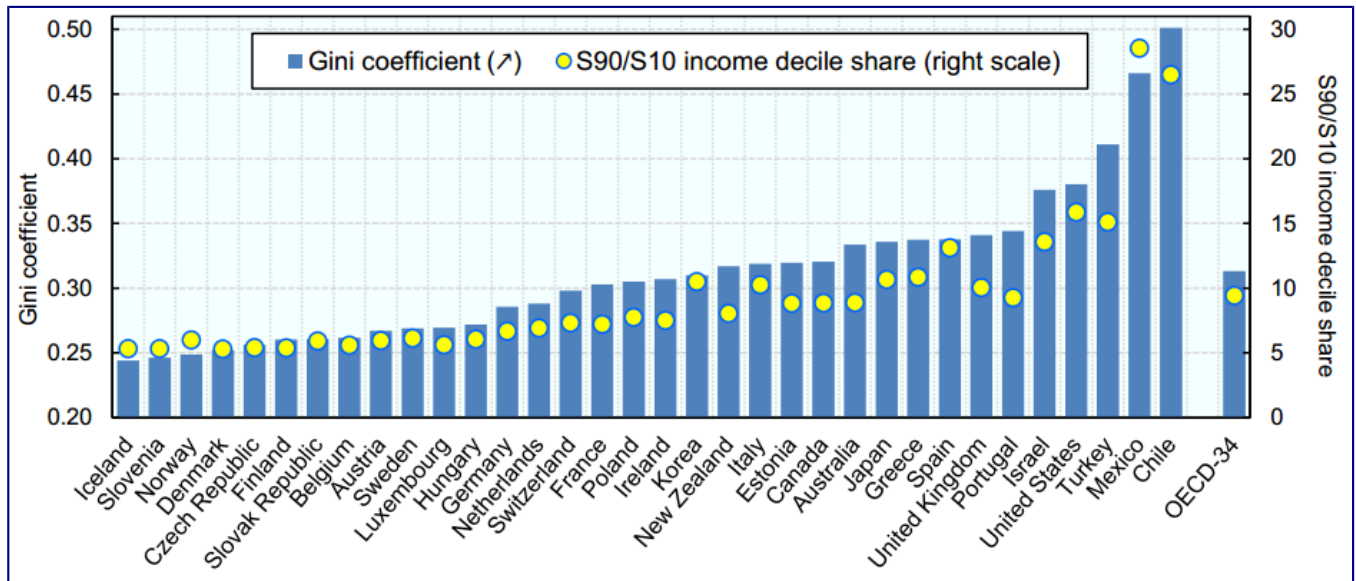


Case Study

Following is a distribution of Annual income [Gini](#) Coefficients across different countries :



Mexico has the second highest Gini coefficient and hence has a very high segregation in annual income of rich and poor. Our task is to come up with an accurate predictive algorithm to estimate annual income bracket of each individual in Mexico. The brackets of income are as follows :

1. Below \$40,000
2. \$40,000 – 150,000
3. More than \$150,000

Following are the information available for each individual :

1. Age , 2. Gender, 3. Highest educational qualification, 4. Working in Industry, 5. Residence in Metro/Non-metro

We need to come up with an algorithm to give an accurate prediction for an individual who has following traits:

1. Age : 35 years , 2, Gender : Male , 3. Highest Educational Qualification : Diploma holder, 4. Industry : Manufacturing, 5. Residence : Metro

We will only talk about random forest to make this prediction in this article.

The algorithm of Random Forest

Random forest is like bootstrapping algorithm with Decision tree (CART) model. Say, we have 1000 observation in the complete population with 10 variables. Random forest tries to build multiple CART model with different sample and different initial variables. For instance, it will take a random sample of 100 observation and 5 randomly chosen initial variables to build a CART model. It will repeat the process (say) 10 times and then make a final prediction on each

observation. Final prediction is a function of each prediction. This final prediction can simply be the mean of each prediction.

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Disclaimer : *The numbers in this article are illustrative*

Mexico has a population of 118 MM. Say, the algorithm Random forest picks up 10k observation with only one variable (for simplicity) to build each CART model. In total, we are looking at 5 CART model being built with different variables. In a real life problem, you will have more number of population sample and different combinations of input variables.

Salary bands :

Band 1 : Below \$40,000

Band 2: \$40,000 – 150,000

Band 3: More than \$150,000

Following are the outputs of the 5 different CART model.

CART 1 : Variable Age

	Salary Band	1	2	3
Age	Below 18	90%	10%	0%
	19-27	85%	14%	1%
	28-40	70%	23%	7%
	40-55	60%	35%	5%
	More than 55	70%	25%	5%

CART 2 : Variable Gender

	Salary Band	1	2	3
Gender	Male	70%	27%	3%
	Female	75%	24%	1%

CART 3 : Variable Education

	Salary Band	1	2	3
Education	<=High School	85%	10%	5%
	Diploma	80%	14%	6%
	Bachelors	77%	23%	0%
	Master	62%	35%	3%

CART 4 : Variable Residence

	Salary Band	1	2	3
Residence	Metro	70%	20%	10%
	Non-Metro	65%	20%	15%

CART 5 : Variable Industry

	Salary Band	1	2	3
Industry	Finance	65%	30%	5%
	Manufacturing	60%	35%	5%
	Others	75%	20%	5%

Using these 5 CART models, we need to come up with single set of probability to belong to each of the salary classes. For simplicity, we will just take a mean of probabilities in this case study. Other than simple mean, we also consider vote method to come up with the final prediction. To come up with the final prediction let's locate the following profile in each CART model :

1. Age : 35 years , 2, Gender : Male , 3. Highest Educational Qualification : Diploma holder, 4. Industry : Manufacturing, 5. Residence : Metro

For each of these CART model, following is the distribution across salary bands :

CART	Band	1	2	3
Age	28-40	70%	23%	7%
Gender	Male	70%	27%	3%
Education	Diploma	80%	14%	6%
Industry	Manufacturing	60%	35%	5%
Residence	Metro	70%	20%	10%
Final probability		70%	24%	6%

The final probability is simply the average of the probability in the same salary bands in different CART models. As you can see from this analysis, that there is 70% chance of this individual falling in class 1 (less than \$40,000) and around 24% chance of the individual falling in class 2.