Spatial Data Science MOOC

Exercise

Create a prediction model

Section 2 Exercise 1

03/2020

THE SCIENCE OF WHERE™

Create a prediction model

Time to complete
90 minutes

Introduction

Prediction is an important part of spatial data science. You can use prediction to forecast future values (for example, predicting tomorrow's air quality for a specified location), downscale information (for example, using voter turnout data at the county level to predict voter turnout at the tract level), or fill in missing values in a dataset.

ArcGIS provides various prediction tools to help you complete these types of analyses. In this exercise, you will use the Forest-based Classification and Regression tool, which uses an adaptation of Leo Breiman's random forest algorithm. This supervised machine learning algorithm allows you to use existing data to train models that may be useful for predictive analysis.

The tool creates many decision trees, called an ensemble or a forest, that are used for prediction. Each tree generates its own prediction and is used as part of a voting scheme to make final predictions. The strength of the forest-based method is in capturing commonalities of weak predictors (the trees) and combining them to create a powerful predictor (the forest). You will use this tool to train and evaluate a predictive model, modifying variables and parameters to improve the model performance.

Exercise scenario

After preparing and visualizing your data, you are ready to begin your predictive analysis. In this exercise, you will create models that predict voter turnout. These models will use explanatory variables, such as income and age, to predict the dependent variable, voter turnout.

You will use this model to downscale voter turnout from the county to the tract level. This information will be used to organize a "Get Out the Vote" canvassing campaign by identifying local regions that are expected to have low voter turnout.

Step 1: Download the exercise data files

In this step, you will download the exercise data files.

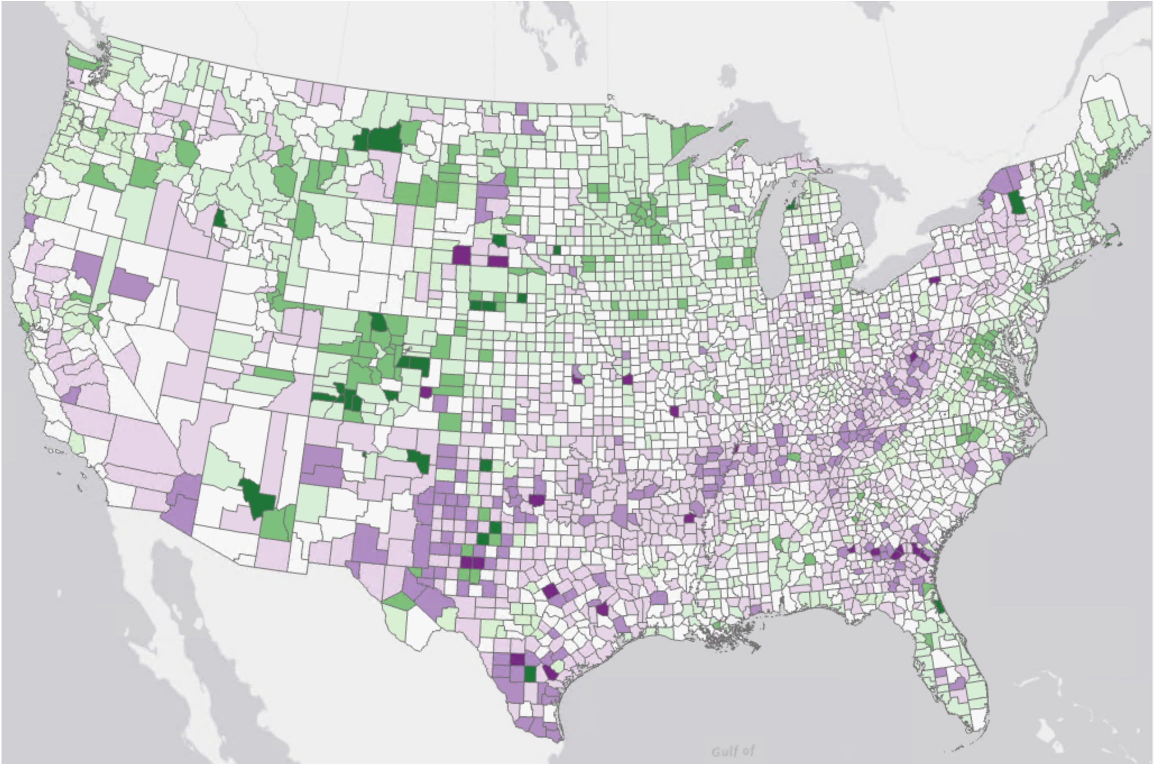
- a Open a new web browser tab or window.
- b Go to https://bit.ly/37OhTZm and download the exercise data ZIP file.

Note: The complete URL to the exercise data file is https://www.arcgis.com/home/item.html?id=6c177c0b07ca481698065354b958c8d9.

- c Extract the files to a folder on your local computer, saving them in a location that you will remember.

Step 2: Open an ArcGIS Pro project

- a Start ArcGIS Pro.
- b If necessary, sign in using the provided course ArcGIS account.
- c Under Open, click Open Another Project.
- d In the Open Project dialog box, browse to the Prediction folder that you saved on your computer.
- e Click Prediction.aprx and click OK.



A Prediction map tab opens to a gray basemap with a map layer that represents the 2016 election results for each county. Counties with a voter turnout value under the mean are purple, and counties with a voter turnout value over the mean are green.

Step 3: Create a prediction model

During the data engineering exercise, you enriched the 2016 election data with various demographic variables. During the data visualization exercise, you explored the relationship of these variables to voter turnout, identifying variables that have a strong relationship to voter turnout. You will use these variables in your first prediction model.

a. From the Analysis tab, in the Geoprocessing group, click Tools.

b. In the Geoprocessing pane, search for **Forest-Based Classification And Regression**.

c. In the search results, click the Forest-Based Classification And Regression (Spatial Statistics Tools) tool.

Note: Be sure that you are using the Spatial Statistics tool and not the GeoAnalytics Desktop tool.

The Forest-Based Classification And Regression tool opens in the Geoprocessing pane.

d. In the Geoprocessing pane, enter the following parameters:

- Prediction Type: Train Only
- Input Training Features: CountyElections2016
- Variable To Predict: Voter_Turnout

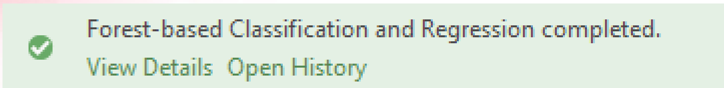
e. Under Explanatory Training Variables, next to Variable, click the Add Many button .

f. In the variable window, check the box for the following variables:

- 2019 Median Age
- 2019 Per Capita Income
- 2019 Education: High School/No Diploma : Percent
- Own A Selfie Stick : Percent

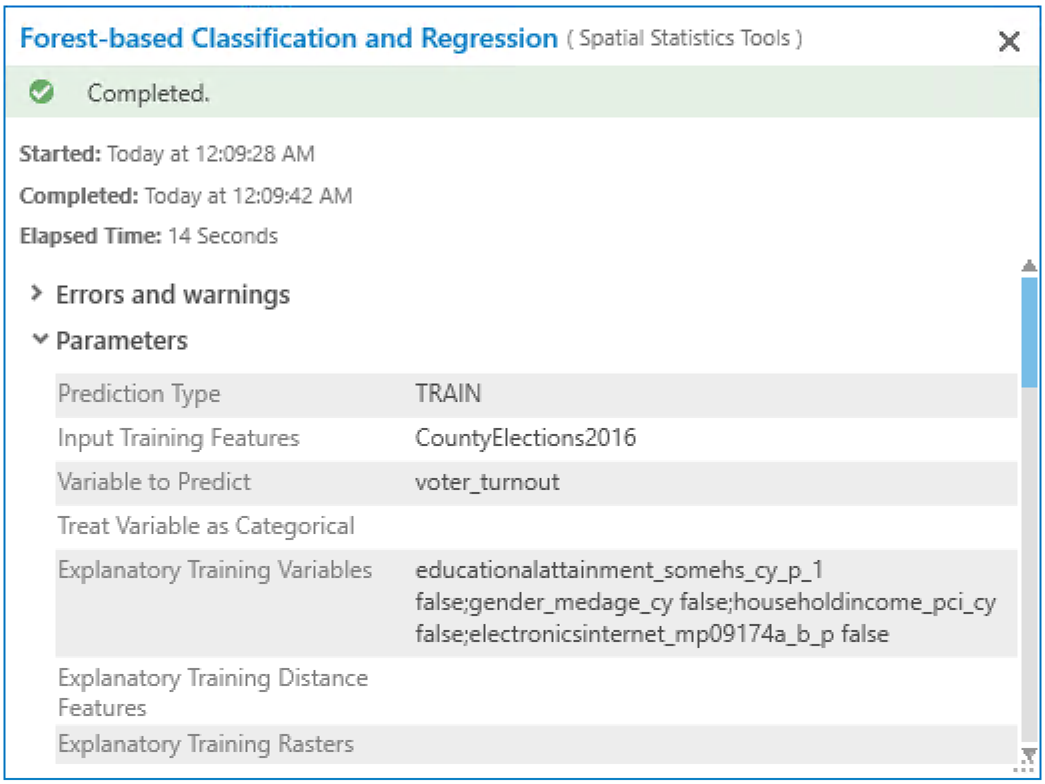
g. In the variable window, click Add.

h. In the Geoprocessing pane, click Run.



At the bottom of the Geoprocessing pane, you will see a message confirming that the tool completed. You did not specify in the tool to create an output. Instead, you will review the model's performance using the tool messages.

i. At the bottom of the Geoprocessing pane, click View Details.



The Forest-Based Classification And Regression (Spatial Statistics Tools) tool message window appears. Tool messages contain information such as the parameters used to run the tool, how long the tool ran, and model performance diagnostics.

j. Scroll down to Messages.

k. Under Messages, locate the Training Data: Regression Diagnostics section.


```
----- Training Data: Regression Diagnostics ------
R-Squared                                    0.909
p-value                                      0.000
Standard Error                               0.005
*Predictions for the data used to train the model
compared to the observed categories for those features

---- Validation Data: Regression Diagnostics -----
R-Squared                                    0.519
p-value                                      0.000
Standard Error                               0.029
*Predictions for the test data (excluded from model
training) compared to the observed values for those
test features
```

Note: Each time that you run the Forest-based Classification and Regression tool, you may get slightly different results due to the randomness introduced in the algorithm to prevent the model from overfitting to the training data.

By default, Forest-based Classification and Regression reserves 10 percent of the data for validation. The model is trained without this random subset, and the tool returns an R-Squared value measuring how well the model performs on the unseen data.

When a model is evaluated based on the training dataset rather than a validation dataset, it is common for estimates of performance to be overstated due to a concept called overfitting. Therefore, the validation R-Squared is a better indicator of model performance than the training R-Squared.

The model returned a validation R-Squared value of 0.519, indicating that the model predicted the voter turnout value in the validation dataset with an accuracy of about 52 percent.

Next, you will review how important each explanatory variable was in generating a prediction.

Note: Throughout the exercise, you will rerun the same geoprocessing tool using different parameters.

l. Close the Forest-Based Classification And Regression tool message window.

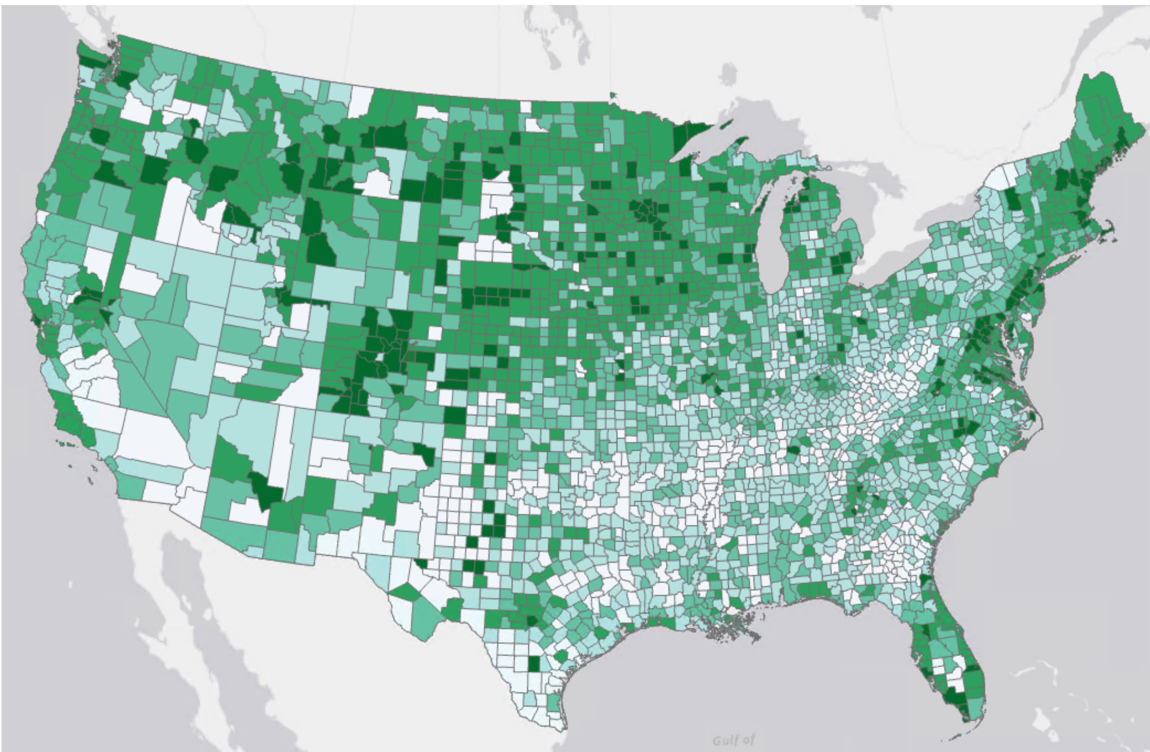
m. In the Contents pane, turn off the CountyElections2016 layer.

Step 4: Explore variable importance

a In the Geoprocessing pane, expand Additional Outputs, and then enter the following parameters:

- Output Trained Features: **Out_Trained_Features**
- Output Variable Importance Table: **Out_Variable_Importance_Table**

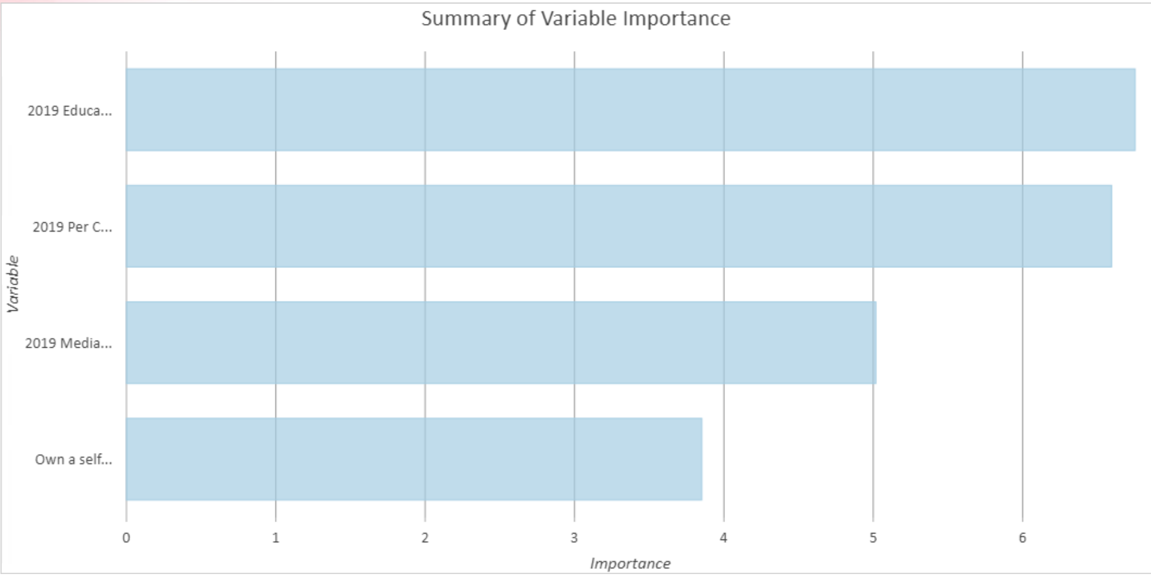
b Click Run.



The Out_Trained_Features layer displays the predicted voter turnout for each county in the contiguous United States. A variable importance table and associated bar chart are added to the Contents pane and can be used to explore which variables were most important in this prediction.

c In the Contents pane, open the Summary Of Variable Importance chart.

Hint: In the Contents pane, under Out_Variable_Importance_Table, right-click Summary Of Variable Importance and choose Open.



The 2019 Education: High School/No Diploma : Percent and 2019 Per Capita Income variables have the highest importance, meaning that they were the most useful in predicting voter turnout.

Each time that you run the Forest-based Classification and Regression tool, you may get slightly different results due to the randomness introduced in the algorithm to prevent the model from overfitting to the training data. To understand and account for this variability, you will use a parameter that lets the tool create multiple models in one run. This will allow you to explore the distribution of model performance.

Step 5: Examine model stability

a. Close the Summary Of Variable Importance chart.

b. In the Geoprocessing pane, expand Validation Options, and then enter the following parameters:

   - Number Of Runs For Validation: **10**
   - Output Validation Table: **Out_Validation_Table**

c. Under Output Validation Table, check the box for Calculate Uncertainty.

Note: If you do not see the Calculate Uncertainty check box, you may need to scroll down in the Geoprocessing pane.

d. Run the tool.

e At the bottom of the Geoprocessing pane, click View Details.

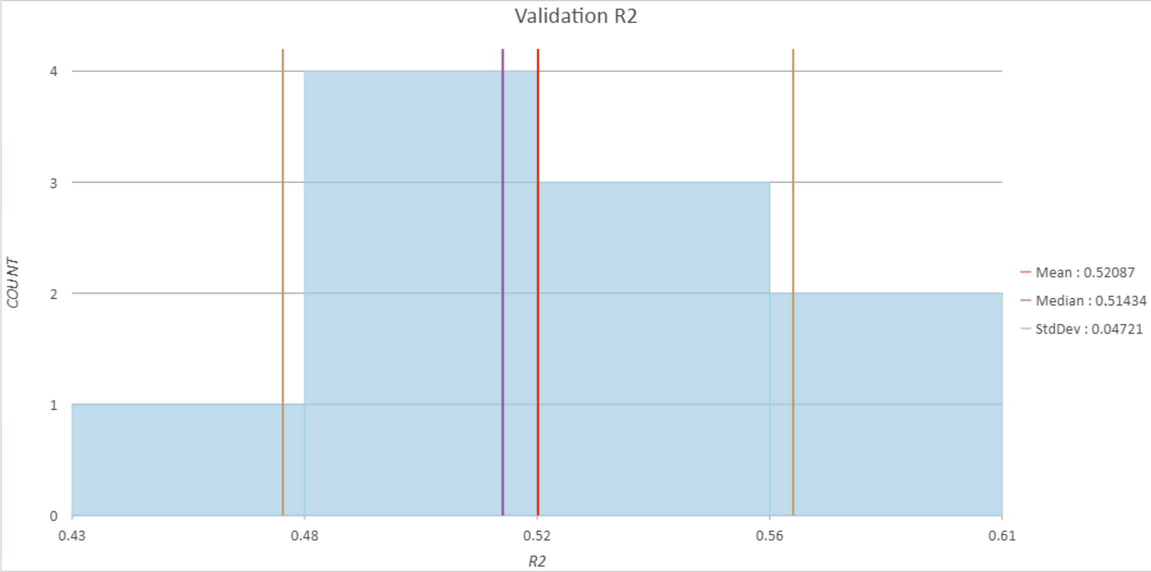
f In the tool message window, expand Messages, if necessary, and scroll to the Validation Data: Regression Diagnostics section.

```
---- Validation Data: Regression Diagnostics -----
R-Squared                                    0.527
p-value                                      0.000
Standard Error                               0.028
*Predictions for the test data (excluded from model
training) compared to the observed values for those
test features
```

The tool trained 10 models with random subsets of validation data. The most representative R-Squared across the 10 runs is 0.527, corresponding to about 53 percent accuracy in prediction of the validation data. You can use a histogram to review the distribution of R-Squared values returned over the 10 runs.

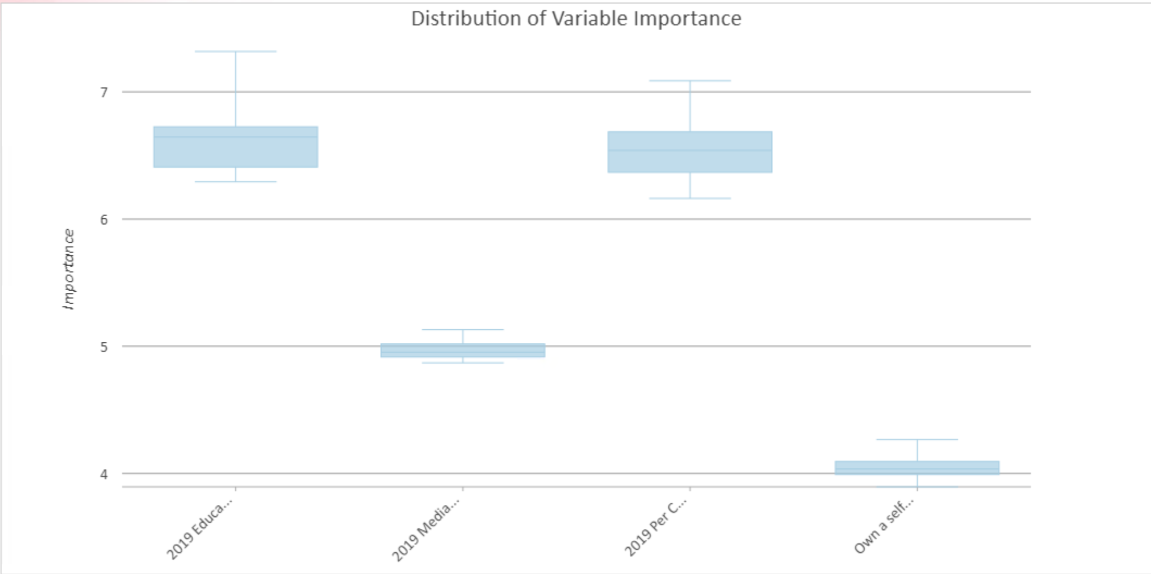
g Close the tool message window.

h In the Contents pane, open the Validation R2 chart.



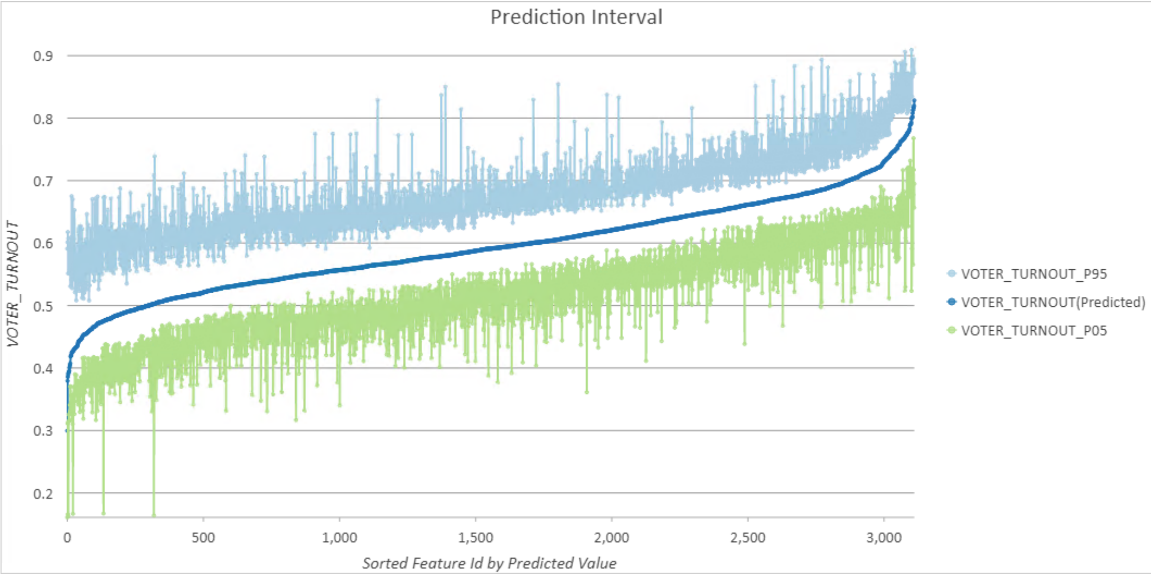
The histogram shows the variability in model performance by visualizing the distribution of R-Squared values returned over the 10 runs. The mean R-Squared for the 10 runs of this model is 0.52.

i In the Contents pane, open the Distribution Of Variable Importance chart.



Instead of a bar chart, the variable importance is visualized using a box plot to show the distribution of importance across the 10 runs of the model. There is overlap in the distribution of importance of the 2019 Per Capita Income and 2019 Education: High School/No Diploma : Percent variables. In some runs of the model, Per Capita Income was more important, and in other runs, Education: High School/No Diploma was more important. Overall, both variables are strong candidates for your predictive model.

j In the Contents pane, under Out_Trained_Features, right-click Prediction Interval and choose Open.



The Prediction Interval chart visualizes the level of uncertainty for any given prediction value. By considering the range of prediction values returned by the individual trees in the forest, prediction intervals are generated indicating the range in which the true value is expected to fall. You can be 90 percent confident that new prediction values generated using the same explanatory variables would fall in this range. This chart can help you identify if the model is better at predicting some values than others. For example, if the confidence intervals were much larger for low voter turnout values, then you would know that the model is not as stable for predicting low voter turnout as it is for predicting high voter turnout. The prediction intervals in this model are fairly consistent, indicating that the model performance is relatively stable across all values.

At this point, you have used the attributes in your dataset as the explanatory variables in your model. With the Forest-based Classification and Regression tool, you can also calculate new variables based on distances to meaningful locations. In the next step, you will calculate new variables and assess their importance to the model.

k Close the charts.

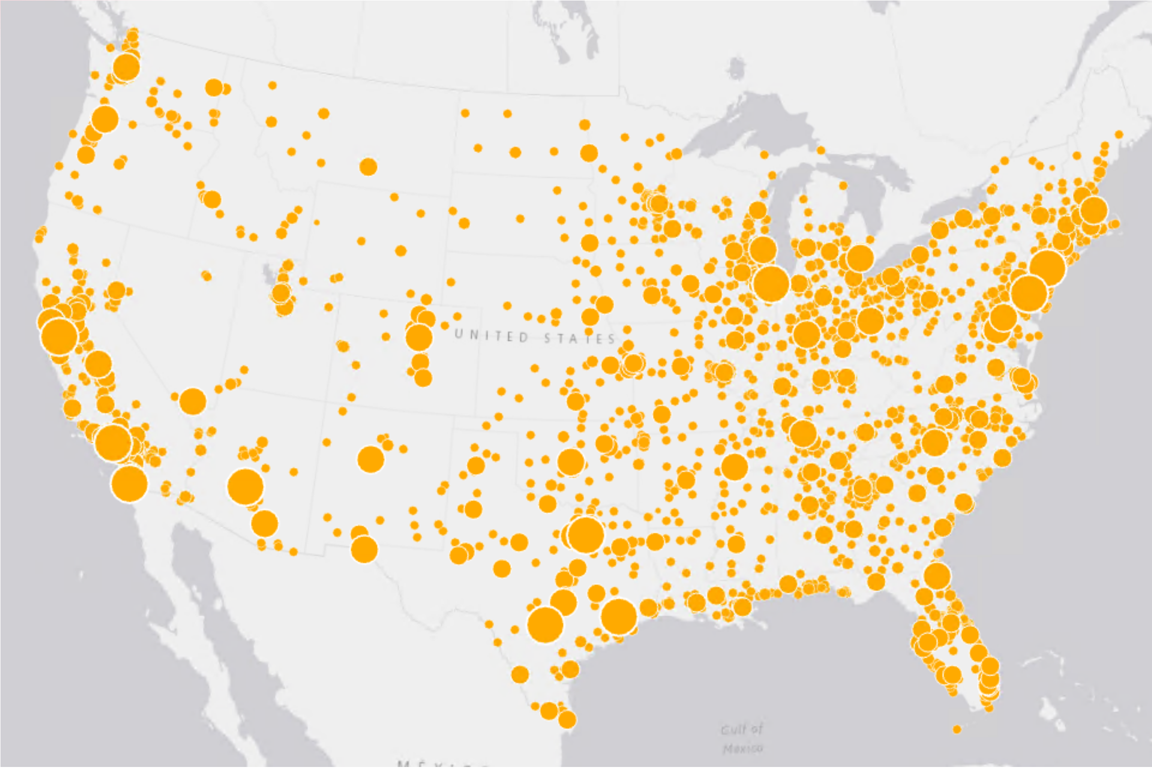
Step 6: Add distance variables to the model

You want to incorporate each county's urban and rural characteristics into the model to determine if these variables improve voter turnout predictions. To represent urban and rural characteristics, you will calculate the distance between each county and cities of various sizes. The proximity to each of these cities will be used to represent the urban and rural characteristics, with more rural counties being further from cities.

a In the Contents pane, turn off the Out_Trained_Features layer.

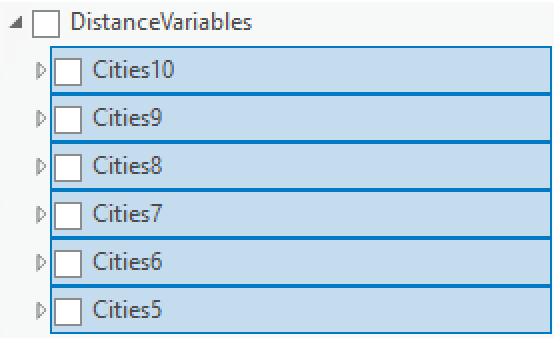
b In the Contents pane, expand DistanceVariables, and then turn on the following layers:

- DistanceVariables
- Cities10
- Cities9
- Cities8
- Cities7
- Cities6
- Cities5



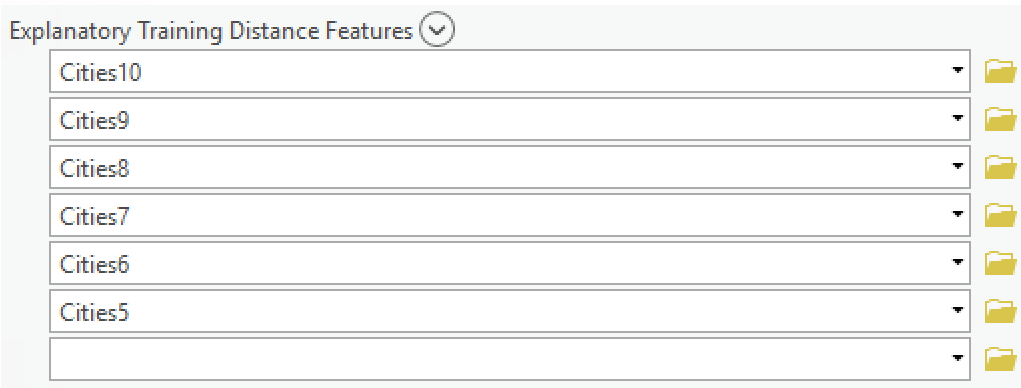
Each Cities layer represents a class of city size based on population. Cities10 represents cities with the largest populations, and Cities5 represents the cities with the smallest populations.

- **c** In the Contents pane, turn off the DistanceVariables and Cities layers.
- **d** In the Contents pane, click Cities10.
- **e** Press and hold the Shift key on your keyboard, and then click Cities5.



The six distance variables are selected.

f. Drag the selected layers from the Contents pane into the Geoprocessing pane, under Explanatory Training Distance Features.



g. Click Run.

h. In the Contents pane, right-click Out_Trained_Features and choose Attribute Table.

i. Scroll to the Cities attribute fields.

CITIES10	CITIES9	CITIES8	CITIES7	CITIES6	CITIES5
1007783.447616	467299.554413	12723.383042	91100.873325	0	427621.759861
819023.706977	566502.329637	4940.430496	20653.18596	0	422569.363134
1097517.892448	428772.323189	52174.578718	50363.593022	0	355994.640857
973335.016097	396462.1964	45547.712767	31097.869895	17657.98708	363624.639765
1068573.846971	261723.491894	35767.384935	53475.566964	16909.193194	413247.248244
1084712.54391	473636.975597	37790.391671	49118.422059	21940.985023	397675.474009

Note: When a city point is contained within a county, the distance will be zero.

The Forest-based Classification and Regression tool calculates the distances from each county to the nearest city of each class (the closest class 5 city, the closest class 6 city, and so on). These distances are added to the Out_Trained_Features layer as separate attribute fields.

j. Close the attribute table.

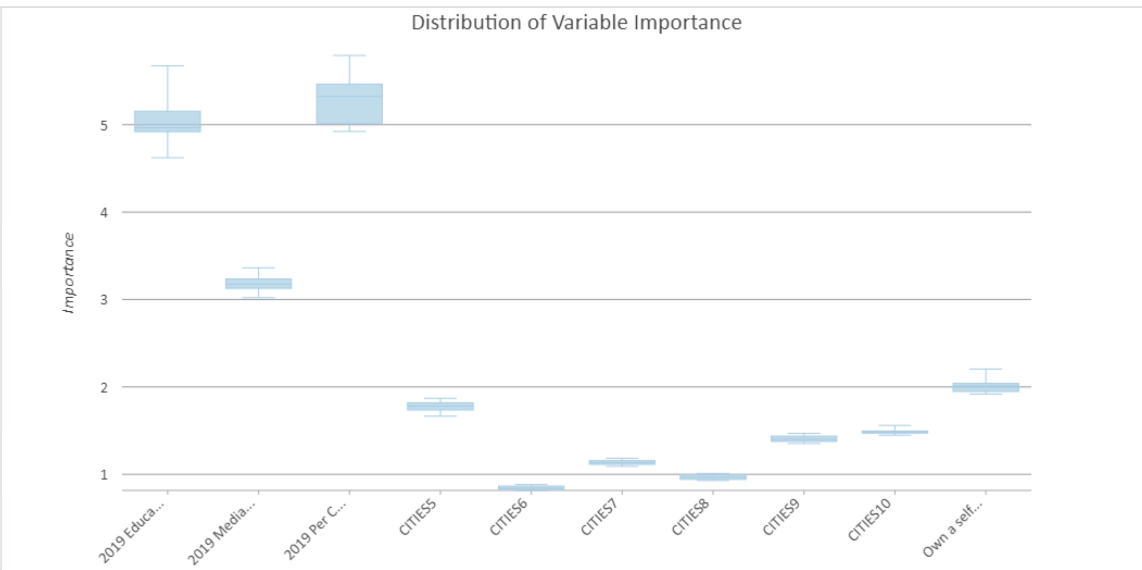
k. At the bottom of the Geoprocessing pane, click View Details.

l. In the tool message window, expand Messages, if necessary, and scroll to the Validation Data: Regression Diagnostics section.

```
---- Validation Data: Regression Diagnostics -----
R-Squared                                      0.614
p-value                                        0.000
Standard Error                                 0.025
*Predictions for the test data (excluded from model
training) compared to the observed values for those test
features
```

The model's R-Squared has increased to 0.614, which means that you are predicting with more than 61 percent accuracy based on the validation data. You will review the variable importance chart to see how influential each of these distance variables are to the model performance.

- **m** Close the tool message window.
- **n** In the Contents pane, open the Distribution Of Variable Importance chart.



The distance to the smallest cities (Cities5) and the distance to the largest cities (Cities10) are more important than the other distance variables. Overall, however, these variables were not as helpful as the income and education variables.

In the next step, you will add additional demographic variables in an attempt to make a more robust model.

- **o** Close the Distribution Of Variable Importance chart.

Step 7: Create a prediction model with many variables

The Forest-based Classification and Regression tool uses a random subset of the available explanatory variables in each decision tree. Commonalities in the predictions and variables used among all the trees in the forest are quantified in the variable importance diagnostic. In general, this means that you can test adding variables to the model without diminishing the model's predictive power. Variables that are useful result in higher variable importance scores, and variables that are not useful result in lower variable importance scores.

a. In the Geoprocessing pane, under Explanatory Training Variables, click the Add Many button.

b. In the variable window, click the Toggle All Checkboxes button.

c. Uncheck the box for the following variables:

- County
- Shape_Area
- Shape_Length
- Voter_Turnout
- 2019 Median Age
- 2019 Per Capita Income
- 2019 Education: High School/No Diploma : Percent
- Own A Selfie Stick : Percent

d. Click Add.

e. Run the tool.

f. Review the R-Squared value in the validation data regression diagnostics.

Hint: In the Forest-Based Classification And Regression tool message window, scroll to the Validation Data: Regression Diagnostics section.

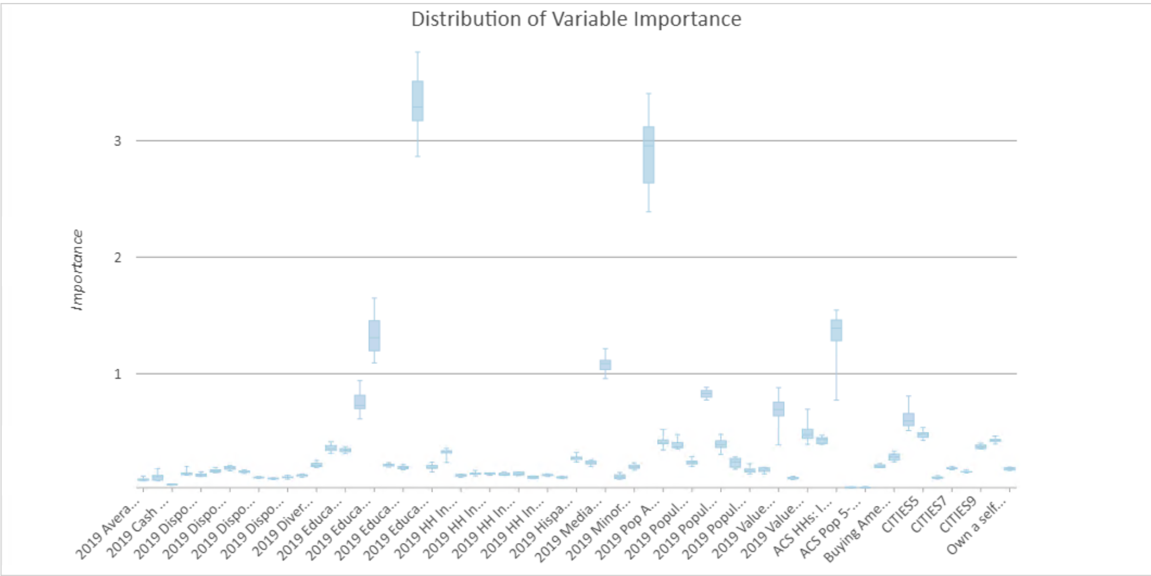
```
---- Validation Data: Regression Diagnostics -----
R-Squared                                    0.707
p-value                                      0.000
Standard Error                               0.022
*Predictions for the test data (excluded from model
training) compared to the observed values for those
test features
```

The model's R-Squared has increased to 0.707, which means that you are now predicting with more than 70 percent accuracy based on the validation data.

g Close the tool message window.

h Review the Distribution Of Variable Importance chart.

Hint: In the Contents pane, open the Distribution Of Variable Importance chart.



Note: You can zoom in to the chart to more clearly see the distribution for a particular variable.

2019 Per Capita Income and 2019 Education: High School/No Diploma : Percent still have the highest variable importance in the model, but there are several new variables that have contributed to the model and raised its performance. There are also several variables that may not be helping the model, represented by their low variable importance.

All these variables represent continuous numerical values. In the next step, you will add a categorical variable to the model.

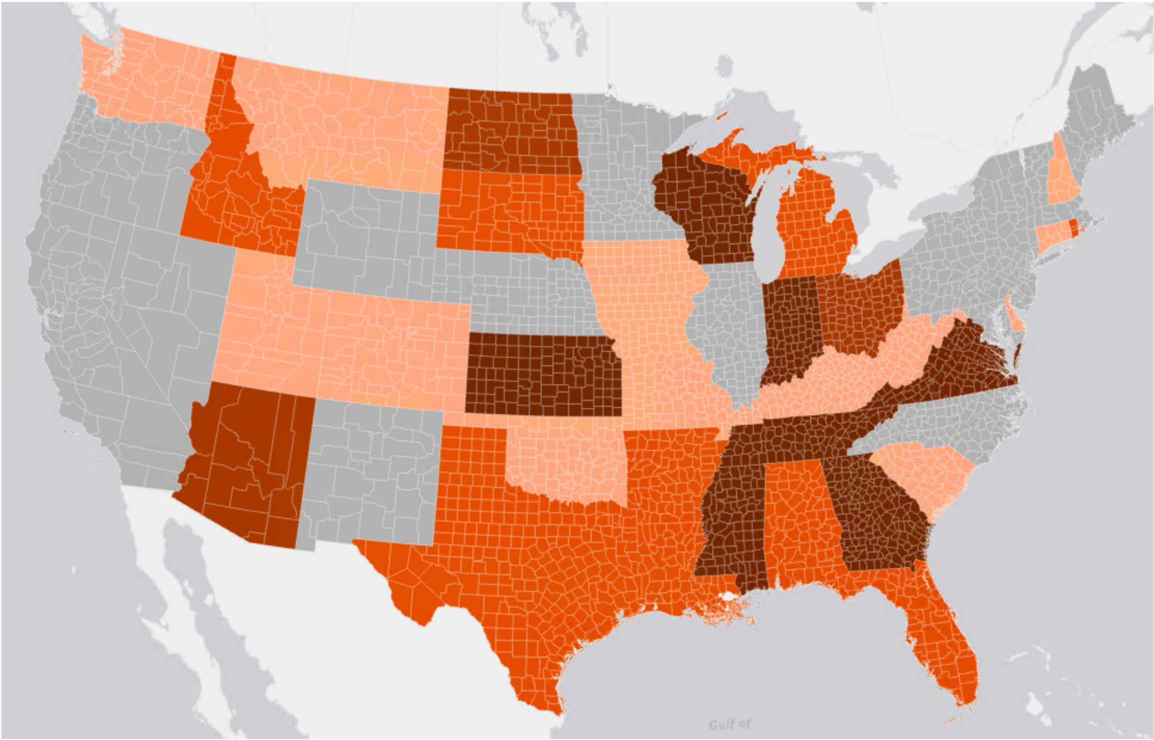
i Close the Distribution Of Variable Importance chart.

Step 8: Add categorical variables to the model

Research indicates that state voting requirement laws may affect voter turnout. You can add voting requirement laws to the model as a categorical variable to see if it helps predict voter turnout.

a. In the Contents pane, turn off the Out_Trained_Features layer.

b. In the Contents pane, turn on the CountyElections2016_VotingRequirements layer.



This layer includes all the attributes from the CountyElections2016 layer and an additional attribute that represents the following categories for state voting requirements:

- No document required
- ID without photo
- ID with photo
- Strict ID without photo
- Strict ID with photo

You will add this categorical variable to the model and assess the model performance.

c. In the Contents pane, turn off the CountyElections2016_VotingRequirements layer.

d. In the Geoprocessing pane, for Input Training Features, choose CountyElections2016_VotingRequirements.

e. Under Explanatory Training Variables, click the Add Many button.

f. In the variable window, check the box for State Voting Requirement Laws.

g. Click Add.

The State Voting Requirement Laws variable should be added to the list of explanatory training variables and marked as a categorical variable.

h. Click Run.

i. Review the R-Squared value in the validation data regression diagnostics.

Hint: In the Forest-Based Classification And Regression tool message window, scroll to the Validation Data: Regression Diagnostics section.

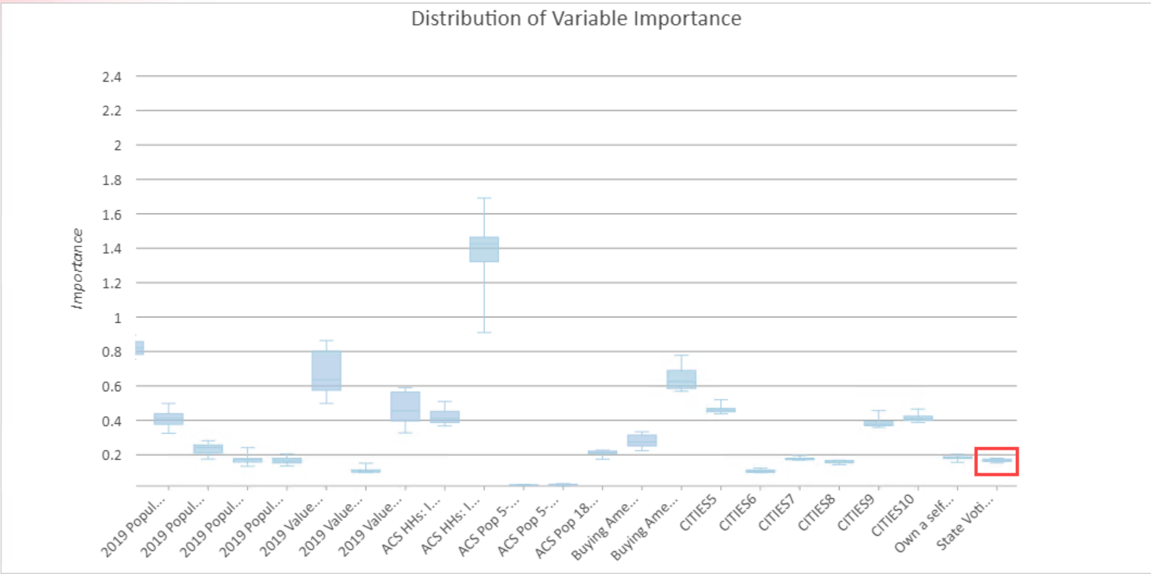
```
---- Validation Data: Regression Diagnostics -----
R-Squared                                    0.703
p-value                                      0.000
Standard Error                               0.022
*Predictions for the test data (excluded from model training)
compared to the observed values for those test features
```

The R-Squared value is about the same, with no improvements to the model. You can review the variable importance to determine how helpful state voting requirement laws are compared to the other variables.

j. Close the tool message window.

k. Open the Distribution Of Variable Importance chart.

l. Zoom to the bottom right of the chart to locate the State Voting Requirements variable.



Although voting requirement laws are likely important in voter participation, they do not help the model very much—at least compared to the other explanatory variables. You will continue to explore state-related variables that can impact voter participation.

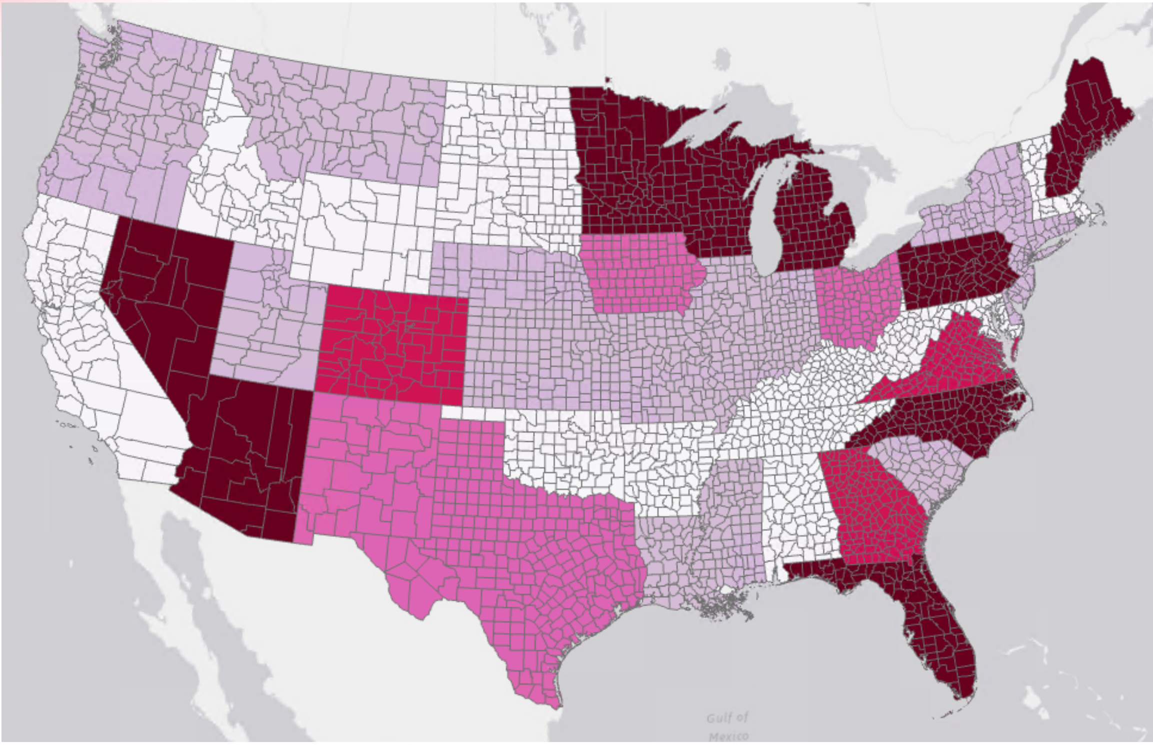
m Close the Distribution Of Variable Importance chart.

Step 9: Add a variable that represents election competitiveness

Additional research and literature associates voter turnout to how competitive each state is in the presidential election, due to a common perception that presidential parties will automatically win certain states. You will add this variable to the model and assess the model performance.

a In the Contents pane, turn off the Out_Trained_Features layer.

b In the Contents pane, turn on the CountyElections2016_PartyVotes layer.



This layer includes the attributes from the CountyElections2016 layer, the State Voting Requirement Laws attribute, and an additional attribute that measures the difference in election party votes as a percent. This attribute, State Percent Votes Difference, represents how competitive each state is in the presidential election, with a lower percent difference indicating a more competitive state.

Note: This ArcGIS Pro project includes an ArcGIS Notebook, ElectionPartyVotes, that was used to calculate the State Percent Votes Difference.

c. In the Contents pane, turn off the CountyElections2016_PartyVotes layer.

d. In the Geoprocessing pane, for Input Training Features, choose CountyElections2016_PartyVotes.

e. Under Explanatory Training Variables, click the Add Many button.

f. In the variable window, check the box for State Percent Votes Difference.

g. Click Add.

h. Run the tool.

1. What is the validation R-Squared value for this model?

Hint: In the Forest-Based Classification And Regression tool message window, scroll to the Validation Data: Regression Diagnostics section.

____

____

2. **Compared to the other variables, is State Percentage Votes Difference a helpful variable in this model?**

   Hint: In the Contents pane, open the Distribution Of Variable Importance chart.

____

____

Identifying a "good" model is subjective and varies greatly based on the industry and how the model will be used. In many fields, including many of the social sciences, an R-Squared value over 0.70 might be considered satisfactory for making a prediction. Before using this model to predict, you will simplify the model to only include the most important variables.

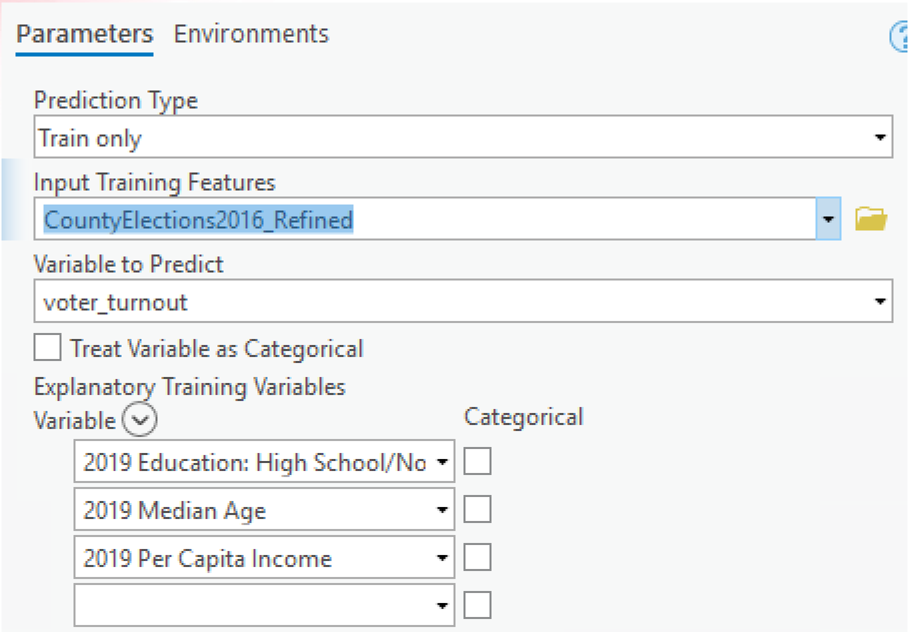
i. Close the Distribution Of Variable Importance chart and the tool message window.

Step 10: Refine the model

There are many different ways to select variables to include in a model. In this analysis, the most important variables were chosen by defining a threshold in the Variable Importance Table. The variables with importance above this threshold will be included in this refined version of the model.

a. In the Contents pane, turn off Out_Trained_Features.

b. In the Geoprocessing pane, for Input Training Features, choose CountyElections2016_Refined.



2019 Median Age, 2019 Per Capita Income, and 2019 Education: High School/No Diploma : Percent are already listed under Explanatory Training Variables.

c Under Explanatory Training Variables, click the Add Many button .

d In the variable window, click the Toggle All Checkboxes button .

e Uncheck the box for the following variables:

- County
- FIPS
- Shape_Area
- Shape_Length
- State
- Voter_Turnout
- 2019 Median Age
- 2019 Per Capita Income
- 2019 Education: High School/No Diploma : Percent
- 2019 Population Age 18+

> You are unchecking these variables in the variable window to ensure that these variables are not listed under Explanatory Training Variables twice.

f Click Add.

g Expand Advanced Forest Options.

h For Number Of Trees, type **1000**.

Increasing the number of trees improves the chance that each variable will be used in a decision tree, resulting in a more accurate model prediction. Specifying the number of trees is a balance between the accuracy of the model and the processing time to generate the model.

i Run the tool.

Note: Because of the increased number of trees, the tool may take a few minutes to run.

j Review the various geoprocessing tool messages and charts to answer the following questions.

3. **What is the validation R-Squared value for this model?**

___

___

4. **What is the mean R-Squared value over the 10 runs of this model?**

   Hint: In the Contents pane, open the Validation R2 chart.

___

5. **What are the two most important explanatory variables in this model?**

___

The simplified model has approximately the same R-Squared value, meaning that removing the variables with low importance did not compromise model performance. You will review additional model metrics to help you assess if the model requires any additional changes.

k Close the charts.

Step 11: Examine additional model metrics

a. If necessary, open the Forest-Based Classification And Regression (Spatial Statistics Tools) tool message window.

b. Under Messages, scroll to the Model Out Of Bag Errors section.

```
------------ Model Out of Bag Errors ------------
Number of Trees                  500         1000
MSE                            0.002        0.002
% of variation explained      71.738       71.883
```

Model Out of Bag Errors is another diagnostic that can help validate the model. The percentage of variation explained indicates the percent of variability in voter turnout that can be explained using this model. Model Out of Bag Errors also shows how much performance is gained by increasing the number of trees in the model. If the percentage of variation explained significantly increases from the 500 to the 1000 column, you may want to increase the number of trees to improve model performance.

This model does not see a significant increase in percentage of variation explained, so you do not need to increase the number of trees.

c. Scroll to the Explanatory Variable Range Diagnostics section.

```
---------------------------------------- Explanatory Variable Range Diagnostics ----------------------------------------
                                                    Training                Validation               Training  Validation
Variable                                            Minimum     Maximum     Minimum     Maximum      Share(a)    Share(b)
2019 Median Age                                     23.30       61.80       24.80       58.00          1.00       0.86*
2019 Per Capita Income                              11729.00    78564.00    9395.00     58856.00       0.97*      0.71*
2019 Education: Some College/No Degree : Percent    7.58        37.07       12.09       32.27          1.00       0.68*
2019 Education: Bachelor's Degree : Percent         2.59        45.16       2.96        41.21          1.00       0.90*
2019 Education: Associate's Degree : Percent        0.88        22.08       3.03        18.77          1.00       0.74*
2019 Education: Grad/Professional Degree : Percent  0.00        43.89       0.81        31.69          1.00       0.70*
2019 Pop Age 15+: Never Married : Percent           10.40       68.55       13.91       59.81          1.00       0.79*
```

The Explanatory Variable Range Diagnostics lists the range of values covered by each explanatory variable in the datasets used to train and validate the model. For example, median age values spanned from 23 to 61 in the dataset used to train the model and from 24 to 58 in the dataset used to validate the model.

The Validation Share indicates the percentage of overlap between the values used to train and the values used to validate. In this example, 86 percent of the median age values used to train the model were used to validate the model. A value over one indicates that the model predicted values outside the range of values in the training data. To minimize extrapolation, you will review this diagnostic as you predict voter turnout to tracts.

For more information about these additional model metrics, see ArcGIS Pro Help: How Forest-based Classification and Regression works.

d Close the tool message window.

e In the Contents pane, turn off Out_Trained_Features.

Step 12: Predict values

You trained a model using the county data that you had available. You can use this model to predict voter turnout at the tract level, which is much higher resolution and will allow you to get a sense of more detailed spatial patterns.

To predict voter turnout at the tract level, you need census tract data with explanatory variables that match the explanatory variables used to train the model. In this step, you will train the model using the county data and then apply that model to the same variables at the tract level and predict voter turnout.

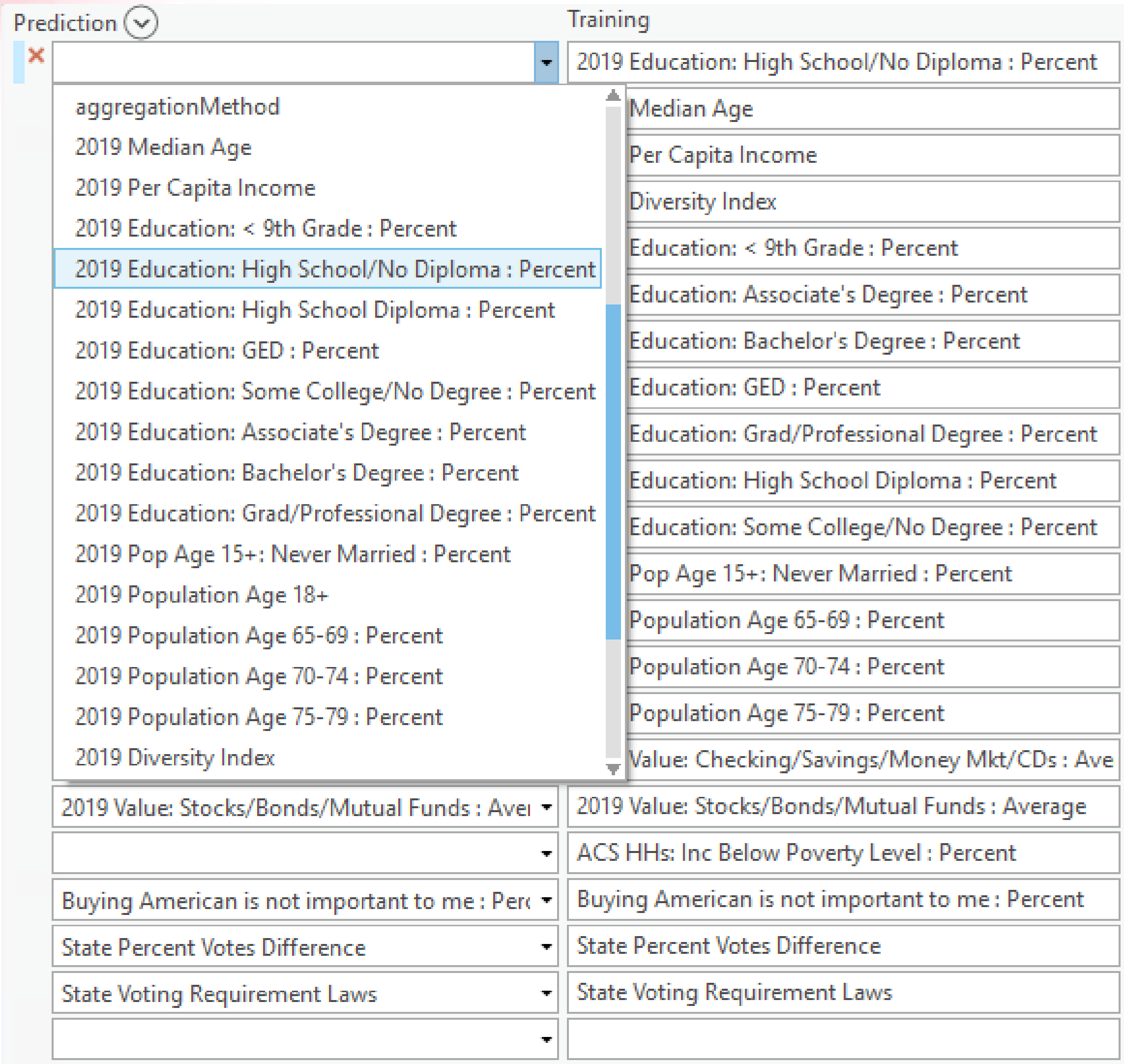
Note: Tracts that were not relevant to this analysis (for example, airports and national parks) were removed.

a In the Geoprocessing pane, enter the following parameters:

- Prediction Type: Predict To Features
- Input Prediction Features: Tracts
- Output Predicted Features: **Out_Predicted_Features**

The prediction features must include the variables used to train the model, but the variables do not have to have the same name. You can use the Match Explanatory Variables to match the variables using their respective name.

b Under Match Explanatory Variables, under Prediction, for the empty cells, click the down arrow and choose the matching Training variable name.



- **c** Expand Additional Outputs.
- **d** Under Output Trained Features, delete Out_Trained_Features.
- **e** Expand Validation Options.
- **f** Next to Training Data Excluded For Validation, type **0**.

You are no longer assessing model performance, so you do not need to remove 10 percent of the training data for validation. Instead, you will use all training data to train the model so that the model can predict to the best of its ability.

- **g** Run the tool.

h When the tool is complete, open the tool message window.

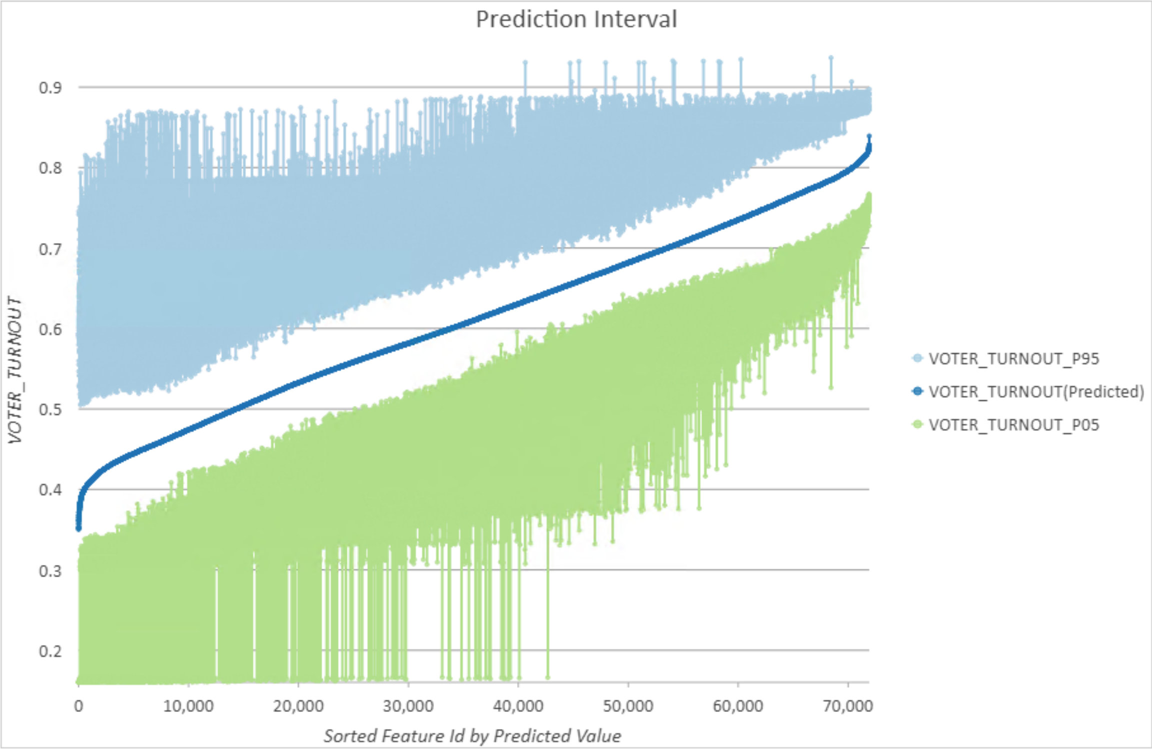
The R-squared value for validation data is no longer available because you are not using a validation subset. The Model Out Of Bag Errors uses training data to evaluate how well each tree in the model predicts, so you will focus on this metric.

i Scroll to the Model Out Of Bag Errors section.

```
------------ Model Out of Bag Errors ------------
Number of Trees                    500        1000
MSE                              0.002       0.002
% of variation explained        71.322      71.574
```

The percentage of variation explained is still fairly high at 71 percent, and it does not vary greatly between 500 and 1000 trees. Because processing is not taking too long, you can keep 1000 as the Number of Trees.

j In the Contents pane, under Out_Predicted_Features, right-click Prediction Interval and choose Open.



The confidence intervals are much larger for low voter turnout values than for high voter turnout values. This indicates that the model is not as reliable for predicting low voter turnout as it is for predicting high voter turnout. Because the goal of your analysis is to identify areas with low voter turnout, this model is not reliable enough to meet your needs. The factors that drive voter turnout are likely very different from place to place, making it difficult to find a model that predicts well for the entire country. It is often good practice to reduce your study area and create more localized models. In the next step, you will attempt to model voter turnout in the state of Iowa.

Step 13: Change the scale of your analysis

The state of Iowa is a competitive state, which means that voter turnout is very important. You will perform a more localized analysis in the state of Iowa. You will train your model using only upper Midwest county-level data and predict voter turnout at the Iowa tract level.

a. In the Contents pane, turn off Out_Predicted_Features.

b. In the Geoprocessing pane, for Input Training Features, choose CountyElections2016_NorthMidwest.

c. For Input Prediction Features, choose Tracts_Iowa.

d. Expand Validation Options and enter the following parameters:

- Training Data Excluded For Validation: **10**
- Number Of Runs For Validation:**100**

e. Run the tool.

Note: It may take several minutes for the tool to complete.

f. Review the Model Out Of Bag Errors.

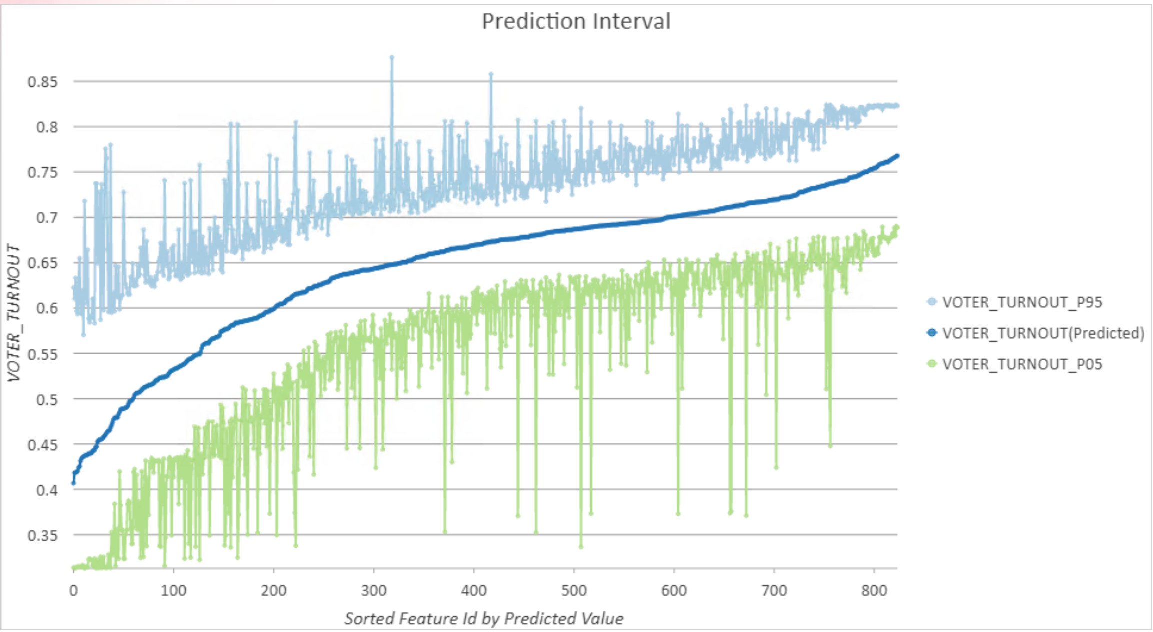
Hint: Open the tool message window and scroll to the Model Out Of Bag Errors section.

```
------------ Model Out of Bag Errors ------------
Number of Trees                   500         1000
MSE                             0.002        0.002
% of variation explained       71.621       71.758
```

The percentage of variation explained is approximately 71 percent.

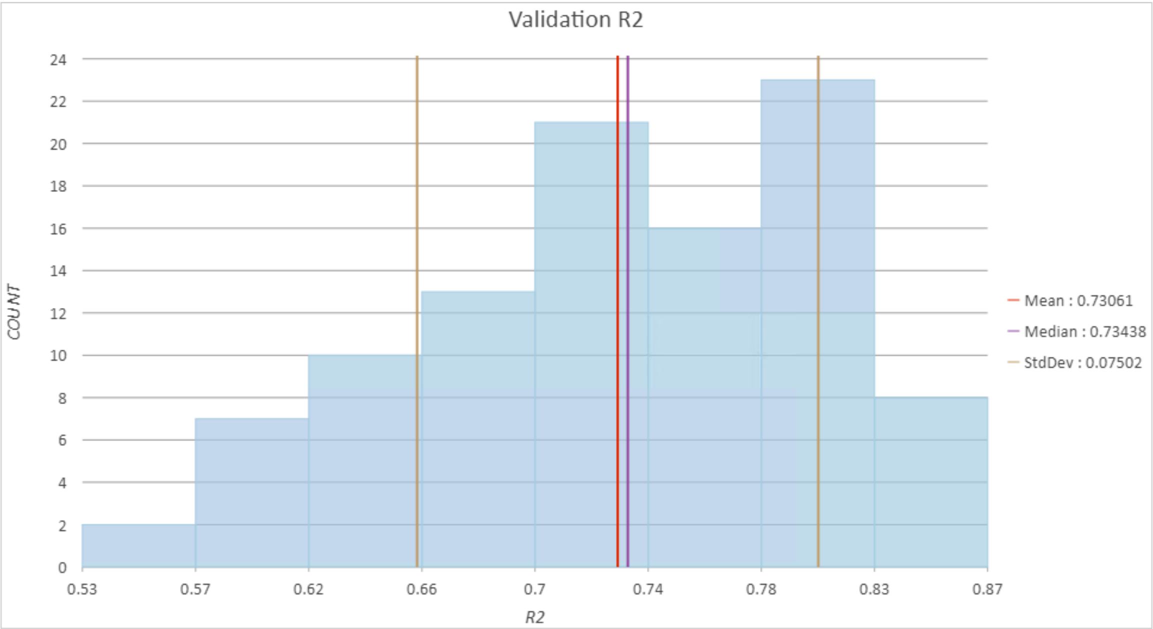
g. Open the Prediction Interval.

Hint: In the Contents pane, under Out_Predicted_Features, right-click Prediction Interval and choose Open.



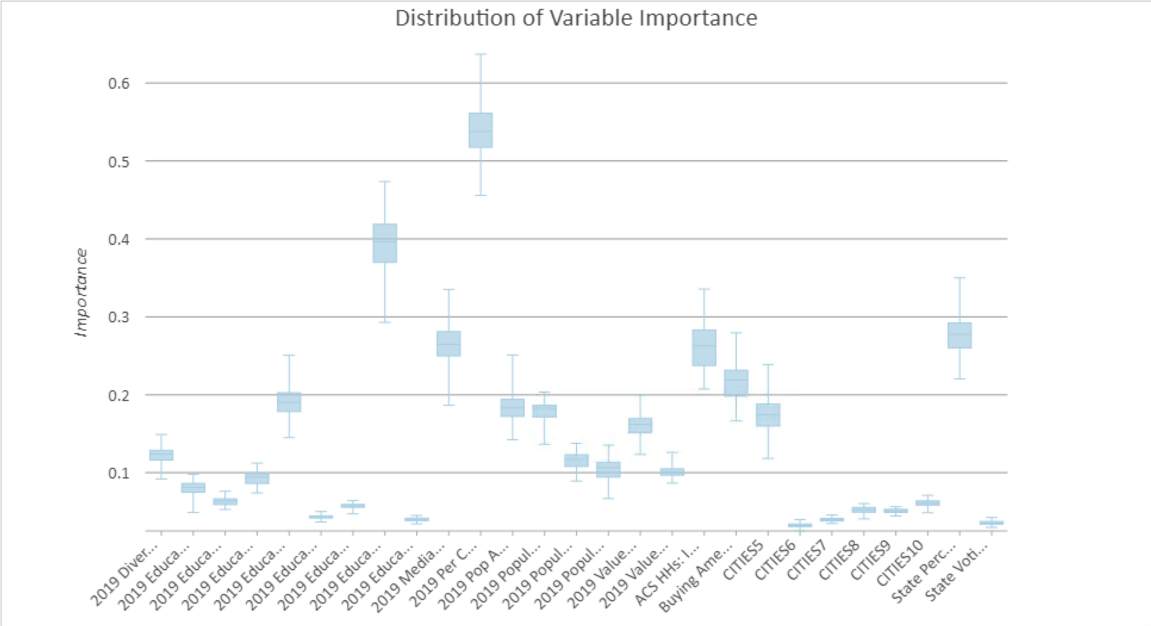
The confidence intervals are much smaller for low voter turnout values, indicating that the model has become more stable for predicting these values.

h Open the Validation R2 chart.



The distribution of R-Squared values suggests that the model has stabilized R-Squared values for the validation subset with a mean of approximately 0.73. You will review the variable importance chart to determine if there are any variables that you can remove to improve model performance.

Open the Distribution Of Variable Importance chart.



You will remove the variables of least importance and rerun the model to determine if these refinements improve model performance.

Note: Typically, this is an iterative process, where you remove some variables and then rerun and evaluate the model.

Step 14: Refine the prediction

a. In the Geoprocessing pane, under Explanatory Training Variables, remove the following variables:

- 2019 Education: High School/No Diploma : Percent
- 2019 Diversity Index
- 2019 Education: Associate's Degree : Percent
- 2019 Education: GED : Percent
- 2019 Education: Grad/Professional Degree : Percent
- 2019 Education: High School Diploma : Percent
- 2019 Education: Some College/No Degree: Percent
- 2019 Population Age 70-74 : Percent
- 2019 Population Age 75-79 : Percent
- 2019 Value: Stocks/Bonds/Mutual Funds : Average
- ACS HHs: Inc Below Poverty Level : Percent

b. Under Explanatory Training Distance Features, remove the following features:

- Cities10
- Cities9
- Cities7
- Cities6
- Cities5

c. Under Match Explanatory Variables, under Prediction, in an empty cell, click the down arrow and choose the matching Training variable name.

d. Run the tool.

e. When the tool is complete, open the tool message window.

f. Review the Model Out Of Bag Errors.

```
------------ Model Out of Bag Errors ------------
Number of Trees                      500          1000
MSE                                0.002         0.002
% of variation explained          70.090        70.052
```

The percentage of variation explained is approximately 70 percent.

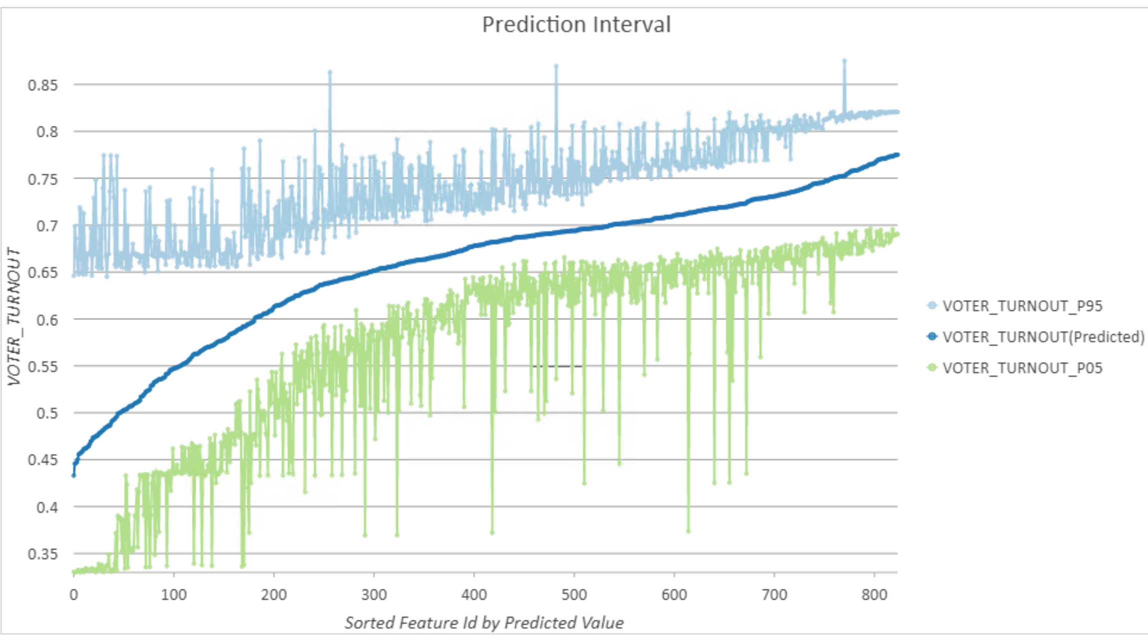
g Review the Explanatory Variable Range Diagnostics.

Explanatory Variable Range Diagnostics

Variable	Training Minimum	Maximum	Validation Minimum	Maximum	Prediction Minimum	Maximum	Training Share(a)	Validation Share(b)	Prediction Share(c)
2019 Median Age	25.00	55.90	29.30	54.40	18.10	59.40	1.00	0.81*	1.34+
2019 Per Capita Income	9395.00	46933.00	19303.00	39151.00	5132.00	67796.00	1.00	0.53*	1.67+
2019 Education: Bachelor's Degree : Percent	6.18	35.60	7.26	30.57	0.00	48.97	1.00	0.79*	1.66+
2019 Pop Age 15+: Never Married : Percent	10.40	59.81	14.54	46.54	11.43	99.96	1.00	0.65*	0.98+
2019 Population Age 65-69 : Percent	2.96	11.03	3.27	10.87	0.00	12.27	1.00	0.94*	1.52+

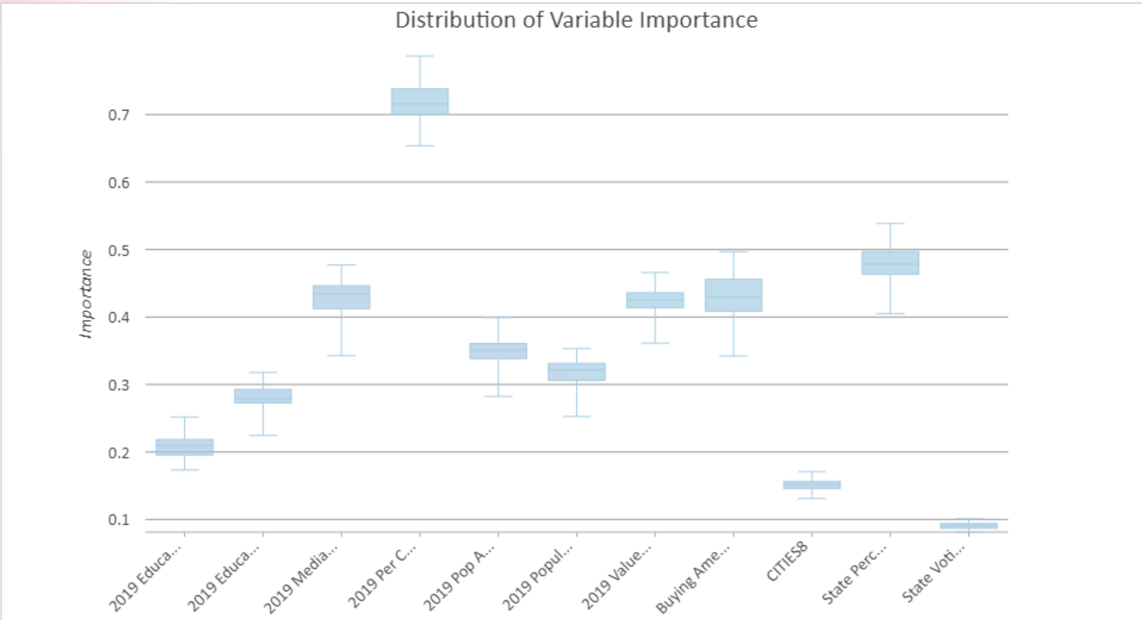
There are still some variables that have a larger prediction range (tract-level) than the training range (county-level). So, you will review the Prediction Interval to evaluate the model's stability.

h Review the Prediction Interval.



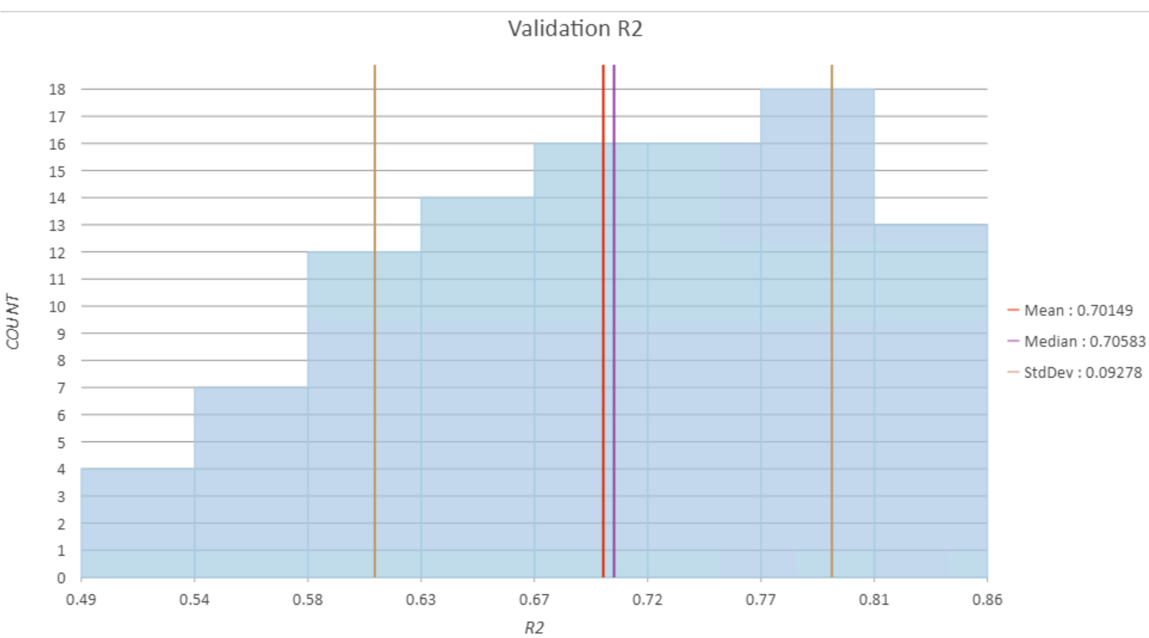
The confidence intervals are much smaller for low voter turnout values, indicating that the model is more reliable. You can also use the Distribution of Variable Importance chart to evaluate the stability of the model.

i Open the Distribution Of Variable Importance chart.



You can evaluate the stability of a model by the length of the interquartile range of the explanatory variables. A large interquartile range (a long box) can indicate that the model is unstable because one variable can be more important in one run of the model compared to another. In this model, the interquartile ranges are fairly short, reconfirming that this model is stable.

j Open the Validation R2 chart.

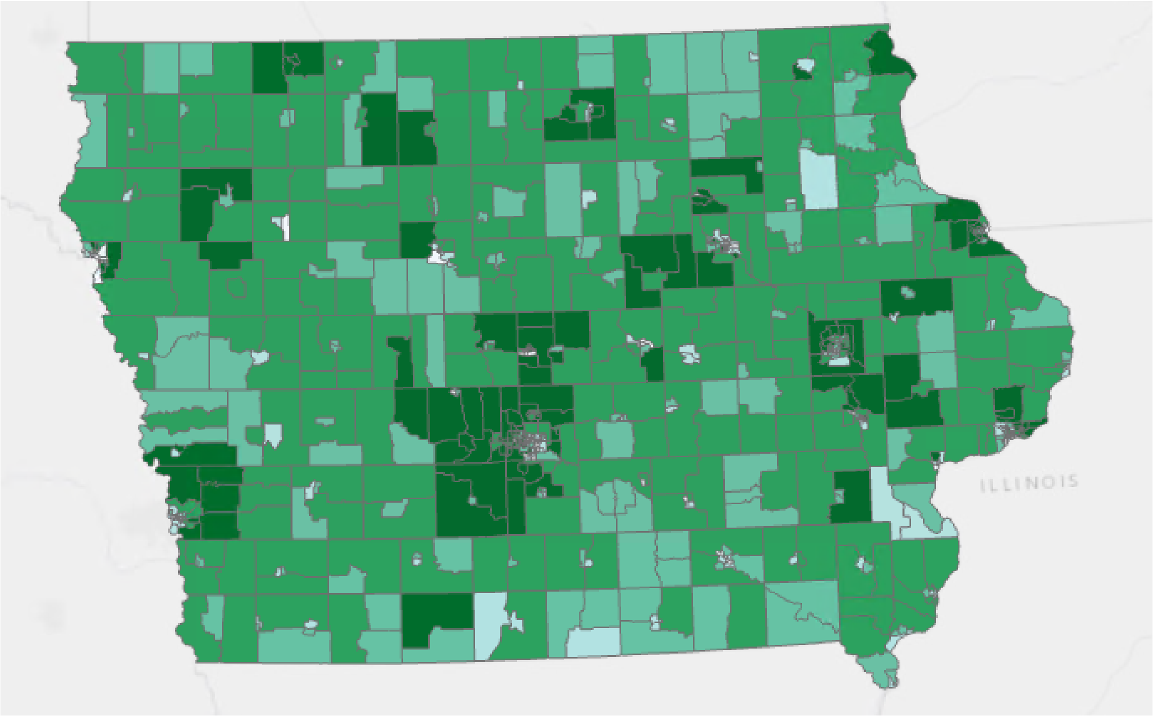


The distribution of R-Squared values suggests that the model has stabilized R-Squared values for the validation subset with a mean of approximately 0.70.

k. Close the charts.

l. Go to the Iowa bookmark.

Hint: From the Map tab, in the Navigate group, click Bookmarks and choose Iowa.



The Out_Predicted_Features layer contains the predicted voter turnout for Iowa. Exploring this map can help you identify the tracts with lower predicted voter turnout values and assess which regions of the state could be good locations for a campaign to get out the vote.

Overall, the model is performing well for this analysis question. You can continue modifying and improving the model (for example, changing the Training Data Excluded For Validation parameter to zero) or proceed with these results. Remember, your model will not be perfect. Your goal is to find a model that is useful for your objective, which, in this case, is a campaign to get out the vote.

m. If you would like to continue this analysis, proceed to the optional stretch goal; otherwise, save the project and exit ArcGIS Pro.

Stretch goal (optional)

The goal of prediction is to use the predicted values to make more informed decisions. If you would like to continue this analysis, you can apply the results of this prediction to organize a canvassing effort.

For this canvassing effort, you used the prediction model to identify a tract in Florida that has low predicted voter turnout. You will assign 50 volunteers to a specific set of houses that they will visit to inform potential voters about an upcoming election.

The following is a list of high-level steps that you can complete to continue this analysis:

1. Turn off the Out_Predicted_Tracts layer.
2. Go the Naples, FL bookmark.
3. Add AddressPointsCanvassing to the map.
4. Use the Build Balanced Zones (Spatial Statistics Tools) tool to define 50 zones. One volunteer will be assigned to each zone.
5. Share your results in the Lesson Forum, using the hashtag **#stretch** in the posting title.

Use the Lesson Forum to post your questions, observations, and syntax examples. Be sure to include the **#stretch** hashtag in the posting title.

Answers to Exercise Questions

1. What is the validation R-Squared value for this model?

   Hint: In the Forest-Based Classification And Regression tool message window, scroll to the Validation Data: Regression Diagnostics section.

   The R-Squared value is approximately 0.74, meaning that the model predicted voter turnout in the validation data with an accuracy of about 74 percent.

2. Compared to the other variables, is State Percentage Votes Difference a helpful variable in this model?

   Hint: In the Contents pane, open the Distribution Of Variable Importance chart.

   Comparatively, the State Percentage Votes Difference is one of the more helpful variables in this model. This indicates that knowing how competitive each state is can help in predicting voter turnout.

3. What is the validation R-Squared value for this model?

   The R-Squared value is approximately 0.74, meaning that the model predicted voter turnout in the validation data with an accuracy of about 74 percent.

4. What is the mean R-Squared value over the 10 runs of this model?

   Hint: In the Contents pane, open the Validation R2 chart.

   The R-Squared values for each run of the model range from 0.63 through 0.77 with a mean value of 0.722.

5. What are the two most important explanatory variables in this model?

   The two most important variables are 2019 Education: High School/No Diploma : Percent and 2019 Per Capita Income.