A Decision Tree Analysis on NYC poverty Status

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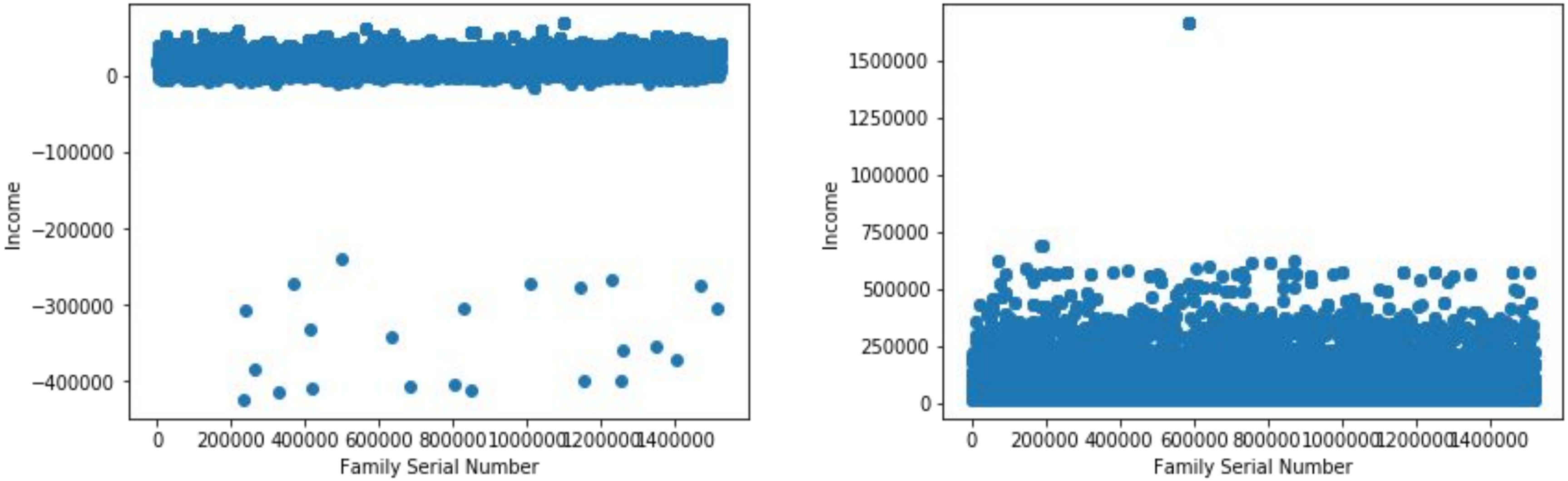
Introduction

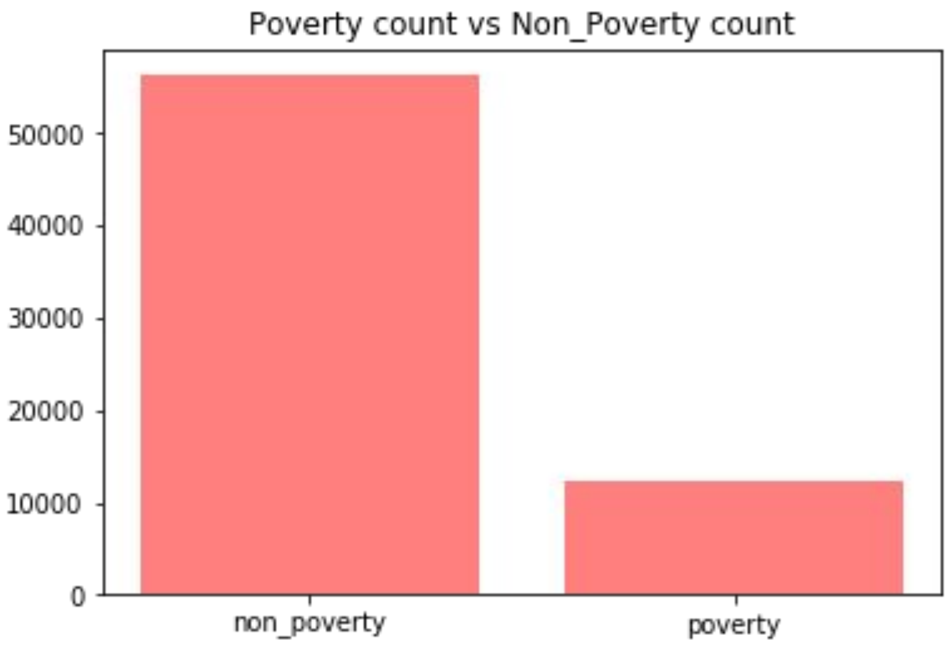
- Poverty is one of many topics that have been researched by Economists and Data Scientists.
- The main objective of this project is to predict the poverty status of families in New York City using a decision tree model analysis.
- The dataset used is the NYCgov poverty measure, which is generated annually by the poverty research unit of the Mayor’s Office of Economic Opportunity (NYC Opportunity).

Exploratory Data Analysis

Yearly Income in Poverty vs Non Poverty Families

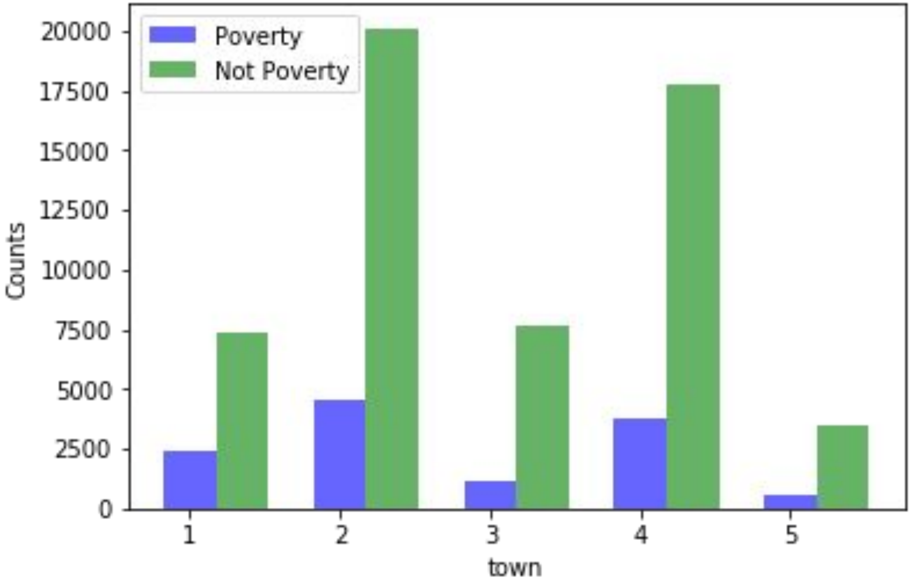


Exploratory Data Analysis - Cont'd



The count of poverty is 12409, The count of Non_poverty is 56235
The percentage of non_poverty is 22

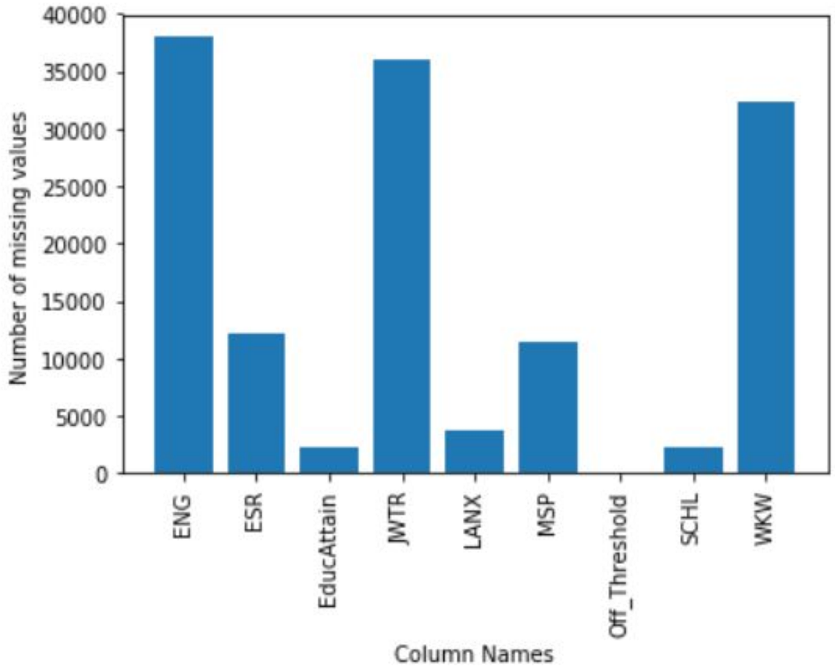
Exploratory Data Analysis - Cont'd



Graph presents the poverty and non-poverty count in different towns of New York.

1: Bronx
2: Brooklyn
3: Manhattan
4: Queens
5: Staten Island

Missing Data?



<u>Variable Keys</u>
ENG : English
ESR : Employment Status
EducAttain: Educational Attainment
JWTR: Means of Transportation to work
LANX: Other Languages spoken home
MSP: Married, spouse present/absent
Off_Threshold: Fed. Poverty Threshold
SCHL: Educational Attainment
WKW: Weeks worked in the past 12 months

```
[('ENG', 38015), ('ESR', 12198), ('EducAttain', 2240), ('JWTR', 36009), ('LANX', 3738), ('MSP', 11419), ('Off_Threshold', 2),
('SCHL', 2241), ('WKW', 32406)]
```

Before Imputation vs After Imputation

```
ENG
1.0    16275
2.0     6832
3.0     5366
4.0     2156
Name: ENG, dtype: int64
ESR
1.0    32618
2.0      875
3.0     2253
4.0       17
6.0    20683
Name: ESR, dtype: int64
EducAttain
1.0    20618
2.0    13081
3.0    12397
4.0    20308
Name: EducAttain, dtype: int64
```

```
ENG
1.0    39370
2.0    14161
3.0    10547
4.0     4566
Name: ENG, dtype: int64
ESR
1.0    39317
2.0     1136
3.0     2849
4.0       18
6.0    25324
Name: ESR, dtype: int64
EducAttain
1.0    21830
2.0    13315
3.0    12639
4.0    20860
Name: EducAttain, dtype: int64
```

Decision Tree:

- Preprocessing:
    1. Feature selection
    2. Instance selection
    3. Imbalance classes
- Implementing tree
- Random Forest

Decision Tree

Feature selection:

- Redundant and irrelevant variables: UnitID, Agecateg, Federal Poverty Status, Total Income, etc.
- The number of attributes down to 60 from 79.

Instance selection:

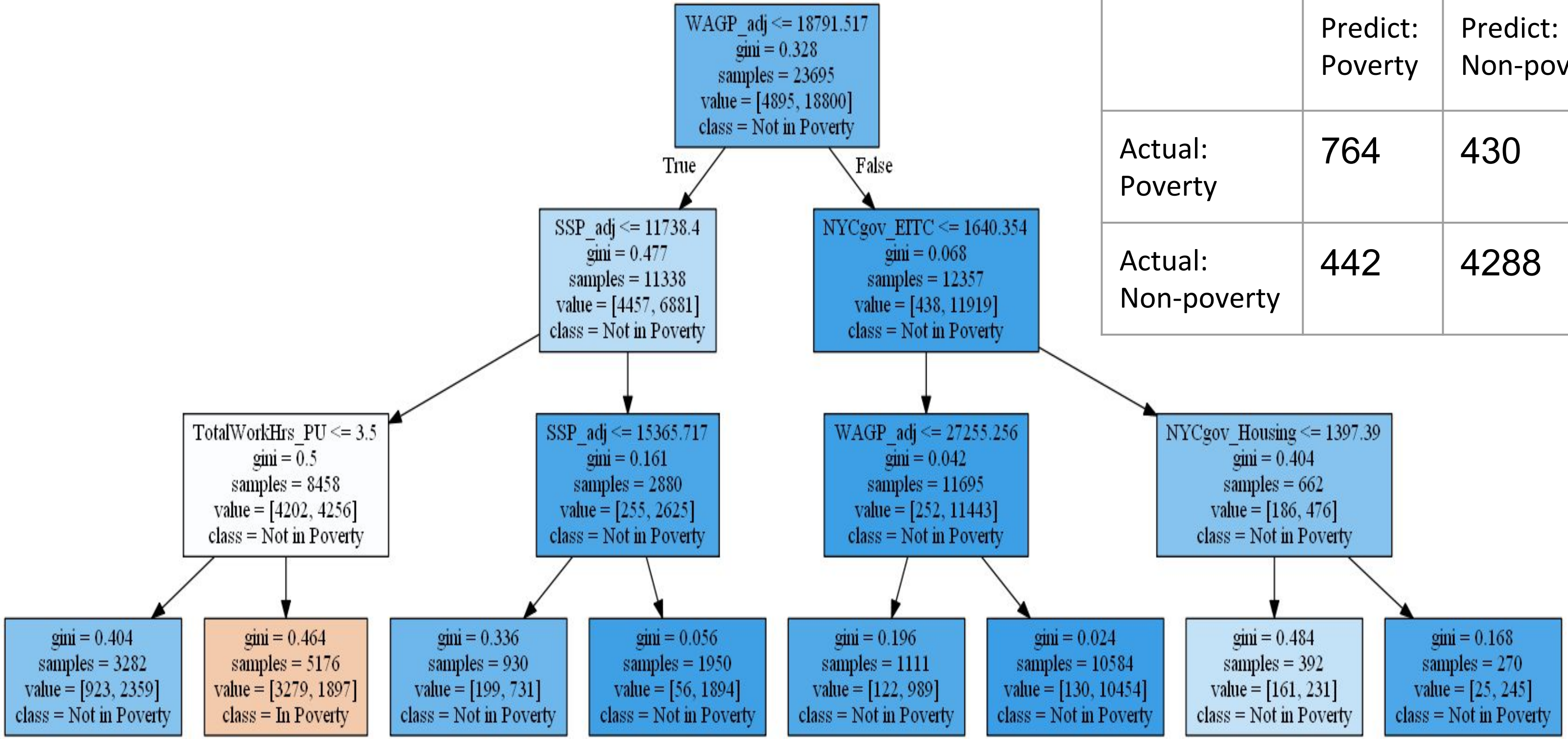
- Remove all other household members except the head of the household.
- The number of observations down to 30000 from 68000

Decision Tree

Imbalanced classes:

- Imbalanced classes in the training set will cause the model bias toward the dominated class.
- The dataset contains about 80% of non-poverty individuals, which dominate the poverty class.

Accuracy on training set: 0.85
Accuracy on testing set: 0.85



	Predict: Poverty	Predict: Non-poverty	ACC%
Actual: Poverty	764	430	64%
Actual: Non-poverty	442	4288	90%

Decision Tree

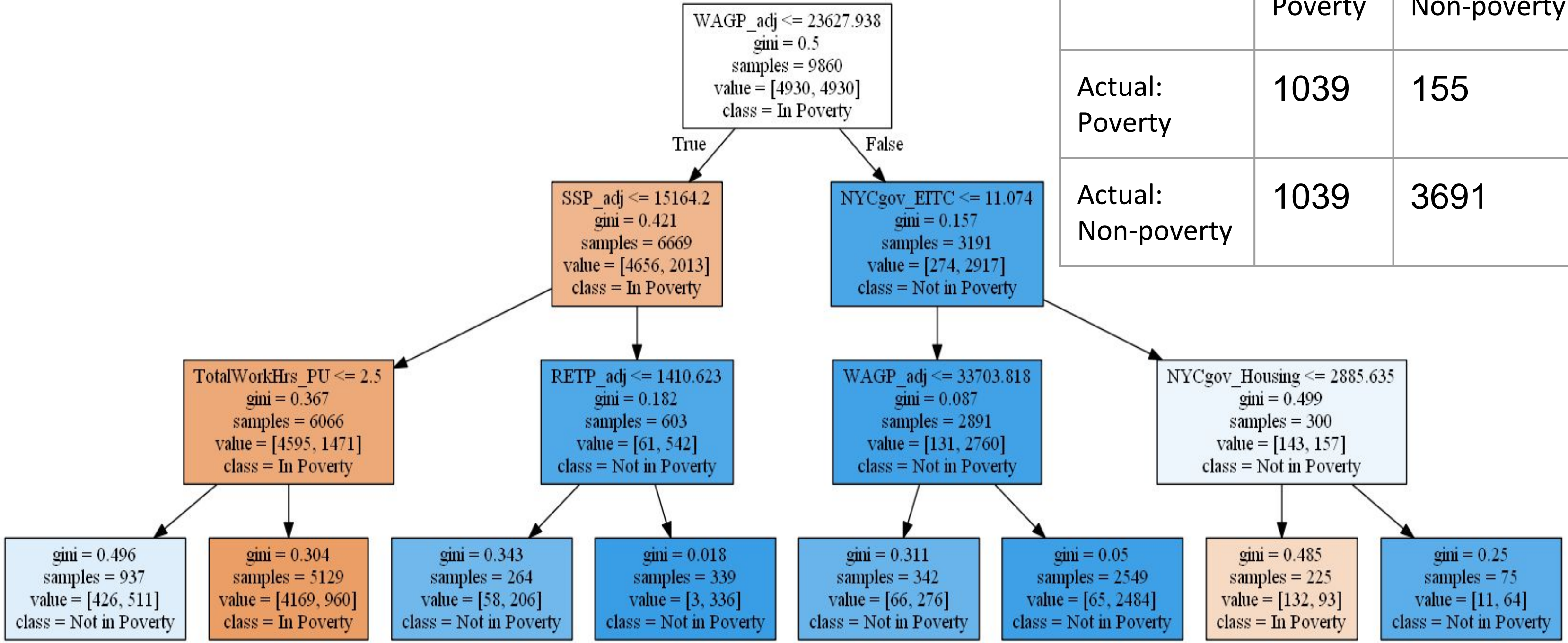
Imbalanced classes:

- Use *resample* function to randomly draw from non-poverty group in the training set without replacement, downsize the dominated class.
- The new training set would have more balanced distribution between two classes.

Decision Tree

Accuracy on training set: 0.83
Accuracy on testing set: 0.79

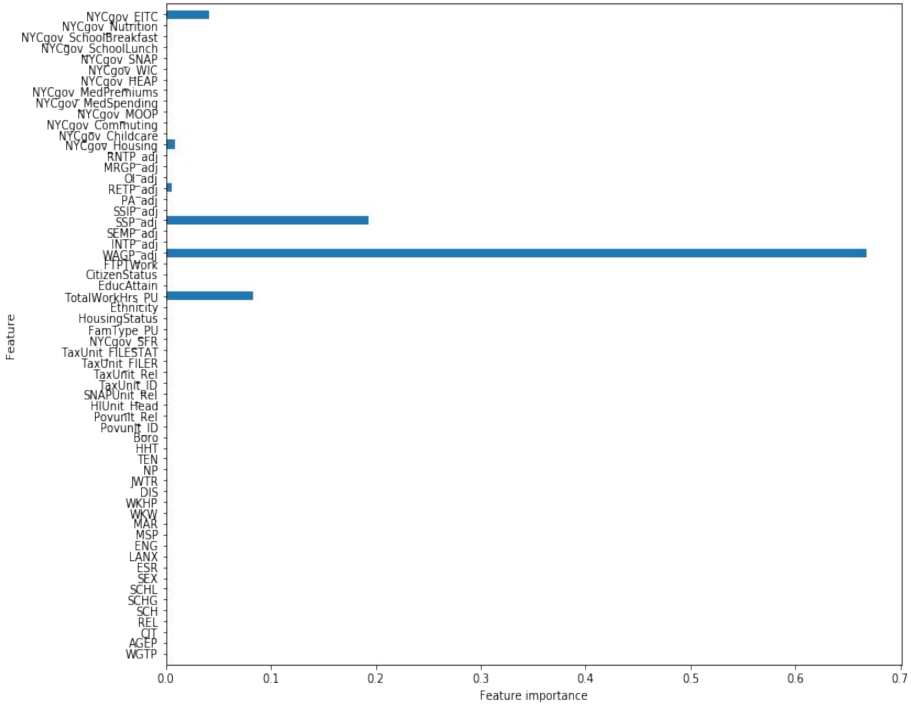
	Predict: Poverty	Predict: Non-poverty	ACC %
Actual: Poverty	1039	155	87%
Actual: Non-poverty	1039	3691	78%

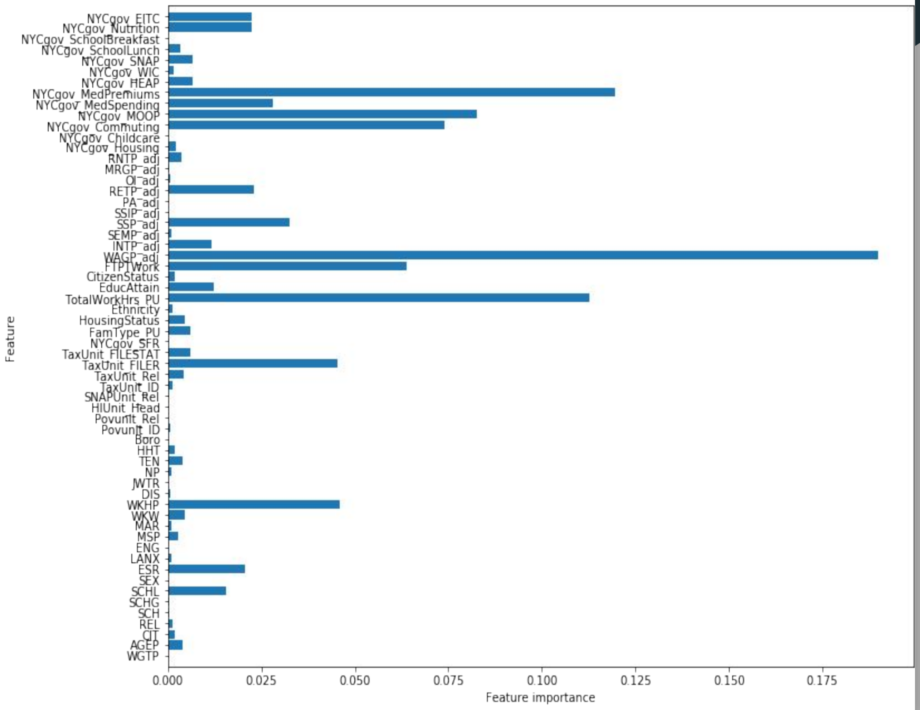


Random Forest

- Single decision tree would produce unstable result due to the variation of the data.
- Random Forest combine many unique trees to produce a more stable and robust result.
- We created a random forest that contains 1000 tree.

Random Forest

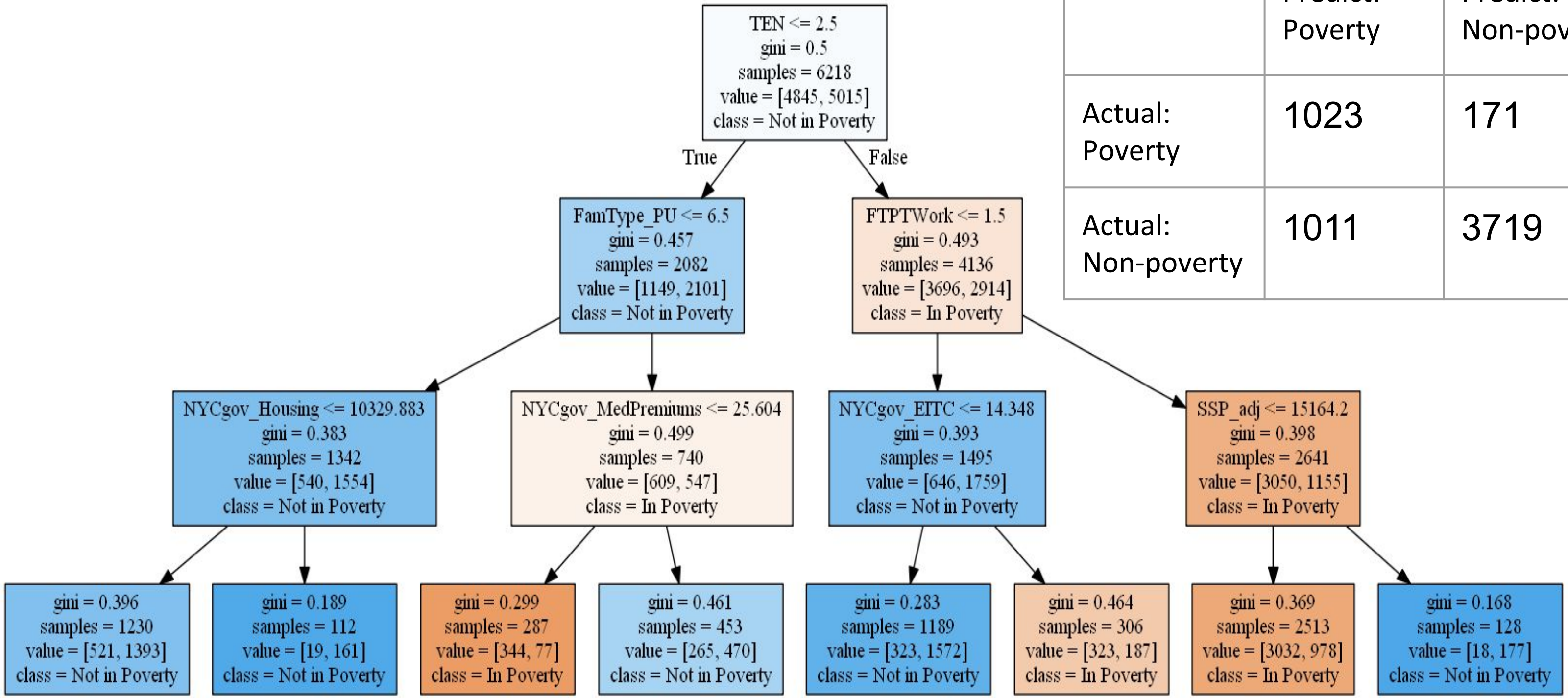




Random Forest

Accuracy on training set: 0.83
Accuracy on testing set: 0.80

	Predict: Poverty	Predict: Non-poverty	ACC %
Actual: Poverty	1023	171	86%
Actual: Non-poverty	1011	3719	79%



Conclusion

- Base on the feature importance, the most important feature on deciding people’s poverty status is the wage for past 12 months, followed by medical premium cost, and working hour.
- There are potentially high correlation between wage, medical premium cost and working hour(person has less wage income may also has less working hour and medical premium spending)
- This correlation will cause the model underestimate the impact of other independent variables.
- Run correlation map for all the attributes and identify the collinearity.

Reference:

Mayor's Office For Economic Opportunity. NYCgov Poverty Measure Data(2016). Retrieved from: https://data.cityofnewyork.us/City-Government/NYCgov-Poverty-Measure-Data-2016-/y9gu-cxxw

"How to Handle Imbalanced Classes in Machine Learning"(July 5,2017), EliteDataScience. Retrieved from:https://elitedatascience.com/imbalanced-classes

THANK YOU!!