Disparity in Medicare

Investigating unintended bias in Medicare coverage

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Background:

The overrepresentation of African Americans among Covid-19 infections and death has renewed the national attention to racial disparities in health care. To investigate and measure ways that access to and use of health systems, we may turn to the national Medicare program's publicly available datasets.

While Medicare predominantly affects people 65 years and older, using its data can:

a. offer insight into potential discrimination currently hiding in Medicare service payment distributions
b. develop a method for all public and private insurance companies to measure the effects of their coverage on racial minorities
c. reveal gaps in data collection whose repair will allow better models to catch overall patterns of bias or individual cases of wrongful lapses in coverage.

Medicare data is available at data.cms.gov

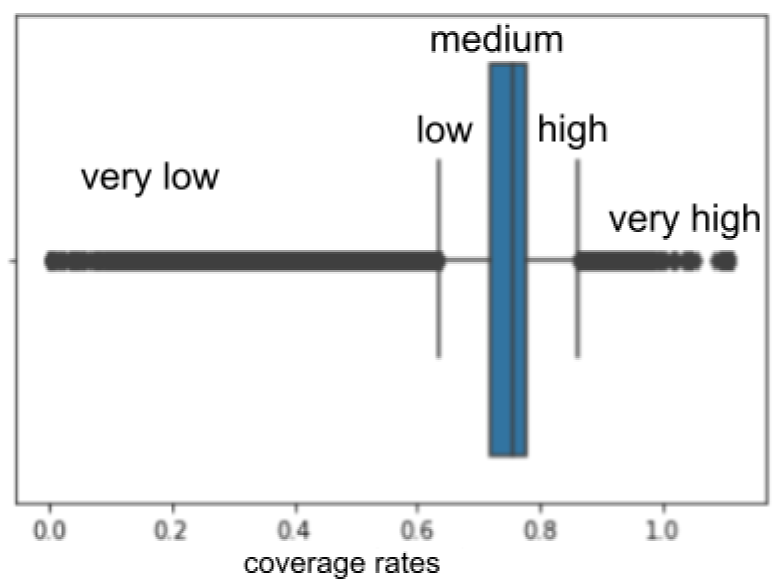
Machine Learning approach:

To measure Medicare coverage, I created a new feature that describes the proportion between the total Medicare payment and the total payment Medicare allows the provider to charge.

A classification model can learn the patterns between low, medium, and high coverage rates and other factors relating to the provider, including the kind of service provided, the rates requested by the provider, the location of the service, and the demographics of that location.

The “important features” of the best performing model reveal both the most influential features on the general algorithm as well as the relative significance of each column as compared to the others.

The mislabeled samples of the data are also useful. Which provider receives a “very low” coverage rate, but is predicted by the model to be “very high”? By looking at the location, type of service, and zip code demographics of these mislabeled providers, we can infer the importance of race on Medicare coverage rates.



Data Wrangling

The available data included columns for “African-American,” “white,” “Asian Pacific-Islander,” etc. but over half of the sample were missing information for one or all bins, making comparisons of providers by the populations they serve very difficult.

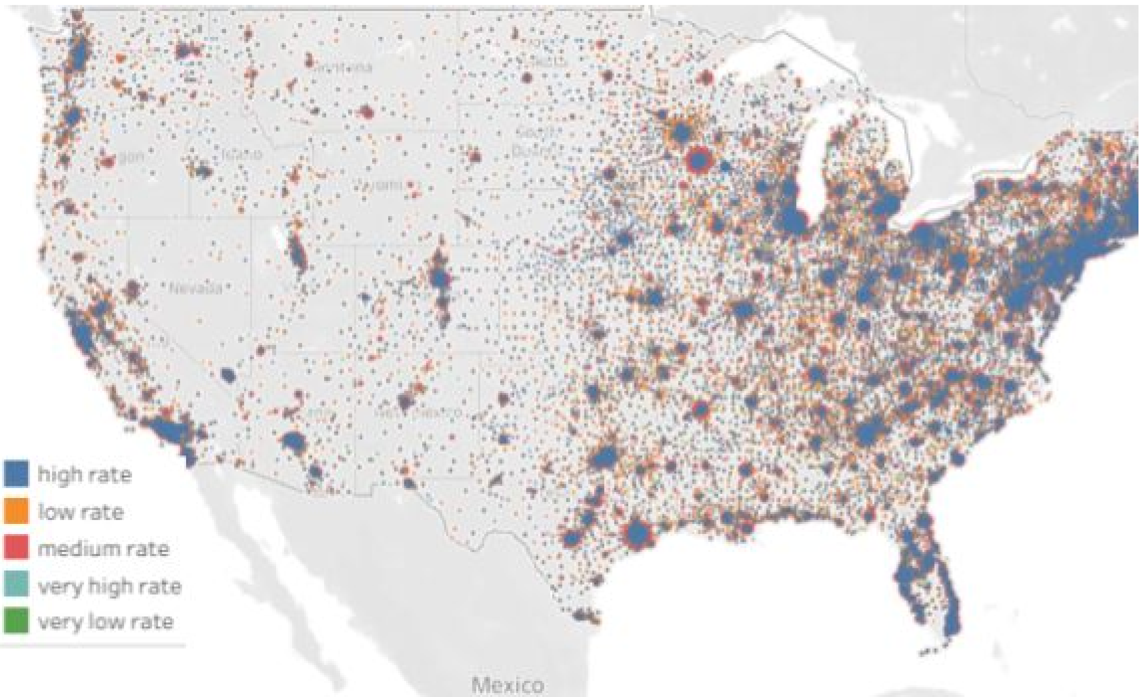
After experimenting with imputing missing values with “0” if missing (this didn’t add up to total number of beneficiaries) or subtracting missing values from the total patients (this didn’t work for rows with multiple missing values), I considered only using rows that included information for the number of African-American patients. This would have cut my dataset from about 1,000,000 rows to about 500,000, which is still a lot of information but only 50% of the original set. Also, which providers would leave out the number of African American patients -- perhaps the providers that don’t serve many? This may introduce bias in the dataset.

Finally, I dropped the columns with missing values. To make up for the missing race information, I merged the dataset with zip-code level population numbers for different races from the American Community Survey. This gives an impression of the population that the provider serves although the racial makeup of the zip code is less granular and less reliable. The American Community Survey data, while containing nulls in other columns, had no missing information for race-specific population.

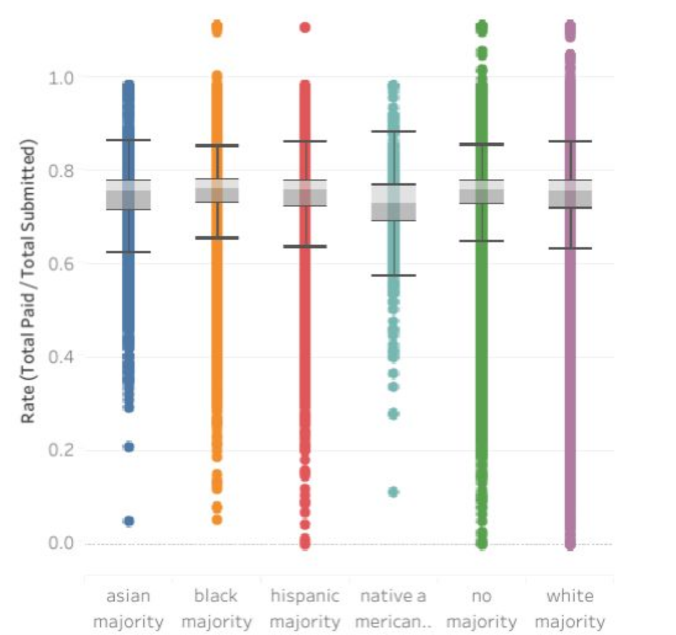
The other cleaning required looking at unique entries for country and state and decoding unfamiliar entries (including codes for American military service-people abroad). I decided to drop rows that weren’t American states or territories. The zip codes included also need processing, ranging from 1-9 digits. Some were nulls that needed dropping, others were variations of 5-digit zips that needed leading zeros, and other were variations of 9-digit zips that need leading zeros.

Exploratory Data Analysis

Initial data exploration showed a lot of variation in coverage rates with many low and many high outliers. But race-specific geography did not obviously correspond to the geographical distribution of rates.



While white zip codes were predominant in the Midwest, Black zip codes in the South, Hispanic zip codes along the southern border, Asian zip codes in the Pacific and Northeast and Native American zip codes in the Midwest and Alaska, the coverage rates were diffused throughout all regions.



Similarly the distribution plots revealed similar interquartile ranges for all populations but Native Americans who were covered less than other groups.

The spread of the payrates *did* differ particularly when looking at the low outliers with were lower for white, Hispanic, Black, and no-majority zip codes.

Modeling

The algorithms tested for classification were Random Forest, Gradient Boosting, and Logistic Regression. While I considered SVM, even when training a very small subset of my data (5,000 samples) the model required too much memory to train so I eliminated this algorithm.

Using the F1 score to judge performance, Random Forest ended up out performing the other two by 0.05 and requiring almost 1/10 of the computation time.

models	CV: Scale1, all feats	CV: Scale2, all feats
Random Forest	0.590946	0.591320
Gradient Boosting	0.606442	0.606779
Logistic Regression	0.596830	0.596491

Further model processing including using hyperparameter tuning using Randomized Search. The best-judged parameters were then applied to the Random Forest model to improve upon the F1 score. There were improvements but they were small.

models	F1 Scores, out-of-box	F1 Scores, Tune1	F1 Scores, Tune2	F1 Scores, Tune3	F1 Scores, Tune4	F1 Scores, Tune5
Random Forest	0.656930	0.658595	0.656472	0.655376	0.657754	0.655587

Analysis

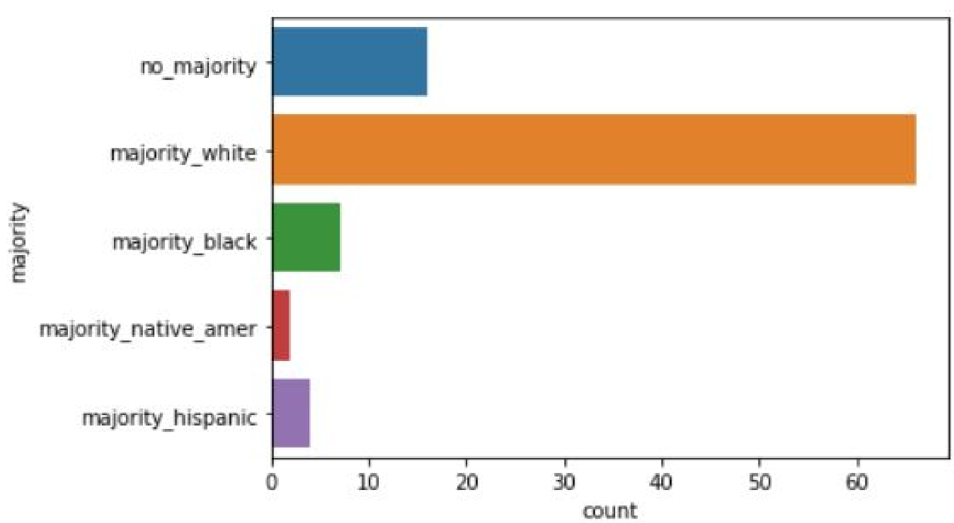
Does the model show bias? According to the Random Forest feature importances, the details about the provider related to charges, submitted, charges per service, number of services, and number of patients were more important in determining coverage than race.

While “percent_” Black, Asian, white, etc. did appear within the top 20 features they were closer to the bottom of these 20. The “majority” features, explaining which group made up the majority of the zip code population, didn’t appear at all. White-majority cities did not reveal patterns of high coverage nor did other-majority cities reveal patterns of low coverage.

Overall the importances of all the top 20 features were 0.09 or below, showing that different factors were important in different estimators. The percent_race columns were 0.03 or below in ‘importance.’

Outliers

Examining the major errors of the model, did the predicted “very high” but actually “very low” samples come from non-white zip codes? Few did. The majority were white cities or no-majority cities, concentrated in the South and Pacific, and tended to be Nurse Practitioners, Physician Assistants or Family Practice. In other words, patterns *do* exist but not revealing overrepresentation of racial minorities.



Further Modeling

If the mislabeled entries are in fact incorrectly compensated, this model can be deployed to find providers whose patients are undercompensated for services by training to finding other samples like these mislabeled samples.

On the other hand, it can also be used to examine mislabeled samples who are predicted “very low” but were actually given “very high” coverage. Using the model for this end can have the consequences of reducing expenses and finding wasteful distributions.