# FinalPresentation

February 26, 2021

UMD Data Challenge 2021

Team 61

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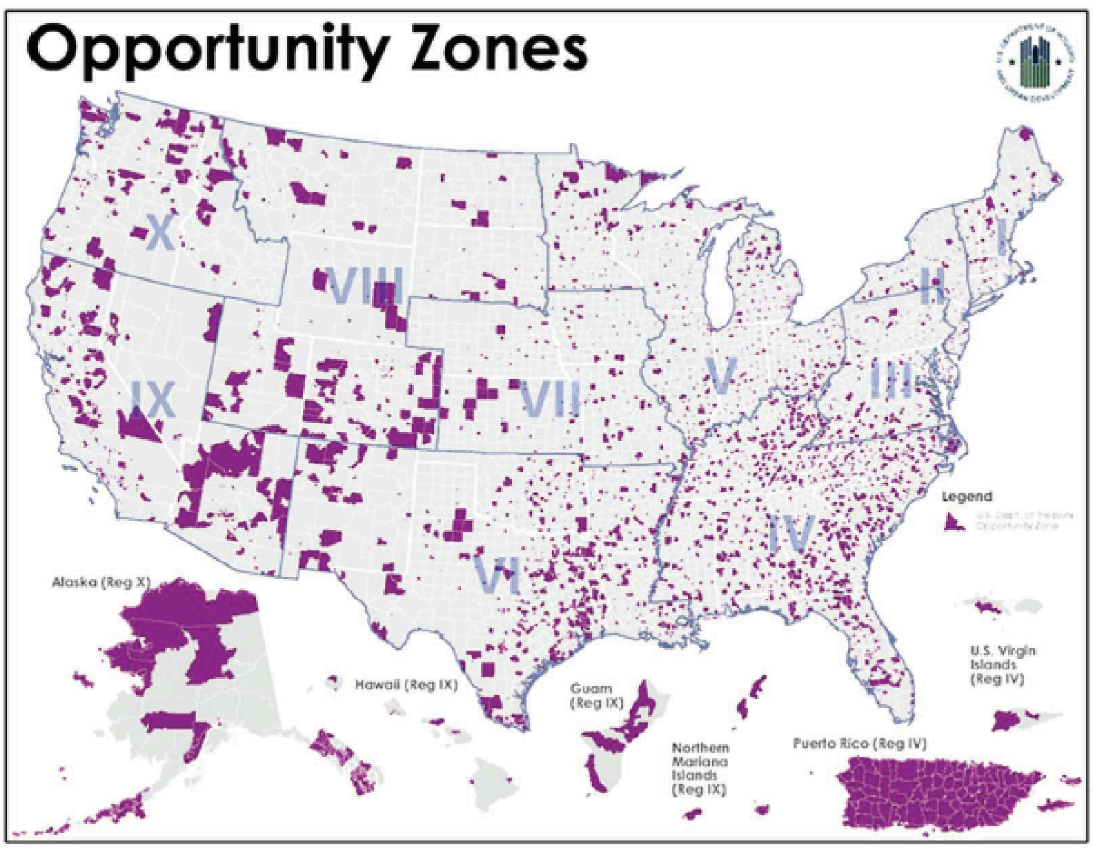
This analysis will be looking at the HUD Opportunity Zones (OZ) Dataset. Locations are denoted in the graphic below.

**Exhibit 1**

Locations of Opportunity Zones in the United States




*Source: HUD*

Under the 2017 Tax Cuts and Jobs Act, Governers were able to nominate up to 25% of low income census tracts to be designated as an OZ. Designated tracts receive tax benefits meant to stimulate investments and job growth into the areas.

The main goal of this analysis is to investigate the relationship between ACS 5 year data and the classification of these OZ.

[2]:
```
import pandas as pd
import us
df = pd.read_pickle('./data/AllDataMerged.pkl')
state_list = [i for i in range(1,57)]
drop_list = [3,7,14,43,52]

for drop in drop_list:

    state_list.remove(drop)
df = df[df.STATE.isin(state_list)]
#df.STATE.nunique()
```

[3]:
```
df1 = df[df.DESIGNATED==True]
df1 = df1[['STATE','DESIGNATED']].groupby('STATE').agg('count')
df1 = df1.rename(columns={'DESIGNATED':'true'})
df2 = df[df.DESIGNATED==False]
df2 = df2[['STATE','DESIGNATED']].groupby('STATE').agg('count')
df2 = df2.rename(columns={'DESIGNATED':'false'})

df3 = df[df.DESIGNATED=='NotEligible']
df3 = df3[['STATE','DESIGNATED']].groupby('STATE').agg('count')
df3 = df3.rename(columns={'DESIGNATED':'NotEl'})

df4 = df2.merge(df1, left_index=True, right_index=True)
df4 = df4.merge(df3, left_index=True, right_index=True)

df4['state_abbr'] = [us.states.lookup(str(n).zfill(2)).abbr for n in df4.index.
 ↪to_list()]
df4['total'] = df4.false + df4.true + df4.NotEl
df4['true/false'] = df4.true/df4.false
df4['true/total'] = df4.true/df4.total
```

Distribution of tracts. Each state can be scrolled over to view the number of Designated, Non Designated and Non Eligible tracts for each state. The color is a visual representation of the ratio of Designated to Non Designated Tracts. Most states fall into a 4:1 to 5:1 range with only Wyoming and Alaska exceeding the 2:1 rate.

For purposes of this Data Challenge, I will only be looking at the 50 US States (+DC)

[4]:
```
import plotly.graph_objects as go
import plotly.express as px
import pandas as pd

for col in df4.columns:
```

```
    df4[col] = df4[col].astype(str)

df4['text'] = df4['state_abbr'] + '<br>' + \
    'Total: ' + df4['total'] + '<br>' + \
    'Designated: '+df4['true'] + '<br>' +\
    'NotDesignated: ' + df4['false'] + '<br>' + \
    'Not Eligible: '+df4['NotEl']

fig = go.Figure(data=go.Choropleth(
    locations=df4['state_abbr'],
    z=df4['true/false'].astype(float),
    locationmode='USA-states',
    colorscale='jet',
    autocolorscale=True,
    text=df4['text'], # hover text
    marker_line_color='white', # line markers between states
))
fig.update_layout(
    title_text = 'Ratio of Selected to Non Selected Tracts',
    geo = dict(
        scope='usa',
        projection=go.layout.geo.Projection(type = 'albers usa'),
        showlakes=True, # lakes
        lakecolor='rgb(255, 255, 255)'),
)


fig.show()
```

In order to get a feel for the data, I started with looking at NY state (FIPS = 36).

[5]:
```
import json
ny = df[df.STATE == 36]
ny = ny[ny.DESIGNATED.notnull()]
true = ny[ny.DESIGNATED==True].shape[0]
false = ny[ny.DESIGNATED==False].shape[0]
with open('./data/variable_names.json', 'r') as fp:
    variable_translate = json.load(fp)
print(f'NY has {ny.shape[0]} tracts entered.\n'
      f'There were {true} selected and {false} not selected')
print(f'The preprocessed data has {ny.shape[1]} features')
```

```
NY has 4892 tracts entered.
There were 514 selected and 2121 not selected
The preprocessed data has 512 features
```

Take a look at what data is missing/null.

[6]:
```python
ny = ny.drop(columns=['OBJECTID', 'OBJECTID_1', 'STATE',
                      'COUNTY', 'GEOID', 'TRACT', 'NAME',
                      'CNTY_FIPS', 'EACODE', 'EANAME',
                      'GEOID_CHANGE', 'LIC', 'CROSS_STATE', 'SUBTRACTIONS',
                      'ADDITIONS', 'TRACT_TYPE', 'FID', 'STUSAB',
                      'Shape__Area', 'Shape__Length'
                      ], inplace=False)
null_cols = ny.columns[ny.isnull().sum()!=0]
print(f'There are {len(null_cols)} columns that have missing data\n\n')
for col in null_cols:
    if col in variable_translate.keys():
        print(f'{variable_translate[col]}: {ny[col].isna().sum()}')
    else:
        print(col)
many_null_cols = []
drop_frac = 0.2
n_to_drop = drop_frac * ny.shape[0]
for col in null_cols:
    count = ny[col].isna().sum()
    if count>n_to_drop :
        many_null_cols.append(col)
ny_clean = ny.drop(columns=many_null_cols, inplace=False)
```

```
There are 29 columns that have missing data


Median Year Structure Built for Renter Occupied Units: 134
Median number of rooms: 96
Median number of rooms -- Owner occupied: 224
Median number of rooms -- Renter occupied: 132
Median Contract Rent: 201
Median value -- Owner-occupied housing units: 510
Median value for units with a mortgage: 557
Median value for units without a mortgage: 636
Average Household Size of Occupied Housing Units: 79
Average Household Size of Owner occupied Housing Units: 158
Average Household Size of Renter occupied Housing Units: 94
Aggregate Travel time to work in minutes: 86
Average Travel time to Work for Workers 16 years and over who did not work at
home: 27
Median Household Income In The Past 12 Months: 108
Aggregate Household Income In The Past 12 Months: 96
Median Family Income In The Past 12 Months: 119
Median Nonfamily Household Income In The Past 12 Months: 350
Population 25 years and over: 3805
Population 25 years and over having less than High School education: 3986
Population 25 years and over having less than High School education having High
```

```
school graduate education(includes equivalency): 3829
Population 25 years and over having Some college or associate's degree: 3818
Population 25 years and over having Bachelor's degree: 3821
Population 25 years and over having Graduate or professional degree: 3845
Management, professional, and related occupations: Median earnings in the past
12 months in 2009 dollars for full time, year round civilian employed population
16 and over: 116
Service occupations: Median earnings in the past 12 months in 2009 dollars for
full time, year round civilian employed population 16 and over: 3477
Sales and office occupations: Median earnings in the past 12 months in 2009
dollars for full time, year round civilian employed population 16 and over: 2459
Farming, fishing, and forestry occupations: Median earnings in the past 12
months in 2009 dollars for full time, year round civilian employed population 16
and over: 192
Construction, extraction, maintenance, and repair occupations: Median earnings
in the past 12 months in 2009 dollars for full time, year round civilian
employed population 16 and over: 958
Production, transportation and material moving: Median earnings in the past 12
months in 2009 dollars for full time, year round civilian employed population 16
and over: 2533
```

Some of these variables seem like they should be important factors in distinguishing eligibility.

An example is "Median Household Income In The Past 12 Months:", which should be among the most important factors

In order to include as much data into the modeling, we set a threshold for dropping features. Since this will be extrapolated to a state by state level, I will set 20% as the cutoff. If the percentage of null values exceeds that threshold for a given state, it will be excluded from the model.

Missing values will be imputed using `sklearn.impute.SimpleImputer(strategy='mean')`. This replaces missing values with the mean value of the feature across all tracts

Data preparation.

The target variable that we wish to predict is the `DESIGNATED` column. This can be either `True`, `False`, `NotEligible`. I will look at modeling just the True/False categories, and I will numerically encode them as 1/0 respectively.

After removing null values over the given threshold, the inputs are taken to be all of the numeric columns. I drop all of the geographic and ID related features (such as GEOID - which is numeric but has no relationship to an area's designation).

Since many of the variables have two representations: a total and a percent, I will remove all of the total variables (keeping the related percent). The reasoning is to remove the population dependence.

The first thing to look at will be the correlation between the variables. Here I take the 20 most correlated variables

[7]:
```python
import numpy as np
```

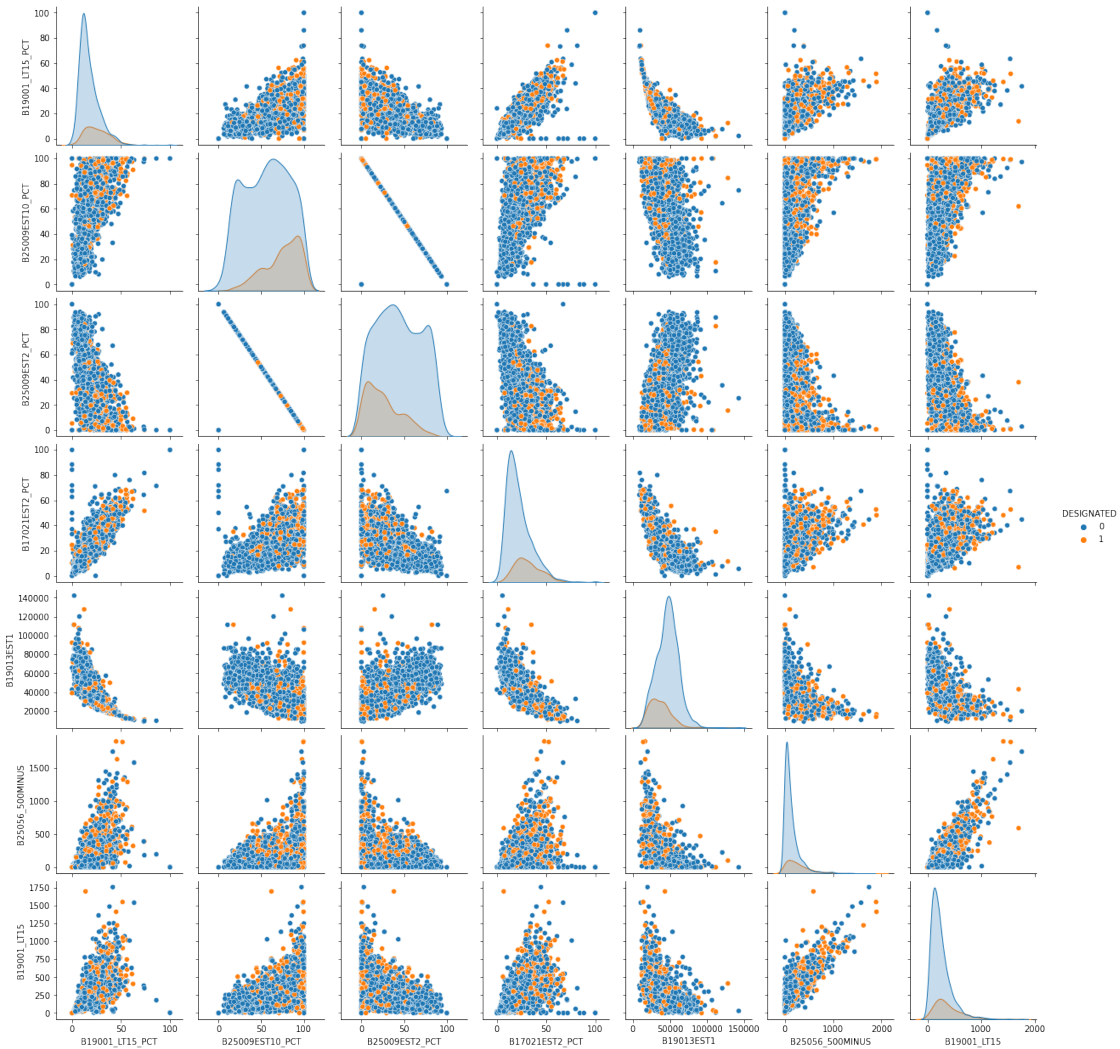
```
ny_clean = ny_clean[ny_clean.DESIGNATED != 'NotEligible'].
 ↪reset_index(inplace=False)
ny_clean.DESIGNATED = (1*ny_clean.DESIGNATED).astype(int)
corrs = np.abs(ny_clean.corr()['DESIGNATED']).nlargest(21)
for i,j in zip(corrs.index[1:], corrs[1:]):
    print(f'Correlation = {j:.4f}: Variable = {i}: Name =␣
 ↪{variable_translate[i]}')
```

```
Correlation = 0.2782: Variable = B19001_LT15_PCT: Name =     as a %
Correlation = 0.2775: Variable = B25009EST10_PCT: Name =     as a %
Correlation = 0.2724: Variable = B25009EST2_PCT: Name =     as a %
Correlation = 0.2592: Variable = B17021EST2_PCT: Name = Poverty Rate
Correlation = 0.2543: Variable = B19013EST1: Name = Median Household Income In
The Past 12 Months
Correlation = 0.2538: Variable = B25056_500MINUS: Name = With cash rent less
than $499
Correlation = 0.2463: Variable = B19001_LT15: Name = Household Income in the
Past 12 Months Less than $14,999
Correlation = 0.2304: Variable = B19113EST1: Name = Median Family Income In The
Past 12 Months
Correlation = 0.2236: Variable = B25068EST13: Name = Less than $200
Correlation = 0.2232: Variable = B25106_CB_R_LT35: Name = Renter Occupied
Earning Less than $35,000 paying > 30%
Correlation = 0.2177: Variable = B17019_RENT: Name = Renter occupied
Correlation = 0.2128: Variable = B17019_OWN_PCT: Name =     as a %
Correlation = 0.2119: Variable = B25068_1BDR_200TO499: Name = $200 to $499
Correlation = 0.2087: Variable = B17019_RENT_PCT: Name =     as a %
Correlation = 0.2042: Variable = B17021EST2: Name = Total: Persons in Poverty
Correlation = 0.2042: Variable = B19001EST13_PCT: Name =     as a %
Correlation = 0.2041: Variable = B25041_3PLUS_BDR_PCT: Name =     as a %
Correlation = 0.2012: Variable = B19001EST14_PCT: Name =     as a %
Correlation = 0.2010: Variable = HSND_45TO64_PCT: Name =    as a %
Correlation = 0.1983: Variable = B17019EST2: Name = Families with Income in the
past 12 months below poverty level:
```

The top three are * Household Income in the Past 12 Months Less than $14,999 (pct) * Renter Occupied (pct) * Owner Occupied (pct)

We can visualize the most correlated variables to see if there are any patterns in the NY data.

[8]:
```
import seaborn as sns
import matplotlib.pyplot as plt
corrs8 = np.abs(ny_clean.corr()['DESIGNATED']).nlargest(8)

df1 = ny_clean[corrs8.index.to_list()]

sns.pairplot(df1, hue = 'DESIGNATED')
plt.show()
```



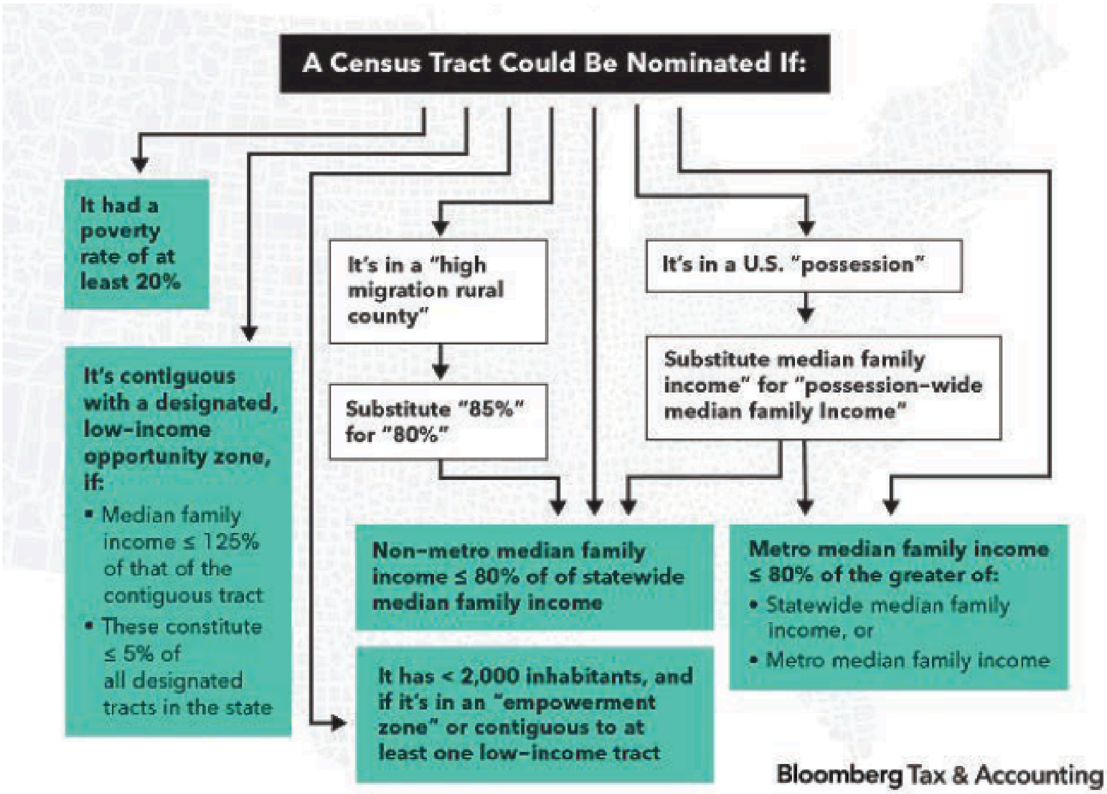

Model selection.

Based on the Policy Brief, which has the image below, I am interested in using Decision Trees to classify the designation. Intuitively, a decision tree would make sense, as it would follow along with the thought process for being selected.

From a technical standpoint, the decision tree does not require any scaling, so no further preprocessing is needed. Additionally, the sklearn library has feature_importance attributes, which measure how much information is gained by splitting a node at the given feature.

**Exhibit 2**

Opportunity Zone Tract Eligibility Criteria




Source: Bloomberg Tax, https://news.bloombergtax.com/daily-tax-report/2020-census-could-expand-opportunity-zones-chosen-for-tax-breaks

The final model that I decided on was a GradientBoostedDecisionTree. Instead of just 1 tree, we allow the model to learn several 'weak' trees and ensemble them.

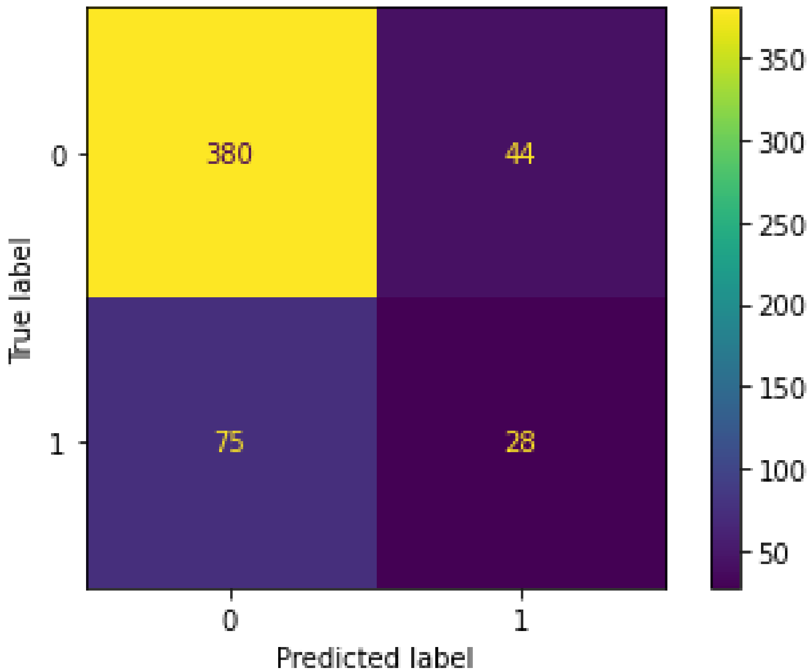
[9]:
```
#cols = [c for c in ny_clean.columns if str(c).endswith('_PCT')]
#drop_cols = [c[:-4] for c in cols if c[:-4] in ny_clean.columns]
#ny_clean = ny_clean.drop(columns = drop_cols)
#ny_clean.shape
y = ny_clean.pop('DESIGNATED')
X = ny_clean.select_dtypes(np.number)
y.loc[y == False] = 'False'
y.loc[y == True] = 'True'
y_map = {'NotEligible': -1,
         'False': 0,
         'True': 1}
y = y.map(y_map)
```

[10]:
```
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
imp = SimpleImputer(strategy='mean')
```

```
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=.2,␣
 ↪random_state=340, stratify=y)
X_train = imp.fit_transform(X_train)
X_test = imp.transform(X_test)
```

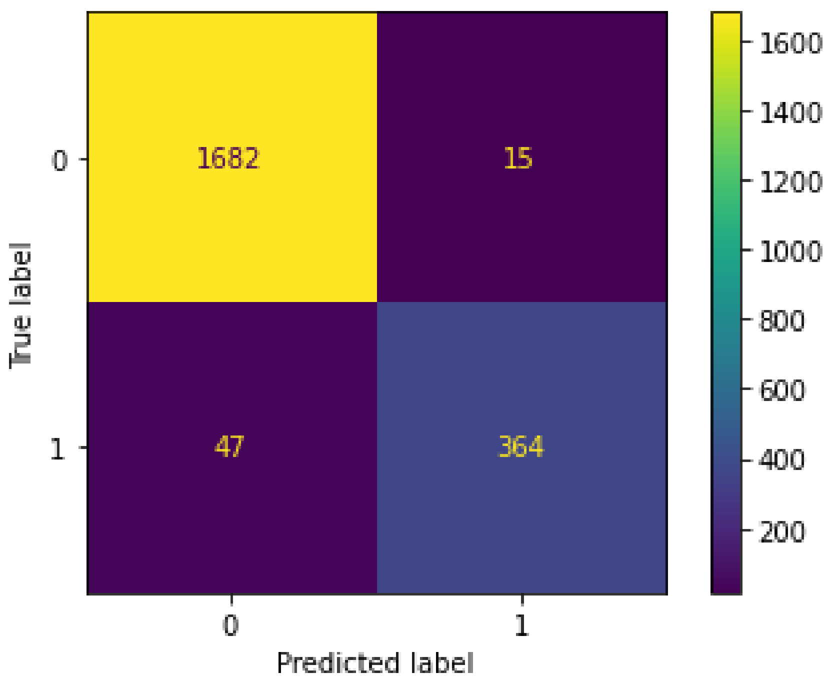
[11]:
```
from sklearn.metrics import␣
 ↪classification_report,confusion_matrix,ConfusionMatrixDisplay
from sklearn.ensemble import GradientBoostingClassifier
clf = GradientBoostingClassifier(**{'learning_rate':.5, 'n_estimators':int(X.
 ↪shape[0]/10),
             'subsample':.9,'min_samples_split':2,
             'min_samples_leaf':1,'max_depth':5,
             'random_state':32,'max_features':'sqrt',
             'verbose':0,'max_leaf_nodes':None,
             'warm_start':False,'validation_fraction':0.1,
             'n_iter_no_change':20 })
clf.fit(X_train,y_train)
print('_____________________________________________\n_______ Test␣
 ↪Classification____________')
print(classification_report(y_test, clf.predict(X_test)))

ConfusionMatrixDisplay(confusion_matrix(y_test, clf.predict(X_test))).plot()
plt.show()
```

```
_____________________________________________
_______ Test Classification____________
              precision    recall  f1-score   support

           0       0.84      0.90      0.86       424
           1       0.39      0.27      0.32       103

    accuracy                           0.77       527
   macro avg       0.61      0.58      0.59       527
weighted avg       0.75      0.77      0.76       527
```




```
[12]: print('_____________________________________________\n_______ Training
       ↪Confusion Matrix ___________')
      print('_____________________________________________')
      ConfusionMatrixDisplay(confusion_matrix(y_train, clf.predict(X_train))).plot()
      plt.show()
```

```
_____________________________________________
_______ Training Confusion Matrix ___________
_____________________________________________
```




This model is not ideal. Since this was one of the larger states, I am trying to prevent overfitting on smaller states.

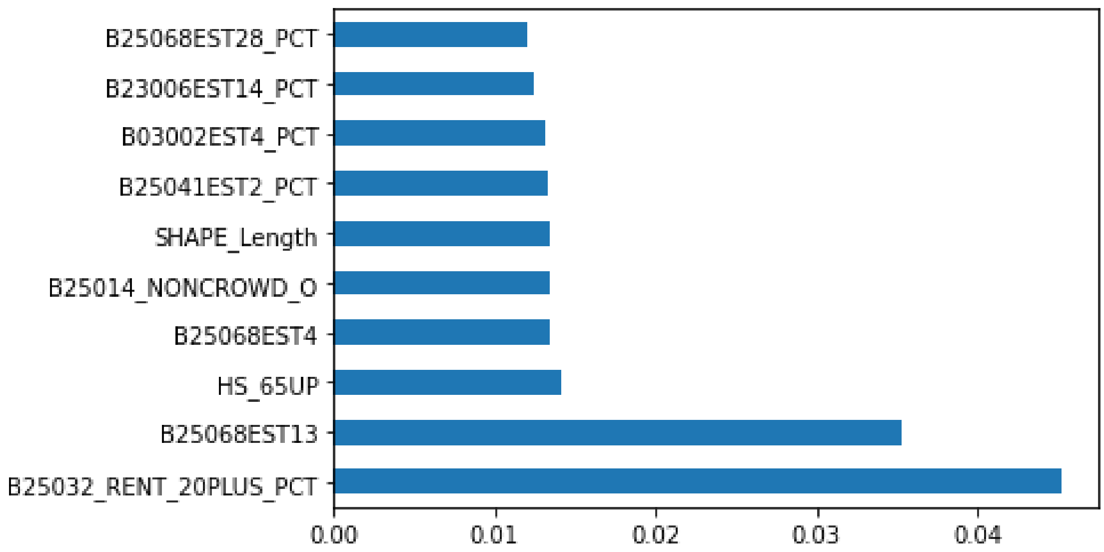
This is post hyperparameter tuning. Adding more estimators and increasing the depth result in what seem like overfitting on the training data, resulting in even worse test performance. In order to generalize for smaller states, I set n_estimators to be the number of entries/10. In the test set, the data is split 80/20, so the accuracy of guessing just not selected is going to be 80%. This model's ccuracy is less than 80%, so I am inclined to think that the model is learning some information.

From the fit model, we can extract the most important features

[13]:
```
feature_imps = pd.Series(clf.feature_importances_, index=X.columns)
feature_imps.nlargest(10).plot(kind='barh')
m_i_f = feature_imps.nlargest(10).index
for i in m_i_f:
    if i in variable_translate.keys():
        print(variable_translate[i])
    else:
        print(i)
plt.show()
```

```
    as a %
Less than $200
Population ages 65 and older having High School educaion
Less than $200
Owner occupied: 1.00 or less occupants per room
```

```
SHAPE_Length
    as a %
    as a %
    as a %
    as a %
```




The above percentages that are listed 'as a %' are * Renter Occupied Earning Less than $35,000 paying > 30% * No bedroom * Population ages 35 to 44 having some High School education (No Diploma) * Cash rent 500 to 599 * Population ages 25 to 34 having a Bachelor's Degree

Most of these features seem that they should have importance. One would expect that higher poverty rates and lower median incomes would result in a designation. Intuitively, housing and education factors should also play a role, as they are likely enticing for investors, but the education/housing factors appearing here seem irrelevant.

[ ]:

```

```

Now that the model is trained on a state level, it can be extended to each state. For each state, a GradientBoostedClassifier is trained with n_estimators being N/10.

For each model, we record the 10 most important features in the model as well as the F1 score for the designated label on unseen testing data.

[14]:

```
import numpy as np
import pandas as pd
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import train_test_split
```

```python
def cleaned_data_model(df, STATE_ID,n_to_keep = 10, drop_pct = 0.2, to_impute =␣
↪True, scale = False , **kwargs):

    df = df[df.STATE == STATE_ID].reset_index(drop=True)
    df = df[df.DESIGNATED != 'NotEligible']
    df = df.drop(columns=['OBJECTID', 'OBJECTID_1', 'STATE',
                          'COUNTY', 'GEOID', 'TRACT', 'NAME',
                          'CNTY_FIPS', 'EACODE', 'EANAME',
                          'GEOID_CHANGE', 'LIC', 'CROSS_STATE', 'SUBTRACTIONS',
                          'ADDITIONS', 'TRACT_TYPE', 'FID', 'STUSAB',
                          'Shape__Area', 'Shape__Length'
                          ], inplace=False)
    df = df.loc[df.DESIGNATED.notnull()]

    drop_count = drop_pct * df.shape[0]
    null_cols = df.columns[df.isnull().sum() != 0]
    many_null_cols = []
    for col in null_cols:
        count = df[col].isna().sum()
        if count > drop_count:
            many_null_cols.append(col)

    df_clean = df.drop(columns=many_null_cols, inplace=False)
    y = df_clean.pop('DESIGNATED')
    X = df_clean.select_dtypes(np.number)
    y.loc[y == False] = 'False'
    y.loc[y == True] = 'True'
    y_map = {'NotEligible': -1,
             'False': 0,
             'True': 1}
    y = y.map(y_map)
    cols = [c for c in X.columns if str(c).endswith('_PCT')]
    drop_cols = [c[:-4] for c in cols if c[:-4] in X.columns]
    X = X.drop(columns = drop_cols)
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.2,␣
↪random_state=2)

    imp = SimpleImputer(strategy='mean')
    ss = StandardScaler()
    if to_impute:
        X_train = imp.fit_transform(X_train)
        X_test = imp.transform(X_test)
    if scale:
        X_train = ss.fit_transform(X_train)
        X_test = ss.transform(X_test)
```

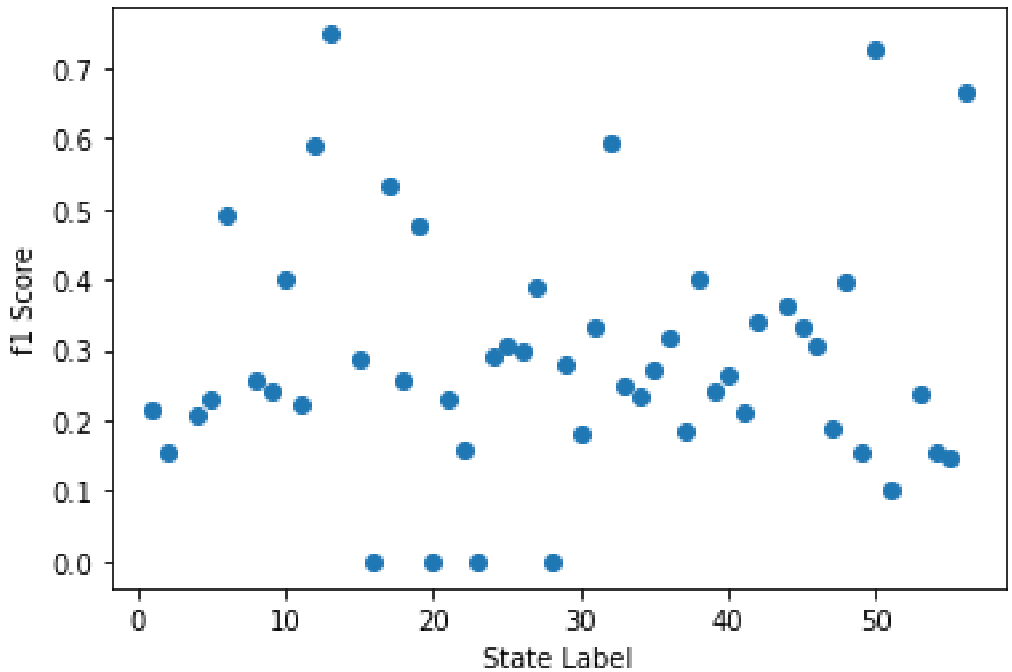
```
    clf = GradientBoostingClassifier( n_estimators = int(X.shape[0]/10),␣
↪**kwargs )
    clf.fit(X_train, y_train)
    cr = classification_report(y_test, clf.predict(X_test), output_dict=True)
    feat_importances = pd.Series(clf.feature_importances_, index=X.columns)
    return feat_importances.nlargest(n_to_keep), clf.score(X_test, y_test),␣
↪cr['1']['f1-score'],cr
```

[15]:

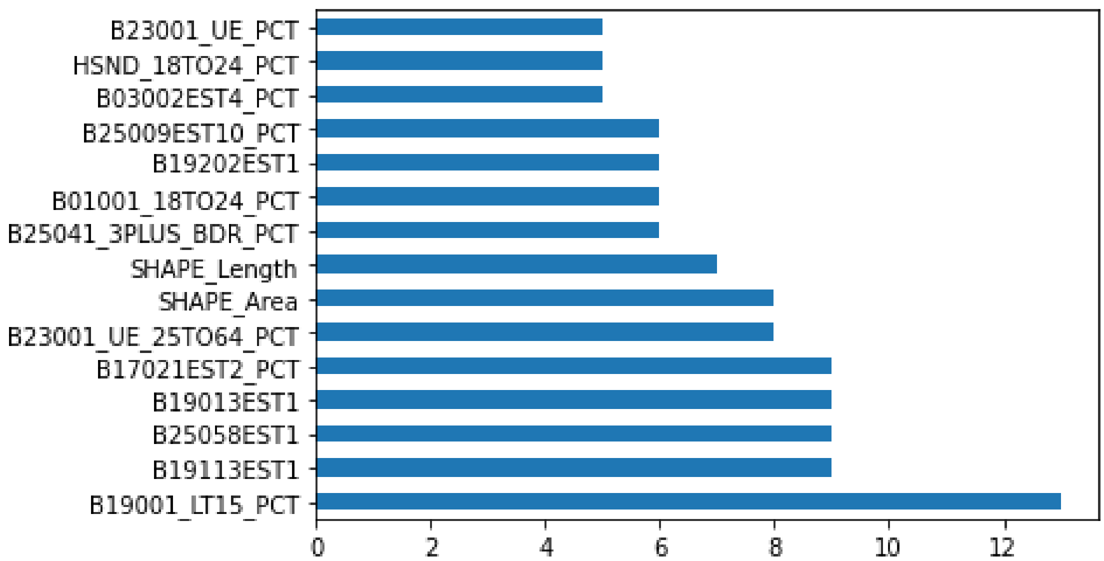
```
df_merged = pd.read_pickle('./data/AllDataMerged.pkl')

#The CONTIGUOUS variable is actually in the dropdown image so lets make it␣
↪numerical
df_merged.CONTIGUOUS = 1*(df_merged.CONTIGUOUS.fillna(0))


model_args = {'learning_rate':.5,
              'subsample':.9,'min_samples_split':2,
              'min_samples_leaf':1,'max_depth':5,
              'random_state':3,'max_features':'sqrt',
              'verbose':0,'max_leaf_nodes':None,
              'warm_start':False,'validation_fraction':0.1,
              'n_iter_no_change':20 }


# Generate a list of the 50 states + DC
state_list = [i for i in range(1,57)]
drop_list = [3,7,14,43,52]

for drop in drop_list:

    state_list.remove(drop)

# Model returns a list of n_to_keep most important features,
# classifier accuracy and True Designation f1-score
feat_dict = {}
scores = []
f1 = []
features =[]
state_names = []
for i in state_list:

    #a,b,c,d = gb_model(df_merged, i, n_to_keep=10 , **model_args)
    a,b,c,d = cleaned_data_model(df_merged, i, n_to_keep=10 , **model_args)

    feat_dict[i] = a
    features.append(a.index.to_list())
    scores.append(b)
```

```
    f1.append(c)
    state_names.append(us.states.lookup(str(i).zfill(2)).abbr)
```

[16]:
```
plt.scatter(state_list, f1)
plt.xlabel('State Label')
plt.ylabel('f1 Score')
plt.show()
```




[17]:
```
import itertools
from collections import Counter
total_features = list(itertools.chain(*features))
feature_counts = Counter(total_features)
counts = pd.Series(feature_counts).sort_values(ascending=True)
counts.nlargest(15).plot(kind='barh')
plt.show()
```




[18]:
```
top_cols = counts.nlargest(7).index.to_list()
for i in counts.nlargest(7).index:
    if i in variable_translate.keys():
        print(variable_translate[i])
    else:
        print(i)
```

```
    as a %
Median Family Income In The Past 12 Months
Median Contract Rent
Median Household Income In The Past 12 Months
Poverty Rate
25 - 65 Unemployment Rate
SHAPE_Area
```

Top feature

- Household Income in the Past 12 Months Less than $14,999

[19]:
```
state = []
i0 = top_cols[0]
for k,v in feat_dict.items():
    if i0 in v.index.to_list():
        state.append(us.states.lookup(str(k).zfill(2)).abbr)

fig = px.choropleth(locations=state, locationmode="USA-states",scope="usa",␣
 ↪title=i0)
fig.show()
```

[20]:
```
state = []
i0 = top_cols[1]
for k,v in feat_dict.items():
    if i0 in v.index.to_list():
        state.append(us.states.lookup(str(k).zfill(2)).abbr)

fig = px.choropleth(locations=state, locationmode="USA-states",scope="usa",␣
↪title=i0)
fig.show()
```

[21]:
```
state = []
i0 = top_cols[2]
for k,v in feat_dict.items():
    if i0 in v.index.to_list():
        state.append(us.states.lookup(str(k).zfill(2)).abbr)

fig = px.choropleth(locations=state, locationmode="USA-states",scope="usa",␣
↪title=i0)
fig.show()
```

[22]:
```
state = []
i0 = top_cols[3]
for k,v in feat_dict.items():
    if i0 in v.index.to_list():
        state.append(us.states.lookup(str(k).zfill(2)).abbr)

fig = px.choropleth(locations=state, locationmode="USA-states",scope="usa",␣
↪title=i0)
fig.show()
```

[23]:
```
state = []
i0 = top_cols[4]
for k,v in feat_dict.items():
    if i0 in v.index.to_list():
        state.append(us.states.lookup(str(k).zfill(2)).abbr)

fig = px.choropleth(locations=state, locationmode="USA-states",scope="usa",␣
↪title=i0)
fig.show()
```

[24]:
```
state = []
i0 = top_cols[5]
for k,v in feat_dict.items():
    if i0 in v.index.to_list():
        state.append(us.states.lookup(str(k).zfill(2)).abbr)
```

```
fig = px.choropleth(locations=state, locationmode="USA-states",scope="usa",␣
↪title=i0)
fig.show()
```

[25]:
```
state = []
i0 = top_cols[6]
for k,v in feat_dict.items():
    if i0 in v.index.to_list():
        state.append(us.states.lookup(str(k).zfill(2)).abbr)

fig = px.choropleth(locations=state, locationmode="USA-states",scope="usa",␣
↪title=i0)
fig.show()
```

Takeaways:

- Machine Learning model does not capture the patterns that lead to designation.
- This likely indicates the fact that the OZ designation was based on more than just ACS data. There is likely more information considered, potentially based on local trends not present in a 5 year picture.
- In terms of modeling, some linear models, such as LinearSVC with l1 regularization did perform marginally better (f1 occasiionally exceeded .6), but the interpretation of the weights coefficient is not as evident as the feature importances in the tree model.

Further Work:

- Models could be more hypertuned.
- Feature selection and engineering could be added. Highly correlated features (such as Poverty rate with median income) could be removed to determine if that results in better performance.
- Feature selection was explored with recursive feature extraction, but the feature importances did not seem to change and the computation time improved.

[ ]:
```

```