| Rate Limit      | No        | No        | Yes            |
| Dependency      | Low       | High      | N/A            |
| Language        | R         | Python    | API            |

Table 2: Comparison across some publicly available services/packages for predicting ethnicity from names. rethnicity provides a free and light-weight package for the R community without rate-limiting.

In general, this study aimed to develop a simple, easy, and free package for use in the R community with guaranteed accuracy and performance, which is achieved by the rethnicity package.

5.2. Accuracy

Tables 3 and 4 present the prediction accuracy on the test data not included during the training process. Table 3 shows the accuracy of the trained teacher model, and Table 4 shows the accuracy of the student model. Note that the full name model performs better than the one that only leverages last name information, for both teacher and student models. Additionally, the precision of the student model degrades compared to the teacher model but is still sufficiently high and close to that of the teacher.

Moreover, if we compare the results within each ethnic group, the accuracy for each group is roughly balanced, and the performance is slightly better for the minority groups. This is the case for both teacher and student models. This suggests that the undersampling approach used in this study to adjust the imbalance (described in Section 2.1) in the dataset works well. If the results are compared to ethnicalr (Sood & Laohaprapanon, 2018), rethnicity shows significantly better results on the prediction of Asian, Hispanic, and black people, albeit the precision is lower for white people.

5.3. Performance

The performance of the package is guaranteed by leveraging distillation for model compression, C++, and multi-threading for low overhead, as discussed in

---

28The accuracies in Sood & Laohaprapanon (2018) are disproportionately high for white people, which might suggest that the classifier tends to always predict white to minimize loss. Therefore, adjustments are performed for an imbalanced dataset.
5.3 Performance 5 COMPARISON WITH EXISTING PACKAGES

| Full name | Lastname |
|-----------|----------|
|           |          |          |          |
|           | precision | recall | f1-score |          |          |          |
|           | precision | recall | f1-score |          |          |          |
|           | support   |        |          |          |          |          |
| asian     | 0.87      | 0.76   | 0.81     | 0.87     | 0.69     | 0.77     | 41861    |
| black     | 0.74      | 0.77   | 0.76     | 0.65     | 0.80     | 0.72     | 41904    |
| hispanic  | 0.86      | 0.87   | 0.86     | 0.84     | 0.85     | 0.85     | 41940    |
| white     | 0.67      | 0.73   | 0.70     | 0.62     | 0.58     | 0.60     | 41707    |
| total     | 0.79      | 0.78   | 0.78     | 0.74     | 0.73     | 0.73     | 167412   |

Table 3: Accuracy on the test data for the teacher model before distillation.

| Full name | Lastname |
|-----------|----------|
|           |          |          |          |
|           | precision | recall | f1-score |          |          |          |
|           | precision | recall | f1-score |          |          |          |
|           | support   |        |          |          |          |          |
| asian     | 0.86      | 0.73   | 0.79     | 0.84     | 0.64     | 0.73     | 41861    |
| black     | 0.70      | 0.76   | 0.73     | 0.61     | 0.75     | 0.67     | 41904    |
| hispanic  | 0.83      | 0.87   | 0.85     | 0.80     | 0.84     | 0.82     | 41940    |
| white     | 0.67      | 0.68   | 0.68     | 0.57     | 0.53     | 0.55     | 41707    |
| total     | 0.77      | 0.76   | 0.76     | 0.70     | 0.69     | 0.69     | 167412   |

Table 4: Accuracy on the test data for the student model after distillation.

Sections 2.4 and 4.3. However, considering speed, there is a need to rigorously test the performance and compare with it the \texttt{ethnicolr} package as a baseline.

Figure 1 shows that the single-threaded performance is on par with that of \texttt{ethnicolr}, and the multi-threaded mode achieve further speeds. First, the distillation method successfully compresses the model and improves performance by having a smaller model. The inference speed of the single-threaded distilled model in \texttt{rethnicity} is roughly comparable to that of the multi-threaded larger model in \texttt{ethnicolr}. This suggests that the distillation closes the gap between the speedup led by multi-threading tensorflow\textsuperscript{29} Second, there is extremely little overhead for multi-threading, and the speedup is almost linear in terms of the number of threads being used. The \texttt{rethnicity} package clearly inherits the efficiency of the \texttt{RcppThread} package. In practice, more threads must be used to

\textsuperscript{29}Multi-threading is the default behavior for tensorflow, based on which \texttt{ethnicolr} is implemented. \texttt{frugally-deep}, on the other hand, only uses single-thread by default.
process a large dataset, depending on the size of the dataset and the total number of threads available in the machine.

6. Using the Package

6.1. Code Snippet

The usage of the package is straightforward, as there is only one function provided.

```r
> predict_ethnicity(firstnames = "Samuel," lastnames = "Jackson")
  firstname lastname   prob_asian  prob_black  prob_hispanic  prob_white race
1    Samuel    Jackson 0.01741119 0.88988490 0.006667824 0.08603610 black
```

Listing 1: Example of the `predict_ethnicity` function.

[30] More examples can also be found at the GitHub repository: [https://github.com/fangzhou-xie/rethnicity](https://github.com/fangzhou-xie/rethnicity)
6.2 DIME data

There are only five arguments for the function `predict_ethnicity`: `firstnames`, `lastnames`, `method`, `threads`, and `na.rm`.

The `firstnames` argument accepts a vector of strings[^31] and is only required when `method = 'fullname'`.

`lastnames` also accepts a Character Vector and is needed for both `method = 'fullname'` and `method = 'lastname'`.

`method` can only be either `'fullname'` or `'lastname'` to indicate whether working only with last names or both first and last names.

`threads` can be chosen to have an integer greater than one to leverage multi-threading support for even faster data processing[^32].

Finally, there is a `na.rm` argument. This allows one to remove missing values from the input names[^33]. Otherwise, an error is thrown if values are missing in the input data. This guarantees that the model has the correct input data and returns meaningful predictions.

6.2. DIME data

The DIME dataset offers rich information on the finance and ideology of political campaigns (Bonica, 2014, 2019). Following the practice of Sood & Lao-haprapanon (2018), this study also considered this dataset to illustrate one potential usage of the `rethnicity` package.

All the donors in the dataset are considered, and their races are predicted using the full-name model, then the total amount of donation separated by the predicted race is aggregated, and finally, the ratio of donations across ethnicity is calculated. The results for 2000 and 2010 are listed in Table 5.

Table 5 shows that, `rethnicity` suggests higher ratios of political donation when compared with `ethnicolor` results. This agrees with the accuracies in Section 5.2 and the discussion on the imbalanced classification problem discussed in Section 2.1, where `rethnicity` reduces the error for minority groups significantly. Without the adjustment, the prediction of white people will be dispropor-

[^31]: Character Vector in R.
[^32]: Theoretically, one can choose a number to equal the number of threads in the machine. The more threads used, more the overhead introduced in parallel processing, and lesser the performance boost gained.
[^33]: For the last name model, only non-missing names are retained for processing and are returned. For the full name model, because it requires both first and last names, only names with both will be processed.
7 CONCLUSION

|         | rethnicity | ethnicolr |
|---------|------------|-----------|
|         | 2000       | 2010      | 2000     | 2010     |
| asian   | 6.29%      | 5.90%     | 2.00%    | 2.28%    |
| black   | 20.83%     | 18.00%    | 8.93%    | 7.92%    |
| hispanic| 4.01%      | 4.44%     | 3.23%    | 3.31%    |
| white   | 68.87%     | 71.66%    | 85.84%   | 86.49%   |

Table 5: Comparison of total donations grouped by predicted race from donors’ names. The right half of the table is taken from Sood & Laohaprapanon (2018).

Tionately higher than that of minority groups, which underestimates the monetary contribution of minority groups for the elections.

7. Conclusion

This study demonstrates the methodology and potential usage of the rethnicity package in R.

It leverages different techniques to predict ethnicities. First, undersampling was used to adjust the imbalance in the racial distribution in the dataset. Second, a character dictionary was used to reduce the dictionary size and make it independent of training data. Third, BiLSTM was chosen as the architecture owing to its superior performance in capturing context. Fourth, after training the gigantic teacher model, the information was distilled by letting it instruct a much smaller student model. Finally, the student model was exported to C++ and then loaded via Rcpp.

The model was trained using the Florida Voter Registration dataset using the voters’ names, along with their identified ethnicity. After training the large model, a smaller student model was also trained and tested.

The objective of building this package was to make the installation and usage easier for any user interested in predicting ethnicity from names for their research. The package is entirely native in R with only dependencies being several mature packages published on CRAN. Additionally, it achieves a high performance by delegating heavy computation to C++ with multi-threading. The aforementioned advantages are leveraged in the rethnicity package, which is free, fast, and available to the R community. It also achieves a good performance, particularly for ethnic minorities.
The code snippet is provided as an example of how to use the package. Application to finance and ideology Data of political candidates is also illustrated.

Conflict of Interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

Acknowledgements

References

Bates, D., & Eddelbuettel, D. (2013). Fast and Elegant Numerical Linear Algebra Using the RcppEigen Package. *Journal of Statistical Software, 52*, 1–24. doi:10.18637/jss.v052.i05

Bonica, A. (2014). Mapping the Ideological Marketplace. *American Journal of Political Science, 58*, 367–386. doi:10.1111/ajps.12062

Bonica, A. (2019). Database on Ideology, Money in Politics, and Elections (DIME). doi:10.7910/DVN/O5PX0B

Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: Synthetic Minority Over-sampling Technique. *Journal of Artificial Intelligence Research, 16*, 321–357. doi:10.1613/jair.953

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *arXiv:1810.04805 [cs]*, .arXiv:1810.04805

Eddelbuettel, D., & Francois, R. (2011). Rcpp: Seamless R and C++ Integration. *Journal of Statistical Software, 40*, 1–18. doi:10.18637/jss.v040.i08

Einav, L., & Levin, J. (2014). Economics in the age of big data. *Science, 346*. doi:10.1126/science.1243089.

Falbel, D., Allaire, J. J., Tang, Y., Eddelbuettel, D., Golding, N., Kalinowski, T., Golding, N., Kalinowski, T., & Tutorials), G. I. E. (2021a). Tensorflow: R Interface to ’TensorFlow’.
Falbel, D., Luraschi, J., Selivanov, D., Damiani, A., Regouby, C., Joachimiak, K., & RStudio (2021b). Torch: Tensors and Neural Networks with 'GPU' Acceleration.

Fawcett, T., & Provost, F. (1997). Adaptive Fraud Detection. *Data Mining and Knowledge Discovery, 1*, 291–316. doi:10.1023/A:1009700419189.

Fernandez, A., Garcia, S., Herrera, F., & Chawla, N. V. (2018). SMOTE for Learning from Imbalanced Data: Progress and Challenges, Marking the 15-year Anniversary. *Journal of Artificial Intelligence Research, 61*, 863–905. doi:10.1613/jair.1.11192.

Fiscella, K., & Fremont, A. M. (2006). Use of Geocoding and Surname Analysis to Estimate Race and Ethnicity. *Health Services Research, 41*, 1482–1500. doi:10.1111/j.1475-6773.2006.00551.x.

Fryer, R. G., Jr., & Levitt, S. D. (2004). The Causes and Consequences of Distinctively Black Names. *The Quarterly Journal of Economics, 119*, 767–805. doi:10.1162/0033553041502180.

Graves, A., & Schmidhuber, J. (2005). Framewise phoneme classification with bidirectional LSTM and other neural network architectures. *Neural Networks, 18*, 602–610. doi:10.1016/j.neunet.2005.06.042.

Hinton, G., Vinyals, O., & Dean, J. (2015). Distilling the Knowledge in a Neural Network. *arXiv:1503.02531 [cs, stat], arXiv:1503.02531*.

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation, 9*, 1735–1780. doi:10.1162/neco.1997.9.8.1735.

Kalinowski, T., Falbel, D., Allaire, J. J., Chollet, F., Tang, Y., Bijl, W. V. D., Studer, M., Keydana, S., Bijl, W. V. D., Studer, M., & Keydana, S. (2021). Keras: R Interface to 'Keras'.

Nagler, T. (2021). R-Friendly Multi-Threading in C++. *Journal of Statistical Software, 97*, 1–18. doi:10.18637/jss.v097.c01.

Sood, G. (2017). Florida Voter Registration Data. doi:10.7910/DVN/UBIG3F.

Sood, G., & Laohaprapanon, S. (2018). Predicting Race and Ethnicity From the Sequence of Characters in a Name. *arXiv:1805.02109 [stat], arXiv:1805.02109*.

Sood, G., & Laohaprapanon, S. (2018). Predicting Race and Ethnicity From the Sequence of Characters in a Name. *arXiv:1805.02109 [stat], arXiv:1805.02109*.
Sun, Y., Wong, A. K. C., & Kamel, M. S. (2009). Classification of imbalanced data: A review. *International Journal of Pattern Recognition and Artificial Intelligence, 23*, 687–719. doi:10.1142/S0218001409007326

Sutskever, I., Martens, J., & Hinton, G. (2011). Generating text with recurrent neural networks. In *Proceedings of the 28th International Conference on International Conference on Machine Learning ICML’11* (pp. 1017–1024). Madison, WI, USA: Omnipress.

Ushey, K., Allaire, J. J., Tang, Y., Eddelbuettel, D., Lewis, B., Kędzierska, S., Hafen, R., Geelnard, M., Hafen, R., library, M. G. T., & http://tinythreadpp.bitsnbites.eu/ (2021). Reticulate: Interface to ‘Python’.

Xue, L., Barua, A., Constant, N., Al-Rfou, R., Narang, S., Kale, M., Roberts, A., & Raffel, C. (2021). ByT5: Towards a token-free future with pre-trained byte-to-byte models. *arXiv:2105.13626 [cs]*, arXiv:2105.13626.

Zhang, X., Zhao, J., & LeCun, Y. (2015). Character-level Convolutional Networks for Text Classification. In *Advances in Neural Information Processing Systems*. Curran Associates, Inc. volume 28.

Zipf, G. K. (1936). *The Psycho-Biology of Language: An Introduction to Dynamic Philology*. (First printing edition ed.). George Routledge & Sons.