

2024 Presidential Election Forecast

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Abstract—This project aims to use historical US County Presidential Election returns from 2000 to 2020 alongside socio-economic indicators such as demographics, employment rates, and median household income, to predict the outcomes of the 2024 Presidential election across US counties.

Keywords—voting, data analysis, election, random forest, swing votes, demographics, linear regression, sentiment analysis

I. INTRODUCTION

Predicting election outcomes is a complex challenge that has significant implications for political strategy, governance, and public policy. The motivation behind this project is to derive meaningful patterns and insights from historical election data and socio-economic indicators to forecast future election results. Such predictions can help in understanding the shifting political landscape and the factors that drive electoral preferences. This project involves analyzing a vast array of data, including past election results and various socio-economic indicators, to identify patterns and factors with a significant impact on voting behavior. The ability to accurately predict election outcomes at the county level can provide valuable insights for political campaigns, policy makers, and analysts. It can identify key battleground counties, explain the socio-economic drivers of voting behavior, and develop strategies tailored to the needs and preferences of specific populations.

II. RELATED WORK

After some research, the team recognizes a lack of data mining experiments and/or projects related to predicting election results based solely on historic demographic data.

A. Split Ticket

The most prominent piece of related work is a political analysis website, Split Ticket. Split Ticket uses historic demographic and electoral data to train models used for an election forecast, then making its best attempt at inferring the actual margin for current candidates using current election data. It must be noted that the CEO of this forecaster has highlighted the high potential for bias to “creep into even a code-based approach to elections” [3].

B. Swing Vote Analysis Experimentation

Another particular experiment seeks to predict the election results of the 2024 Indian General Elections. The research calculates what it calls “swing parameters” using techniques like linear regression, Naive Bayes, Random Forest, Time Series, and more [2]. This research identifies “swing parameters” as reasons for swing voting, satisfaction with the current candidate, and current needs; these are parameters and techniques we should potentially include in our own research and experiment.

C. Sentiment Analysis Experimentation

As it stands, most approaches to our selected problem deal in sentiment analysis on social media sites such as Twitter or Facebook. Seeing as many experiments highlight “...the relationship between social media data and political results...” [5], it is likely that our initial proposed approaches, utilizing solely demographic and electoral data analysis, will not suffice for an accurate solution to our problem. If this is the case, we may opt for including some sentiment analysis in our methodologies in an effort to provide an accurate solution.

III. PROPOSED APPROACHES

We have contemplated using logistic regression and Random Forest models for predicting the 2024 Presidential election outcomes at the county level.

A. Logistic Regression

Logistic regression for its simplicity and effectiveness in binary classification problems which makes it suitable for predicting a binary outcome (Republican or Democrat).

B. Random Forest

The Random Forest model is great at handling high-dimensional data and reducing the risk of overfitting, providing us with robust alternatives that can incorporate the multitude of factors influencing electoral outcomes. The ability to automatically handle non-linear relationships and wide feature spaces aligns well with our goal of utilizing different data sources like demographics, income levels, employment rates, and historical election results. By constructing forests of decision trees trained on different subsets, this approach can inherently account for county-level variations and uncover localized patterns that drive voting behavior.

C. Sentiment Analysis

We must also consider implementing sentiment analysis on Twitter, Reddit, and/or Facebook data to further enhance the model's predictive capability by gauging public sentiment and potential shifts in voter preferences. We still would like to do more research to find the model that is most applicable to our task.

IV. SYSTEM DESIGN AND IMPLEMENTATION

A. Tools and Technology

We will use the Python programming language, renowned for its simplicity and powerful suite of data analysis and machine learning libraries. Each chosen package offers specific functionalities that are crucial for different stages of our analysis, from data manipulation to visualization and modeling, alongside packages and tools that are simple to integrate and easy to use.

a. Numpy

NumPy is the fundamental package for scientific computing in Python. It provides support for large, multi-dimensional arrays and matrices, along with a collection of mathematical functions to operate on these arrays efficiently.

We utilize NumPy for its efficient array operations, which are essential for handling and performing calculations on numerical data. Its functions are used for tasks like data transformation, normalization, and other preprocessing steps that require mathematical operations.

b. Pandas

Pandas is an open-source data analysis and manipulation tool, offering data structures and operations for manipulating numerical

tables and time series. It's particularly well-suited for handling and analyzing input data in various formats, such as CSV or SQL databases.

Pandas is our primary tool for data preprocessing, including loading, cleaning, and transforming the election and demographic datasets. It enables us to filter rows, merge datasets, handle missing values, and create new features with its powerful DataFrame API.

c. Seaborn

Seaborn is a Python visualization library based on matplotlib. It provides a high-level interface for drawing attractive and informative statistical graphics. Seaborn is particularly useful for exploring and understanding data through visualizations.

It aids in understanding the distribution of key features, identifying patterns, and visualizing relationships between variables. Plots such as histograms, box plots, and scatter plots are used to analyze the demographic factors and their relationship with voting patterns.

d. Scikit-learn

Scikit-learn is one of the most popular machine learning libraries for Python. It features various classification, regression, and clustering algorithms, including support vector machines, random forests, gradient boosting, k-means, and logistic regression, among others. It is designed to interoperate with NumPy and Pandas. Scikit-learn is the backbone of our modeling phase.

We use it to train various machine learning models, perform cross-validation, and evaluate model performance. Its comprehensive suite of preprocessing tools also supports feature selection, encoding of categorical variables, and data normalization or standardization for the modeling process.

B. Datasets

The primary dataset for this analysis includes county-level results from US presidential elections spanning from 2000 to 2020. This dataset contains detailed information on votes received by each candidate in every county, alongside metadata such as the election year, state, and county names.

To enrich our analysis and improve the accuracy of our predictions, we also integrate a demographic dataset that includes variables such as median household income, unemployment rate, educational attainment, and racial composition for each county.

This data is sourced from the United States Census Bureau and is aligned with the election dataset based on county code (fip) and year, where available.

Below we list the datasets that were used in the training and testing of the predictive model. The presented datasets require extensive preprocessing before a training or testing model can be applied.

| Dataset | # Entries | Source |
|-------------------------------------|-----------|--|
| County Presidential Returns 2000-20 | 72,617 | Link |
| Unemployment 2000-22 | 3,198 | Link |
| Median Household Income 2004-20 | 15,990 | 2004: Link 2008: Link 2012: Link 2016: Link 2020: Link |

C. Preprocessing

a. Attribute Selection

Irrelevant attributes including state, office, version, and mode are removed. State_po (state postal code) and county_fips (county identification number) are retained until demographic data integration is complete.

b. Row Filtering

Entries for minor party candidates ("Other", "Libertarian", and "Green") are removed to focus the analysis on the major parties, though this step can be adjusted based on the analysis' scope.

c. Feature Engineering

A new feature representing the ratio of "candidatevotes" to "totalvotes" is created to normalize the data, providing a percentage representation of votes received by each candidate.

d. Data Integration

The election dataset is merged with unemployment, data, aligning on county_fips and year. This step enriches the

dataset with additional features that may influence voting patterns.

e. Data Cleaning

Missing values are handled appropriately, either through imputation or removal, depending on their volume and potential impact on the analysis. Categorical variables (e.g., state) are encoded as necessary.

D. Modeling

a. Training

For training the predictive models, the following steps are undertaken:

- Feature Selection:** A subset of features, including the vote ratio and demographic characteristics (income, unemployment rate, etc.), are selected based on their relevance and potential predictive power.
- Model Selection:** The analysis begins with a logistic regression model as a baseline. This simple model will be our initial model and we will look to output a 0 for republican and 1 for democrat based on the various features. Subsequently, more complex models like decision trees, random forests, and gradient boosting machines (e.g., XGBoost, LightGBM) are explored for improved performance. Using the gradient boosting will allow for us to minimize our prediction error and increase the accuracy and AUC-ROC of our model.
- Cross-validation:** To ensure the models generalize well to new data, k-fold cross-validation is employed. This technique also aids in model selection and hyperparameter tuning.
- Training Process:** Models are trained on a preprocessed and cleaned version of the County Presidential Returns 2000-20 dataset with additional augmented features, with performance monitored via metrics appropriate to classification tasks (accuracy, precision, recall, F1 score).

b. Testing

The final phase of the modeling process involves evaluating the trained models on a separate test dataset to assess their predictive performance in a real-world scenario:

- i. **Performance Evaluation:** Models are evaluated based on their accuracy, precision, recall, and F1 score on the test dataset. These metrics provide a comprehensive view of model performance, especially in handling imbalanced classes.
- ii. **Model Comparison:** The performance of different models is compared to select the best-performing model based on the chosen metrics. This comparison considers both the predictive performance and the interpretability of the models.

E. Classification

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